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Stochastic forestry harvest planning under soil compaction conditions

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ABSTRACT

We present a study of annual forestry harvesting planning considering the risk of compaction generated by the transit of heavy forestry machinery. Soil compaction is a problem that occurs when the soil loses its natural resistance to resist the movement of machinery, causing the soil to be compacted in excess. This compaction generates unwanted effects on both the ecosystem and its economic sustainability. Therefore, when the risk of compaction is considerable, harvest operations must be stopped, complicating the annual plan and incurring in excessive costs to alleviate the situation. To incorporate the risk of compaction into the planning process, it is necessary to incorporate the analysis of the soil's hydrological balance, which combines the effect of rainfall and potential evapotranspiration. This requires analyzing the uncertainty of rainfall regimes, for which we propose a stochastic model under different scenarios. This stochastic model yields better results than the current deterministic methods used by lumber companies. Initially, the model is solved analyzing monthly scenarios. Then, we change to a biweekly model that provides a better representation of the dynamics of the system. While this improves the performance of the model, this new formulation increases the number of scenarios of the stochastic model. To address this complexity, we apply the Progressive Hedging method, which decomposes the problem in scenarios, yielding high-quality solutions in reasonable time.

1. Introduction

The last decades have witnessed a growing interest in the sustainable management of the exploitation of natural resources (Heinimann, 2007), as for instance in industrial forestry production (Marchi et al., 2018). One of the most important resources in the latter activities is the quality of soil (Dominati et al., [2010]; Rahman et al., [2020]). The concern for its preservation has led to a number of studies on the impact of forestry on its sustainability (Cambi et al., 2015). The conclusions and recommendations of those contributions are different according to the production specificities of different regions of the world (Kimsey et al., [2011]; García-Carmona et al., [2020]). But all of them share the conclusion that the quality of soil should be preserved, suffering the least damage possible (Ampoorter et al., [2010], Okpara et al., [2020]; Okpara et al., [2020]).

The biggest risk for the soil arising in forestry operations is the possibility of its compaction (Cambi et al., 2015). This happens when the soil yields to the pressure exerted by harvesting machinery (Page-Dumroese et al., 2006). Compacted soil affects the natural movement of fluids (gases and water) and the macroporosity of the edaphic structure (Ballard, 2000). The higher density induced by compaction depends on several factors, as for instance its initial apparent density, the size and distribution of particles, the amount of organic matter, its humidity, the slope of the terrain, the machinery used, the experience and care of the operators of the machinery, etc. (Jamshidi et al., [2008]; Cambi et al., [2015]). The porosity of the soil, can be reduced 50% or 60% due to the compaction induced by the use of machinery (Ampoorter et al., 2007), while the aeration can be reduced up to 50% (Tan et al., 2005). These effects impact on the natural quality of the soil, reducing its capacity to sustain vegetation and, in forestry plantations, affect its site index significantly (Kimsey et al., 2011). As shown by the field study of Camargo

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Corrêa and Mosquera (2011) the losses in site indexes reached 40% in plantations of *Pinus Taeda*.

Several studies aimed to find out how to mitigate the impact of forestry operations have focused on the contact pressure exerted by machinery on the soil (Cambi et al., 2015). Among those studies, one group focused on the resistance of the soil and another on how the machinery distributes its weight. The former class of investigations seeks to find methods and strategies to improve the resistance of the soil, recommending the use of leftovers of the harvest operations to reduce the contact pressure, forcing the machinery to distribute the weight on a wider section (McDonald & Seixas [1997]; Ampoorter et al., [2007]). On the other hand, the studies on the distribution of the weight of machinery focus on its design features, in particular the number of axles and the air pressure in tires. Lower pressure increases the contact surface and lowers the pressure against the soil (Alakukku et al., [2003]; Spinelli et al., [2012]). Even applying these amelioration techniques, their success depends critically on the humidity of the soil (Cambi et al., 2015). Dry soil reduces drastically the possibilities of severe compaction, due to the high degree of union among particles and their interlocking, which creates a resistance to friction-induced deformation (Hillel, 1998, McNabb et al., [2001]; Han et al., [2006]). On the other hand, increased humidity reduces the friction among particles and thus the mechanical resistance of the soil, making it susceptible to severe compaction (McNabb et al., [2001], Han et al., [2006], McNabb et al., [2001]; Han et al., [2006]).

One way to reduce the impact of forest harvesting operations on soil quality is to create good management policies. In this sense, it should be taken into account that the nature and morphology of the soil, as well as the geographical location, affect these policies (Powers et al., 2005). However, a critical factor is the capability of the soil of reducing moisture. Therefore, taking into account this capability, a policy of good management of harvest operations should include the analysis of the level of moisture in the soil before executing the operations. If the moisture level is high, the risk of compaction is also high, and would thus not be advisable to carry out harvesting operations. On the contrary, if the moisture levels are low, harvesting operations can be carried out with a low risk of compaction (Kimsey et al., 2011).

The design of harvest plans involves a complex decision-making process seeking to achieve efficient results for all the parties involved in the operations (Bettinger et al., 2010). Specifically, plans have to cover the operations of transportation, organization of the machinery and work teams, the felling tasks, among other aspects (Epstein et al., [2007]; Bettinger et al., [2010]; Rossit et al., [2019]). Since harvesting and transporting the logs have a big impact on the cost effectiveness of the operations, several mathematical models have been developed to facilitate the planning process (D'amours et al., [2008]; Rönnqvist et al., [2015]). Usually, the objectives considered in those models are of economic nature, like minimizing the costs of collecting felled logs or maximizing the results of the sales of the forestry products, or just to maximize the production of wood or its Net Present Value (NPV) (Weintraub et al., [1994]; Andalaft et al., [2003]; Beaudoin2006]; Broz et al., [2016]). In the last years, non-production goals have also received attention, as for instance the conservation of biodiversity, the protection of the environment (Belavenutti et al., 2018), or social objectives (Meyer et al., 2019).

In this work, we consider the incorporation of concern for the sustainability of the soil into the planning process. The solution requires assessing the risk of compaction posed by machinery, since in normal conditions the forest soil would be resistant enough to support heavy harvesting machinery traffic. However, when the humidity level of the soil grows, the resistance decreases and severe compaction takes place (Corrêa and Mosquera 2011). At that moment harvest operations must be suspended. This situation drastically hinders the plans made by the managers. Currently, they make annual plans some months before the start of the harvest. The managers deal with the risk of soil compaction considering the expected or average compaction scenario in a deterministic model. However, such planning strategy presents serious drawbacks at searching for efficient solutions, since soil resistance depends on uncertain weather conditions, which exhibit a high variability. We can conclude that, in order to model adequately the forest system, a stochastic programming approach seems more appropriate.

In this paper, we address the problem of designing harvesting plans taking into account the conditions of soil compaction. We focus on finding plans that differ from the usual solutions proposed by managers. Company planners generate plans using a deterministic approach on the basis of an expected scenario. Our formulation, instead, solves a stochastic version of the problem, yielding better results than the former setting. This happens because the traditional solutions present serious drawbacks when the actual scenario differs widely from the expected scenario. Meanwhile, the stochastic approach records the information from each possible scenario in the optimization process, yielding optimal solutions even for extreme scenarios.

Then, in a second stage of experimentation, we refine our model, postulating a biweekly time representation, capturing the hydro behavior of the forest system. In this format, the number of periods becomes doubled (our first experiments assume a monthly-based time representation), which implies that a larger number of scenarios have to be considered. To face this increased class of contexts we use Progressive Hedging as a resolution method (Rockafellar and Wets, 1991), which proved to be very efficient in addressing this problem by decomposing it into a set of sub-problems (one per scenario). As far as we know, this is the first work that introduces soil compaction in a stochastic model of forest harvest planning. Addressing this aspect in a plan is of vital significance if the properties of the soil are to be protected, in particular preserving the edaphic mesofauna that contributes to renewing soil nutrients. A compacted soil reduces drastically its capacity of supporting life.

The rest of the paper is organized as follows. In section 2 we present the scheduling problem of planning harvesting operations as well as the details of the soil compaction problem in humid areas affecting harvesting operations. Section 3 introduces the stochastic programming approaches and the Progressive Hedging method applied to solve the model. Section 4 presents the formalization of uncertainty in both the deterministic and stochastic formalization. Then, section 5 presents the results in the analysis of a real-world case. Finally, Section 6 presents the conclusions.

2. Harvest planning and compaction problems

In this section, we introduce the harvest planning problem to be analyzed in this paper. It is based on a real case in the Misiones province of Argentina. In that region, the climate and the soil are very favorable for the production of Pinus Taeda with a yearly growth rate of 40 m^3/h (Broz et al., [2017], Broz et al., [2018], Broz et al., [2017]; Broz et al., [2018]). We first present all the issues that have to be considered to develop an annual harvest plan as well as the guidelines followed by managers in the formulation of such a plan. Then, we discuss in depth how the compaction problem impacts on harvest plans and how to incorporate it as an additional constraint into the planning problem. Finally, we discuss how to model the phenomenon of soil compaction.

2.1. The harvest scheduling problem

This work is based on a case study of annual forest harvest, for industrial forests of the province of Misiones, in the northeast of Argentina. The specific details of this real world case are provided in section 5.1.

In the northeast of Argentina, the stands consist of *Pinus Taeda* and a local firm has to supply four different products to four different customers. These are a pulp mill, a plywood mill, a sawmill and an MDF plant, the standard demanders of primary forest products in Argentina (Peirano et al., 2020). The products are obtained from the harvested logs and differ among them by diameter and length. The production process is carried out in the same harvesting area, which lacks stocking areas. The processed products are delivered directly from there to the market. The demands are already fixed by contracts. When the internal supply from the firm cannot satisfy the contracts, external supply is purchased and delivered to clients. The price of external supply is considerably higher than the production/logistics costs of internal supply.

The stands to be harvested are connected through a network of abandoned roads. The latter were built for the plantation of the forests and abandoned afterwards. Hence, it becomes necessary to rebuild those roads (Broz et al., 2016). The quality of their construction depends on the season for which they are built: roads used in the fall or winter must be of higher quality than those used in spring or summer (consequently incurring in higher costs). Spring and summer have better weather conditions for the logistic operations, lowering the quality requirements for the roads. The cost of rebuilding the roads impacts on the decision of where and when to harvest a stand. An important point is that, even if a road is used in summer, if it is also to be used in the fall (some parts of the road network are shared by more than one stand) it must be built with the higher quality required for that season (Karlsson et al., 2004). Since the roads are used only during the harvesting period, they do not have associated costs of maintenance. The next period in which these roads are going to be used is when the forest has grown again, around 15 years later. It is cheaper to rebuild the roads then than keeping them in good shape for a decade and a half.

According to the conventional planning process, the firm has to define where to locate the harvesting equipment (Epstein et al., 2007). In our case study, the firm usually hires five subcontractors to harvest the surface specified by the plan, providing an adequate number of teams for the surface and volume of wood to be harvested. The stands are assigned to the different subcontractors and the plan specifies how the products will be supplied by the different stands. The subcontractors have different harvesting equipment, and therefore, different productivity rates. Locating a subcontractor in a stand implies incurring in high logistics costs. Consequently, once the harvest starts at a stand, the subcontractor must finish the task before moving to a new stand.

A harvest plan faces the risk of compaction induced by the level of humidity in the soil (Batey, 2009). This is a relevant issue since a compacted soil forces to stop the harvesting operations, affecting the yields of the activity. The issue gets even more complicated by the lack of certainty about the actual risk of compaction, because of the uncertainty about the conditions inducing that risk. Managers apply the simple strategy of developing an annual plan assuming the most probable scenario, with periods of high and low chance of compaction (Solgi and Najafi, 2014). The ensuing plan is carried out unless it becomes apparent that the actual situation differs substantially from that scenario. In that case, when the production is much lower than the planned one, corrective actions are exerted, increasing the purchase of products to third parties. This ensures the satisfaction of the demands of customers and the avoidance of penalties for breaching contracts. This strategy, while useful to satisfy the demand faced by the firm involves higher costs (in money and efficiency) than initially assumed.

The objective is to minimize the operational costs, including the subcontractors' location costs, harvesting and production costs, the costs of building roads, the costs of transportation and the cost of external purchases. The managers address the annual planning process considering monthly periods (Broz et al., 2017). This time representation limits the analysis to twelve periods, which reduces the complexity of the problem. Then, the managers use standard spreadsheet software to tackle the problem. While this simplifies the task for them, this procedure fails to yield optimal solutions for the real-scale planning problem.

2.2. Soil compaction

Soil gets compacted when the weight of harvesting machinery exceeds the resistance of the soil, forcing it to increase its relative density (Ampoorter et al., 2012). The machines used in forestry have a weight in the range of 5 and 40 tons, enough to exert significant pressure on soil (Eliasson [2005]; Cambi et al., [2015]). The first runs of the machines over the soil have the greatest impact; later on, the compacted soil would gain a larger resistance, reducing the impact of further runs (Han et al., 2006). The first run over the soil causes, on average, 62% of the compaction that affects the first 10 cm of soil (Williamson and Neilsen, 2000). The effects of compaction are more intense on the superficial layers of soil, decreasing with the depth (Cambi et al., 2015).

As mentioned before, one key factor contributing to compaction is the humidity of the soil, since it induces a loss in the capacity to resist load, becoming prone to yield to the pressure of machinery (McNabb et al., 2001). The relation between humidity and the susceptibility to compaction is direct up to a certain degree of humidity, after which additional wetness decreases compaction (Hillel, 1998). This is because once the pores in the soil are filled up the soil becomes more resistant, since water is an incompressible liquid (Ampoorter et al., 2012). Nevertheless, the result in this case is the creation of deep grooves in the ground (Williamson and Neilsen, 2000). These grooves affect severely the soil and its capacity to sustain life, with similar or even worse consequences than compaction (Cambi et al., 2015). This has led some authors to postulate the number and depth of grooves as an index of the loss of productivity of a portion of soil (Lacey and Ryan, 2000).

The permeability of the soil to air is also severely affected by compaction. Field studies have shown that after a harvest, if grooves have been created, the permeability to air in the first 5–10 cm becomes reduced between 88% and 96%, while without grooves the reduction is only 50% (Frey et al., 2009). Compaction also affects negatively the size of the mesofauna of the soil (i.e., the little invertebrates that enrich the soil), reducing it to up to 93% if entire trees are extracted jointly with some soil (Battigelli et al., 2004). Compaction may even affect the normal development of roots, limiting their access to water and oxygen. In some cases, this has even hampered the growth of wooden plants for 18 years after the harvest (Cambi et al., 2015).

Soil compaction is thus a phenomenon with severe consequences for the sustainability and the quality of the soil as a natural resource. The most common policies used to limit its impact are: (i) reinforcing the upper layer of the soil with wooden residues, (ii) reducing as much as possible the contact pressure of machines on the soil, (iii) wait for drier conditions of the soil, under which its load capacity becomes larger, and (iv) plan adequately the felling process (Kimsey et al., 2011) (Cambi et al., 2015). In our analysis of forestry planning, policies (iii) and (iv) become particularly relevant, since they amount to design harvest plans that aim to a sustainable management of the soil. This implies, in turn, that appropriate models of humidity in the soil are needed, to provide useful information in the planning process.

2.3. Modelling soil moisture

Misiones borders with Brazil and Paraguay and is close to the Tropic of Capricorn. The climate is tropical, without a dry season. On average, monthly rains are above 100 mm (over 1200 mm annually), and the annual average temperature is 21 °C (in summer the average is 26 °C) (Garreaud et al., 2009). This is why Misiones presents extremely good conditions for forestry: coniferous trees and eucalyptus grow around 35 and 45 cubic meters per year, respectively (Milanesi et al., 2014; Broz et al., 2018; Meyer et al., 2019). Since the whole year is rainy, the soil is permanently moist. This feature requires the analysis of the "hydrobalance" of the soil, i.e., how much water is provided by rains and how much is eliminated by the ecosystem (plants absorption, evaporation, etc.). This, in turn, must be integrated into planning models of the forestry industry. An important hydrologic concept arises as the key to this soil moisture modeling, the *potential evapotranspiration* (PET). PET represents the capacity of the natural system of eliminating water, through evaporation. PET is expressed in terms of depth of water (length units), in the same scale as precipitation measurements. The value of PET is affected by the number of daylight hours, temperature, sunny days, winds and many other climate and geographical conditions. This value changes, in particular, with the cycle of seasons of the year (Lu et al., 2005).

A representation of the soil moisture level is as the hydro-balance between precipitations and PET, expressed as follows:

$$soil\ moisture = precipitations - PET \tag{1}$$

Then, it is necessary to gather from historic reports data necessary for the incorporation of soil moisture as input in the planning activities. Table 1 shows the time series of monthly weather averages obtained from records of the last 27 years (Eibl et al., 2015). Besides temperatures and rainfall (second and third columns of Table 1), we present data on average PET values (in the fourth column of Table 1). Then, the next columns represent the hydric balance, obtained according to equation (1) (fifth column) as well as absolute and relative differences with respect to the mean (i.e. differences expressed as mm and as a percentage in the last two columns, respectively) complete the information in Table 1. This last column shows that in April, May and June soil moisture exceeds widely the mean. In those months (fall in the Southern Hemisphere) soil compaction increases significantly, and thus, becomes crucial for the determination of the optimal plan.

After identifying the fall as the period in which there is a higher risk of soil compaction, it is necessary to analyze how the relevant variables behave in those months. Even if the PET value tends to be constant over the years, the historical records of rainfall show variations, making also variable its impact on hydric balance. Rain at the different months of the fall can be analyzed as independent processes. This means that sometimes the water balance of a given month allows harvesting (because of a lower risk of compaction) while in others the activities must be suspended. Therefore, to define a planning scenario we need to incorporate the water balances at the different months.

2.4. Literature on forestry stochastic programming

Stochastic planning procedures have already appeared in the literature. For instance, Alonso-Ayuso et al. (2011) consider harvesting and road building. In that work, the authors considered a simplified version of the deterministic approach presented in Andalaft et al. (2003), where the objective is the maximization of net revenue, assuming a single product and 25 stands on an extension of 300 ha. The uncertainty is derived from the variability of prices and demand levels. The problem is solved with a Branch-and-Fix Coordination algorithmic approach. In Veliz et al. (2015), the full problem is considered again, this time adding an extra source of uncertainty, inherent in the growth rate and yields of the forest. To deal with the increase in the size of problems they apply a decomposition approach, the Progressive Hedging algorithm (Rockafellar and Wets, 1991). It works by analyzing the problem under different scenarios. Other decomposition methods have been applied to forestry production problems, as in Zanjani et al. (2013), which analyzes the use of sawmills under uncertainty stemming from the variability of production yields and demand. Varas et al. (2014) consider a similar stochastic sawmill production problem, approaching it with a robust method dealing with uncertainties of demand and raw material supply.

Garcia-Gonzalo et al. (2016) consider the impact of climate change on the growth and yield of forestry stands in the context of harvest planning. Those impacts are uncertain, and thus the authors formulate a stochastic version of the problem. In turn, Daniel et al. (2017), add, on top of the previous uncertainties, those caused by wildfires. These authors run Monte Carlo-based simulations to plan timber harvesting while reducing their potential deficits. Buongiorno and Zhou (2017) analyze a problem of forestry planning considering the growth of forests and the evolution of the price of timber as a Markov chain process. They state a Goal Programming problem taking biological and financial considerations into account. Alonso-Ayuso et al. (2018) study the problem of minimizing the risks in forestry planning by considering price and demand uncertainties. Such uncertainties are also addressed by Álvarez-Miranda et al. (2019), who study the impact of the variability in the growth of trees. These authors use a multi-objective approach considering different aspects like NPV, carbon sequestrations and the land erosion caused by road construction. On the other hand, Alonso-Ayuso et al. (2020) use a stochastic approach to solve the forest tactical-strategical planning problem on a years-long horizon. Here the uncertainty refers to timber production. Garcia-Gonzalo et al. (2020) solve a harvest planning problem taking into account the uncertainty generated by the effects of climate change on the growth of forests. Given the magnitude of the problem they face, the authors apply the Progressive Hedging to manage the computational cost of solving it.

To the best of our knowledge, there are no contributions in the literature taking into account the risk of soil compaction. The closest contribution is Álvarez-Miranda et al. (2019), which incorporates the erosion generated by building roads. Nevertheless, as discussed in previous sections, we study here the compaction of production soil and not the compaction of road soil. This difference is critical since that part of the soil used to build roads is discarded for production since the very start of the forest plan. The portion of soil used for growing trees must preserve its productivity. In consequence, we conceive this work as the first in considering the risk of compaction in the process of planning harvesting operations.

Table 1
Monthly average data for a period of 27 years (Eibl et al., 2015).

Month	Temperature (°C)	Rainfall (mm)	PET (mm)	Balance (mm)	Absolute difference with the mean (mm)	Relative difference with the mean (%)
January	26,3	163	152	11	−63	−85%
February	25,9	186	129	57	−18	−24%
March	24,9	161	117	44	−30	−40%
April	21,2	241	75	166	91	**123%**
May	18,1	176	50	126	51	**69%**
June	16,1	175	37	138	64	**86%**
July	15,9	134	39	95	21	28%
August	17,4	103	47	56	−18	−25%
Septembe	18	152	60	92	18	24%
October	21,3	182	90	92	17	23%
November	23,6	178	114	64	−10	−14%
December	25,6	135	146	−11	−85	−114%
Monthly mean	**21,2**	**165**	**88,00**	**77,60**		

3. Stochastic programming and the Progressive Hedging algorithm

The right way of addressing a problem affected by uncertainty like the one stated here is by means of stochastic programming (Birge and Louveaux, 2011). Stochastic programming allows representing the decision-making problem with all the features that decision makers must face, as well as specifically defining the relationships between the decision variables and possible scenarios. Stochastic programming can be approached with mixed-integer mathematical programming (MIP) models in two different ways, either through an extended formulation of the problem, or through a compact formulation. In the extended formulation, the variables and restrictions of the MIP model are indexed in the set of scenarios. This ensures that the values taken by the decision variables are consistent for all scenarios (i.e. they satisfy the conditions of non-anticipation). On the other hand, the compact formulation allows reducing the size of the problem in terms of variables and restrictions, by indexing the variables by information nodes (Birge and Louveaux, 2011). However, solving a problem in its stochastic version implies solving a larger and computationally more costly problem than solving it in a deterministic version (Varas et al., [2014]; García-Gonzalo et al., [2016]). In our case, we have modeled our forestry planning problem using both the extended and compact formulations. However, in both cases, the required computation times are excessive.

One way to overcome this computational limitation is through decomposition techniques, such as Progressive Hedging (PH), which decomposes the problem by scenarios (Rockafellar and Wets, 1991). By breaking down the problem by scenarios, PH allows solving small subproblems (even in parallel) that are much less costly in terms of computation, allowing addressing real-scale problems such as the case study in this work. The main characteristics of PH are detailed below, as well as the implementation used to solve our forestry planning problem.

3.1. Progressive Hedging

The framework of a multistage stochastic optimization problem can be represented as a scenario tree, as at the top of Fig. 1. We can see that paths from the root to the scenarios share some nodes. The information in nodes of a given path up to a bifurcation will be shared by all the scenarios that are reached from there. Consequently, decisions involving events represented in the shared nodes must yield the same value. This condition ensures the consistency of the solution. It is known as a *non-anticipatory constraint*. That is, nodes in the tree have the same value at all the decision vector elements associated with that node. Therefore, a problem of stochastic optimization can be written as follows:

$$
\begin{aligned}
&\min_x \textstyle\sum_{s\in S} \mathrm{Pr}_s f(x,s)\\
&s.t.\\
&\quad x_s \in C_s,\ \text{for all } s \in S\\
&\quad \textstyle\sum_{s\in S} \mathrm{Pr}_s = 1\\
&\quad x \in \mathbb{N}
\end{aligned}
$$

Here, $\mathrm{Pr}(s)$ is the probability of occurrence of scenario *s* and $f(x,s)$ is the value of the objective function for the solution vector *x* in that scenario. The solutions must be feasible at each scenario when they are considered independently and satisfy the non-anticipatory constraint on each node in the tree where the scenarios are combined. C_s represents the class of constraints on scenario *s* while $\mathscr{N}$ is the set of non-anticipatory constraints. Finally, the sum of the probabilities yields 1, as expected. This format is known as the extensive formulation of the problem, which can be either explicit or implicit (Birge and Louveaux, 2011).

As more information is included in the model (i.e., adding more scenarios), the extensive formulation becomes more complex and difficult to solve, requiring a decomposition approach. In our case, as said, we use Progressive Hedging (PH), where the non-anticipatory constraints are relaxed (Rockafellar and Wets, 1991). The basic idea of the Progressive Hedging (PH) algorithm is to relax the non-anticipatory constraints and solve the scenarios problems independently. This reduces drastically the computational effort, down from the effort of solving the entire extensive form formulation. Nevertheless, it could preclude the satisfaction of the non-anticipatory constraints, which can be rarely met in such separated scheme. To address this question, the PH algorithm iteratively solves the sub-problems of the different scenarios, gradually imposing the equalities required by the non-anticipatory constraints. Notice that, when all the variables become equal, they will be also be equal to their average. The PH algorithm works by incrementally applying the non-anticipatory constraints by penalizing deviations from the average of the values of the decision variables. The bottom part of Fig. 1 represents the tree structure decomposed by scenarios, where nodes that must respect the non-anticipatory constraints are framed by dashed circles.

Therefore, each scenario is solved independently as:

$$
\begin{aligned}
&\min_x f(x,s)\\
&s.t.\\
&\quad x_s \in C_s
\end{aligned}
$$

PH then calculates an average solution and a convergence value to determine whether the solutions are sufficiently non-anticipatory. The convergence value quantifies the deviation of the solutions from the "average" solution. If the convergence value achieved is sufficiently small (tolerance parameter), PH stops because the non-anticipation restrictions are satisfied (approximately). Otherwise, PH calculates the penalty terms, ρ, for each decision variable, proportional to both the deviation from the average and a penalty factor ρ. These penalty terms

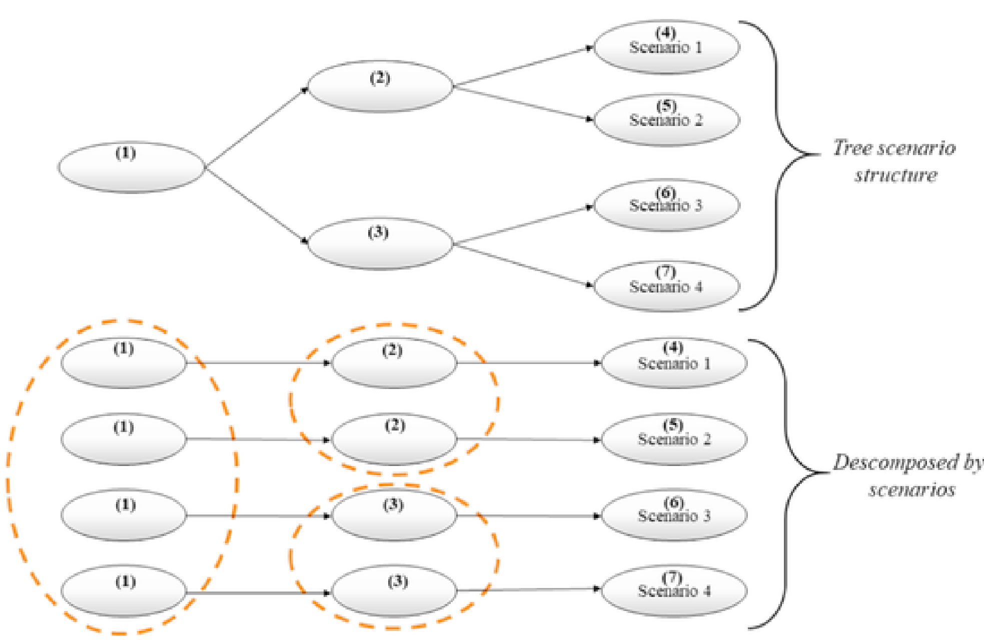

Fig. 1. Representations of the scenarios: Tree-scenario structure (top) and decomposed by scenarios (bottom).

force non-anticipatory values while solving the sub-problems of the scenarios. This process is iterated until the non-anticipatory constraints are satisfied in practice. In our case we use PH in a heuristic way, i.e. the convergence in the variables associated with the non-anticipatory restrictions is only estimated. The main reason for this modification is the high computational cost of waiting for an exact convergence. In addition, it has been shown that for practical purposes, the quality of the solution obtained is widely satisfactory (Haugen et al., 2001; Pais Martínez, 2014; Veliz et al., 2015).

The PH base algorithm used for this work is presented below in the Algorithm illustration. This base algorithm was presented in Rockafellar and Wets (1991).

Pseudocode of the Progressive Hedging Algorithm

1) Initialize: ε *tolerance*

2) $k := 0$; $g^* := \infty$;

3) $\forall s \in S\ x_s^k := argmin_{x_s} f_s(x_s)\ :\ x_s \in Q_s$;

4) $k := k+1$;

5) $\forall t \in T,\ \forall N_t \in N,\ \bar{x}_{n,t}^k := \frac{1}{|N_t|}\sum_{s \in N_t} x_{t,s}^k$;

6) $g^k := \sum_{s \in S}\sum_{t \in T}\left\|x_{t,s}^k - \bar{x}_{n(s,t),t}^k\right\|$;

7) $If\ g^k < g^* \vee \sum_{s \in S} f_s(x_s^k) < \sum_{s \in S} f_s(x_s^*)$, save best solution, $x^* := x^k$;

8) *If* $g^k < \varepsilon \vee k > k^{max}$, go to 13;

9) *If* $k \leq 1,\ \forall x_s^i,\ \rho_s^i = \rho^i(x,k,s)$;

10) $\forall s \in S,\ t \in T,\ w_{s,t}^k := \rho\left(x_{t,s}^k - \bar{x}_{n(s,t),t}^k\right) + w_{s,t}^{k-1},\ w^{(0)} = 0)$;

11)
$$\forall s \in S,\ x_s^k := argmin_{x_s} f_s(x_s) + \sum_{s \in S}\sum_{t \in T}\left[w_{s,t}^k \cdot x_{s,t} + \frac{\rho}{2}\left\|x_{t,s} - \bar{x}_{n(s,t),t}^k\right\|^2\right] : x_s \in \mathbb{Q}_s$$

12) Go to 4;

13) Use x^* as hotstart, solve Extended Formulation $min_x \sum_{s \in S} f_s(x_s)\ :\ x \in \mathbb{Q}$

In steps (1) and (2) the algorithm is initialized. In step (3) solves the decomposed problem for the first time, i.e. each scenario separately, and in step (4) the procedure is iterated, recording the results. With those results, step (5) calculates the expected values of the variables that share information between different scenarios in some node (i.e. variables that intervene in non-anticipatory restrictions). Then, step (6) calculates the distance from the solution of each scenario to the expected value. In step (7) the quality of the current solution is assessed, both in terms of convergence respect to the best one found so far x_s^*, and in terms of the objective function, updating them, if necessary. Step (8) evaluates the satisfaction or not of the halting criteria of the algorithm. Step (9) is completed at the first iteration, where the value ρ is initialized to penalize the deviations. The next step (10) calculates the weights $w_{s,t}^k$ that affect the variables that deviate from the expected value. Step (11) solves each scenario using Lagrangian relaxation considering the weights defined above. Step (12) generates the loop. Finally, once the halting criteria have been satisfied, the solution obtained x_s in the complete problem is evaluated at step (13) without further decompositions.

As stated earlier, the implementation of PH in this work is heuristic (i.e. the convergence procedure stops when practical tolerances are attained). At the same time, different methods and strategies are incorporated in the PH algorithm in order to improve its computational performance. More details can be found in the Supplementary Materials file.

4. Mix integer programming models: deterministic and stochastic

We will apply different mixed-integer linear models to address our main problem. The first one is the deterministic MIP model currently used by the managers in the real world case to design the annual plans. After that, we consider a stochastic version that improves over the former.

4.1. Deterministic model: monthly representation

Managers plan the harvest operations a year before carrying them out. Their model is deterministic. They assume a scenario (which summarizes their subjective expectations). The plan is designed to satisfy the demand contracts signed by the firm, using its own production as well as purchases to third parties. If during the execution the real scenario differs from the assumed one, the firm adjusts by changing the amounts bought to third parties.

These corrections are carried out during the year of harvest, in parallel with the evolution of the compaction of the soil. Fig. 2 depicts the flow diagram of the plan. The first step in the diagram is to calculate the annual plan using the expected scenarios as input for the planning process. Then, the calculated plan is executed. During the execution of the plan, the actual scenario reveals its features and compaction conditions take place. If these conditions still allow satisfying the demand, the plan keeps being carried out. The dashed circles in Fig. 2 under the decision diamond represent this situation, deemed as the Deterministic strategy. On the other hand, if the conditions do not allow satisfying the commitments of the firm, extra supplies are needed to fulfill the contracts. In the dashed circle to the right of the decision diamond we represent the Flexible strategy, consisting of purchasing the missing amounts of timber. Both strategies are aimed at fulfilling the contracts of the firm, but the flexible one involves the higher costs of buying from other purveyors as well as intangible complications ensuing from having to modify continuously the plan. The deterministic strategy does not allow the possibility of external purchases.

The mixed-integer model corresponding to this plan involves the following items:

Sets

- I *:* Stands, indexed by *i*
- *T:* Time periods in the planning horizon, indexed by *t*
- *E:* Harvesting equipment, indexed by *e*
- *R:* Abandoned-roads, indexed by *r*
- *M:* Markets, indexed by *m*
- *P:* Products, indexed by *p*
- *Q:* Quality types of roads, indexed by $q = 1, 2$ (1 for high quality, 2 for the low quality)
- t_{HQ}: high quality periods for road building.

Deterministic Parameters

- A_i: Area of stand *i*
- $TUC_{i,m}$: Unitary cost of transportation from stand *i* to market *m*, expressed in [$/km]
- $d_{i,m}$: Distance from stand *i* to market *m*, expressed in [km]
- s_i: Surface of stand *i* [h], h:hectare
- $vol_{i,p}$: Volume of product *p* obtained from stand *i*, expressed in [m^3h^{-1}], h:hectare
- $coc_{i,t}$: Cost of harvesting and processing 1 m^3 of wood from stand *i* in period *t*.
- $build_{r,q}$: Cost of building road *r* of quality q
- $rc_{i,r}$: Binary parameter: 1 if road *r* is necessary to reach stand *i*, 0 otherwise
- cs_e: Logistic fixed costs of locating harvesting equipment *e*.
- $OrigDes_{p,m}$: Binary relationship between product *p* and market *m*: 1 if product *p* can be delivered to market *m*, 0 otherwise.
- $demand_{m,p,t}$: Lowest possible demand of product *p* in market *m* at period *t*, expressed in [m^3].
- $Cext_{p,t}$: Cost of buying external supplies of product *p* at period *t*.
- *Cap:* Capacity of a delivery truck, expressed in [m^3]
- $N_{i,e}$: Number of time periods at which harvesting equipment *e* is needed to harvest stand *i*.

Variables

- $\delta_{i,e,t}$: Binary variable: 1 if the harvest of stand *i* by equipment *e* starts at period *t*, and 0 otherwise.

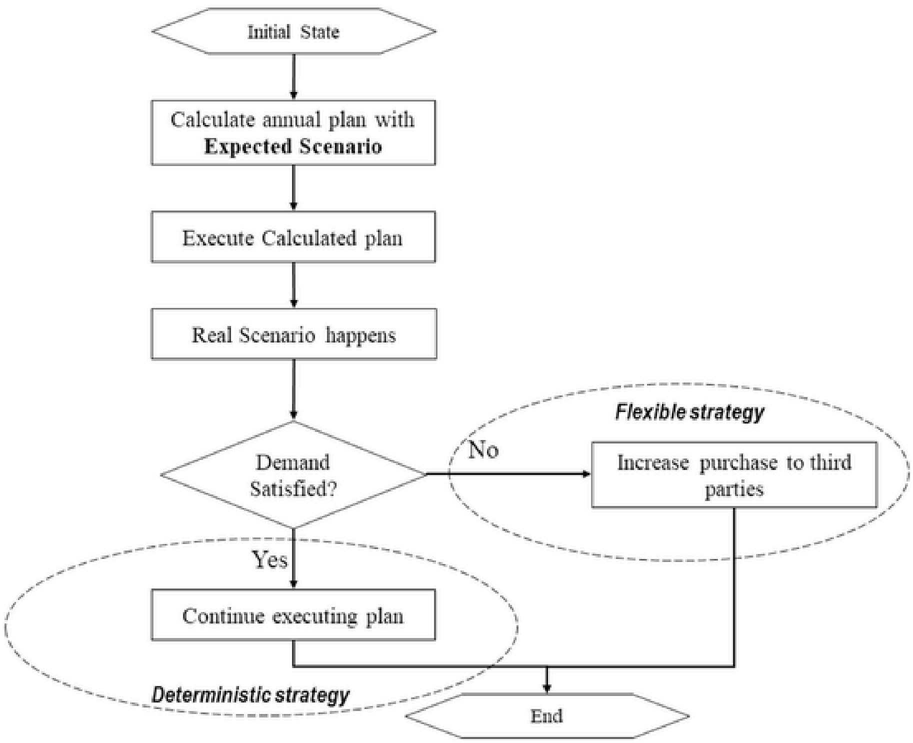

Fig. 2. Harvest plan based on the deterministic approach.

α_r: Binary variable: 1 if road r is built with high quality construction (i.e. $q = 1$), and 0 otherwise.

β_r: Binary variable: 1 if road r is built with low quality construction (i.e. $q = 2$), and 0 otherwise.

$vd_{p,i,m,t}$: Amount of product p produced in stand i delivered to market m at period t in m^3

$vc_{m,p,t}$: Volume of external purchases to supply market m with product p at period t.

z: Total cost of planning

Objective Function:

$$Min\ \ z = \sum_i \sum_e \sum_t \left(cs_e \cdot \delta_{i,e,t}\right) + \sum_m \sum_p \sum_t \left(vc_{m,p,t} \cdot Cext_{p,t}\right) + \sum_i \sum_m \sum_p \sum_t \left(vd_{p,i,m,t} \cdot TUC_{i,m} \cdot \frac{d_{i,m}}{Cap}\right) + \sum_r \left(Cac_{r,q=1} \cdot \alpha_r\right) + \sum_r \left(Cac_{r,q=2} \cdot \beta_r\right) + \sum_i \sum_m \sum_p \sum_t \left(vd_{p,i,m,t} \cdot coc_{i,t}\right) \tag{2}$$

The objective (2) is the minimization of the total cost of the plan. The first term expresses the cost of localizing harvesting equipment, the second term the cost of external purchases, the third term presents the transportation cost corresponding to a fleet of trucks (the parameter $TUC_{i,m}$ indicates different fractions of pavement and dirt roads among the paths). The fourth and fifth terms represent the costs of building roads (high quality and low quality, respectively). The last term incorporates the harvesting and processing costs.

This objective function is subject to:

$$\sum_e \sum_t \delta_{i,e,t} \leq 1,\ \forall i \tag{3}$$

Each stand can be harvested only once in the entire planning horizon and by only one harvesting equipment.

Constraints (4) and (5) indicate that any equipment e that starts harvesting a stand i at period t will be busy for the next $N_{i,e}$ periods. Constraint (4) represents the cases in which e finishes its harvesting operations at a period in T while constraint (5) considers the cases in which it does not.

$$N_{i,e} \cdot \left(1 - \delta_{i,e,t}\right) \geq \sum_{i' \neq i} \sum_{t'=t}^{t+(N_{i,e}-1)} \delta_{i',e,t'};\ \forall e, \forall i, t \in T : t + N_{i,e} - 1 \leq T \tag{4}$$

$$N_{i,e} \cdot \left(1 - \delta_{i,e,t}\right) \geq \sum_{i' \neq i} \sum_{t'=t}^{t+(N_{i,e}-1)} \delta_{i',e,t'};\ \forall e, \forall i, t \in T : t + N_{i,e} - 1 > T \tag{5}$$

Constraint (6) determines whether road r must have the highest quality since it will be used during the rainy season. The restriction is satisfied if the path r is used at any period belonging to the periods that require high quality of road, i.e. t_{HQ}. For that, in the first term, on the right side of the restriction, those stands that begin to be harvested within t_{rain} are added. In the second term, those stands that began to be harvested before the period, but that are still active during $t_{HQ}$are added. Finally, a division is made by T to ensure that the right side of the constraint is < 1.

$$\alpha_r \geq \left[\sum_i \sum_e \sum_{t \in t_{HQ}} \left(\delta_{i,e,t} \cdot rc_{i,r}\right) + \sum_i \sum_e \sum_{t+N_{i,e}-1 \in t_{HQ}} \left(\delta_{i,e,t} \cdot rc_{i,r}\right)\right] \cdot \frac{1}{T} \tag{6}$$

On the other hand, constraint (7) indicates whether road r can be built with a lower quality, considering that it will be used only during the dry season. The right side of this restriction is analogous to the one in (6), except that here we seek to consider periods outside t_{HQ}.

$$\beta_r \geq \left[\sum_i \sum_e \sum_{t+N_{i,e}-1 \notin t_{HQ}} \left(\delta_{i,e,t} \cdot rc_{i,r}\right) + \sum_i \sum_e \sum_{t \notin t_{HQ}} \left(\delta_{i,e,t} \cdot rc_{i,r}\right) \right] \cdot \frac{1}{T} \tag{7}$$

Restriction (8) is an upper bound for α_r and β_r, since the sum of them has to be at most the number of roads used during the harvesting process.

$$\sum_i \sum_e \sum_t \left(\delta_{i,e,t} \cdot rc_{i,r}\right) \geq \alpha_r + \beta_r \tag{8}$$

In restriction (9), the amount of each product p from a stand i at period t is assigned to a suitable market m.

$$\sum_{t'=t-N_{i,e}+1}^{t} \left(\delta_{i,e,t'} \cdot \frac{1}{N_{i,e}} \cdot s_i \cdot vol_{i,p}\right) = \sum_m \left(vd_{p,i,m,t} \cdot OrigDes_{p,m}\right) ; \ \forall i, \forall p, \forall t \tag{9}$$

Finally, the demand must be satisfied by the combination of internal and external supply:

$$\sum_i vd_{p,i,m,t} + vc_{m,p,t} \geq D\min_{m,p,t}; \forall m, \forall p, \forall t \tag{10}$$

4.2. The stochastic model

We can add to the previous approach a model of the uncertainty associated to the harvesting process.

4.2.1. Modeling the risk of soil compaction

The risk of compaction increases with the humidity of the soil, which depends on the rain regime, which in turn, is uncertain. Then, the uncertainty derived from the risk of soil compaction presented in section 2.3 affects the way in which harvesting operations have to be represented. The impact of compaction can be modeled in terms of the delays in the production process due to the impossibility of harvesting during certain periods of time. The displacement of machinery from a stand to another is quite costly and its logistics are complex. Thus, the alternative of changing the stand to be felled on the fly must be discarded. The risk of compaction affects then the length of the harvest at the different stands, represented by the parameter $N_{i,e}$, since delays due to soil compaction affect the stipulated harvest time for stand i. These delays can only happen in the fall and thus can last either one, two or, in the worst case, three months. Then, we replace $N_{i,e}$ by its stochastic counterpart $N^s_{i,e,t}$, representing the time it takes for the harvesting equipment e to harvest stand i under the conditions of scenario s, if operations start at period t. If no uncertainty affects the operations in a given month t then $N^s_{i,e,t}$ will be the same as $N_{i,e}$. So, for instance, if the scenario presents compaction in April and May, the stands that should be harvested in June or later (as well as those whose harvest ends before April) will not be affected by delays.

4.2.2. Generation of scenarios

As said, the uncertainty in this problem can be captured by $N^s_{i,e,t}$. Since we are considering a problem in which the events (periods at which there is risk of compaction) happen in a chronological order, different combinations of events are possible. Nevertheless, the events corresponding to the initial time periods remain fixed with respect to the other events. Then, it seems adequate to illustrate the possible scenarios (that is, the different combination of possible events) with a tree of scenarios, as shown in Fig. 3. The different scenarios represent the set of possible values of the risk of compaction.

In Fig. 3 the information is represented on a monthly basis. The root is labeled "0″ since the periods before April are basically unaffected by uncertainty (i.e. $N^s_{i,e,t} = N_{i,e,t}$, for $t \leq 3$). At t = April we get the first bi-

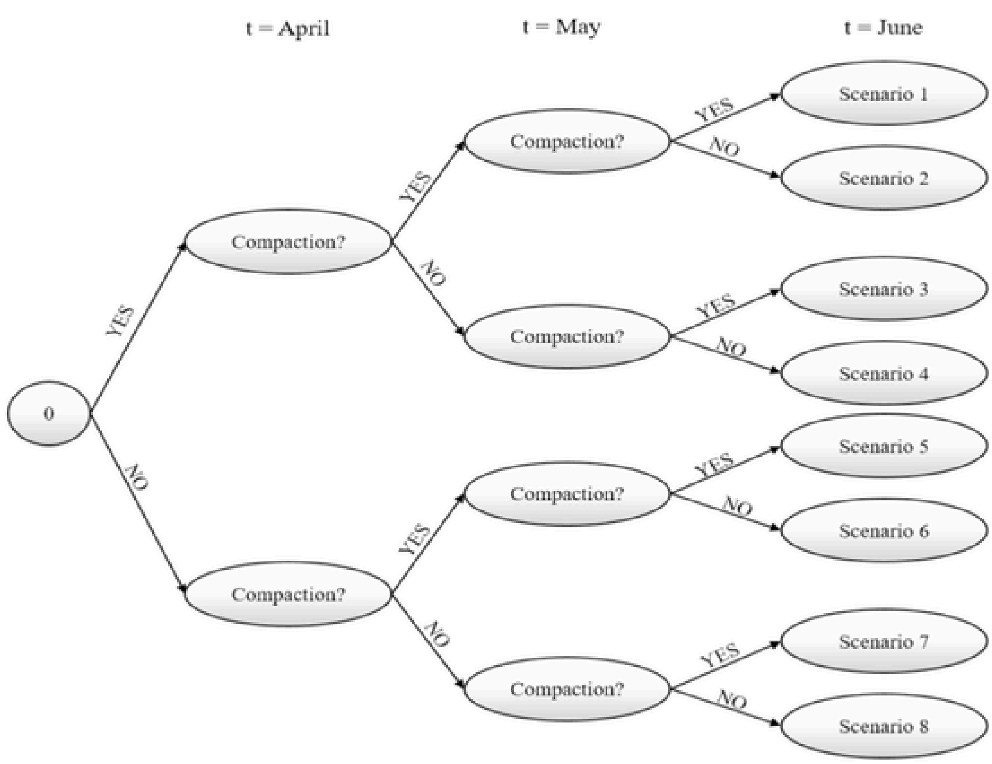

Fig. 3. Scenarios for a monthly representation of time.

furcation, corresponding to whether there is a (high) risk of compaction or not. The same goes for t = May and t = June. The different scenarios are formed according to whether the risk of compaction at each month is high or not. We choose, as usual in local practice (Broz et al., 2018), values over 45 mm per month to characterize a month as being risky. Since this is a binary variable the total number of possible scenarios is 8 (2^3), each of which is a terminal node in the tree. The probabilities of occurrence of each scenario are determined according to the historical records of rainfall, according to the independent possibility that a month's balance surpasses 45 mm. Since PET is constant, rainfalls influence stochastically the balance, thus, the probability of each scenario depends on the probability of rainfall. Then, risky months have a probability of 0.6 of surpassing the PET value in more than 45 mm.

The Stochastic MIP model is presented in full detailed in the Supplementary Material file. The main differences of the Stochastic model with the Deterministic model defined by equations (2-10) is that a new set S is incorporated, grouping the possible s scenarios. Then, in the stochastic model the decision variables become dependent on the scenario s, as for example $\delta^s_{i,e,t}$, which defines the period t in which the stand i begins to be harvested by the contractor equipment e for scenario s. The same happens with the rest of the variables.

4.3. Two-week modeling

A finer time representation would yield a more realistic model of the system. But the current practice is to generate an initial plan for 12 monthly periods, and then adjust it by hand as real-time elapses (Broz et al., 2018). These adjustments are required, for example, when a stand takes, in real terms, 1.5 months to be harvested. Since the planning period differs only by months, the parameter $N_{i,e}$ for that stand must be forced to be 1 or 2 (considering only integer values). For example, if it is forced to be 2 when e has finished harvesting that stand, the harvesting team should wait idly until the two months are over or be moved to another stand in a shorter time than planned. Another relevant consideration is that a unit (a single month) must be either labeled as "rainy" or "not rainy" while it is likely that within a month there will actually be rainy and not rainy lapses. Dry and wet streaks in a month generate efficiency losses requiring frequent reprogramming of purchases to third parties.

We propose, instead, to duplicate the number of periods in the planning horizon by considering half months (a biweekly frequency). This fits better the possible weather events affecting the system. On the other hand, this representation of time increases the size of the problem. The original 3 months become 6 periods increasing the number of possible scenarios to 64 (2^6). The same considerations as in the case of monthly periods will be valid for parameter $N^S_{i,e,t}$although T and S will be now different. This means that the schema of scenarios is similar to that described in Fig. 3, only that the branching depends on the possibility of compaction in a two-week period. Reducing the lag between two bifurcations in the diagram makes, on one hand, the representation more realistic, but on the other increases the number of scenarios, complicating the computation of solutions. To face this additional difficulty, we have to apply decomposition strategies, using the Progressive Hedging algorithm presented in section 3.1.

5. Computational experiments

5.1. The case study

A total of 40 stands are involved in the design of the plan, reaching a total harvesting area of around 1000 ha and over 300,000 m^3 of timber to be processed. There are twenty-six roads to be covered by five harvesting equipment belonging to different subcontractors, each of them with different production rates. Each of them consists of a harvester, a forwarder and loader, and all the machines and staff required for forest harvest. Four different products are obtained, each one supplying a different market (an MDF plant, a pulp mill, a plywood mill and a sawmill). The volume of each product in the stands is informed by the firm.

As indicated, the planning problem is currently addressed by the company on a monthly basis for a one-year period following a deterministic approach (Broz et al., 2018). That is, a *deterministic plan* defines the month-by-month operations to be carried out next year. The deterministic plan is defined on the basis of the expected scenario for the following year and has very little flexibility for unforeseen events that have an a priori low probability of occurrence. The managers, knowing this, address this issue by being ready to reprogram the purchases to third parties to meet the demands. Once the planned year begins, it is possible that the necessary delays to avoid soil compaction are different from expected. The managers have then to implement a "flexible" strategy consisting of acquiring different amounts to third parties than specified in the deterministic plan. We call this reprogrammed version the *flexible plan*. Here, instead, we consider an alternative based on stochastic programming. This plan assumes a decision-making process in a multistage format where the scenarios are pre-defined by the possibility of soil compaction in certain periods. As said, we require that the scenarios share the same solutions for the common segments and up to the point at which they differ.

We study the three strategies, deterministic, flexible and stochastic, for the two periodizations, monthly and biweekly. We run experiments using real-world data. We also run a sensitivity analysis of the demand to see, on one hand, how the level of demand affects production costs, and on the other, how the demand affects the robustness of the stochastic solution. The demand levels considered for this exercise are 25%, 50%, 75%, 90%, 95% and 100% of the real demand.

5.2. Results

The results obtained for the different planning models are presented below. First, the whole analysis is shown for the monthly planning case, and then for the biweekly planning one.

5.2.1. Computational justification for using Progressive Hedging

The first approach to solve the stochastic problem is to try its optimal solutions. This requires using the extensive formulation of the model. But for many real-world problems (as the one analyzed here) the use of the extensive form of the model can be unfeasible since it requires heavy use of computation resources, sometimes exceeding the capacities of the computer systems devoted to the analysis of the problem. This is exactly our case: we cannot find efficient solutions in a reasonable time if we use the extensive format.

In the case of the monthly representation (8 scenarios), the extensive form required 7200 s (i.e. 2 h) to find the best solution with a gap of more than 9%, using the CPLEX commercial solver. With the biweekly representation (64 scenarios), the same time, i.e. 7200 s, yielded a solution with a gap of more than 83%, even allowing the solver to use 20 cores of a high-performance computer cluster. Allowing it to run for 36,000 s (10 h), the gap exceeded 27%. With 72,000 s (20 h) and using 20 cores, the gap was reduced to 7.8%.

For a realistic representation of the solution process, we also run it on a personal computer with 4 cores, similar to the one that is actually used by the firm. After 72,000 s, the optimality gap was 10.3%. It is clear that it is unfeasible to devote 20 h of the managers of the firm to obtain a solution. Thus, the use of PH contributes to reducing the time required to solve the problem.

5.2.2. Monthly representation

The results of the three strategies (deterministic, flexible and stochastic) for monthly planning periods are presented in Table 2, which shows the total costs of meeting the demands of the four markets to be

Table 2
Costs of stochastic, flexible and deterministic production plans for the eight scenarios, the % differences are defined with respect to the stochastic cost.

Scenarios	Stochastic [$]	Deterministic		Flexible	
		Scenario cost [$]	% Difference	Scenario cost [$]	% Difference
1	10,664,883	*infeasible*	–	99,868,544	13.2%
2	88,148,260	99,868,864	13.3%	99,868,864	13.3%
3	88,445,574	99,868,864	12.9%	99,868,864	12.9%
4	65,954,816	*infeasible*	–	100,641,173	52.6%
5	89,118,015	*infeasible*	–	99,868,544	13.2%
6	65,401,338	99,868,864	52.7%	99,868,864	52.7%
7	67,851,661	99,868,864	47.2%	99,868,864	47.2%
8	47,602,801	*infeasible*	–	100,641,173	111.4%
Expected	$85,690,150				

supplied. The results of the deterministic model respond to an expected scenario, which may not coincide with any particular scenario, but it is still possible to calculate the potential performance of the plan at each particular scenario (as shown in Table 2). To do this, we apply the solution of the deterministic plan taking up the value of the parameters of each particular scenario. This yields the value of the objective function at each scenario. Let us note that the deterministic solution can be infeasible for some particular scenarios. All this is evidenced in Table 2.

The procedure to find the results with the flexible strategy is similar, but is only executed in the cases in which the deterministic solution fails to meet the demand (as indicated in Fig. 2). It is clear that in their planning process managers will not accept computer runs taking more than 20 h.

Table 2 shows that the expected cost of the stochastic plan is around AR$ 85 million (AR $ 85,690,150), while the cost of the deterministic plan is almost AR $ 100 million (AR $ 99,868,864). This implies that the stochastic solution reduces costs by 15% with respect to the deterministic plan, around AR $ 15 million. This improvement obtains thanks to the incorporating of more information into the problem. Furthermore, if the solutions obtained are analyzed on specific scenarios, the stochastic plan shows even more benefits, since the deterministic plan is not feasible for four of the eight possible scenarios. On the scenarios in which the deterministic plan works, the stochastic plan yields a considerably lower cost. For example, at scenario 6 the stochastic plan costs 50% less than the deterministic plan.

In the scenarios in which the deterministic plan is not feasible, we implement the flexible strategy, as it would be done by the managers. But this strategy only solves the infeasibility, increasing purchases from third parties until reaching the demanded amounts. But this implies incurring in a high cost since a cubic meter of any of the four products purchased from third parties is significantly more expensive than one produced by the firm. This is clear in the case of scenario 8, in which the flexible plan generates a cost that more than doubles that of the stochastic plan.

We can also analyze the impact of varying the level of demand. Fig. 4 shows the variation of costs of the annual stochastic plan as a function of the demands. We can see that this relationship tends to be linear. A closer look reveals the existence of two different responses, one for values up to 90% of the demand and the other for those between 90% and 100%. In both, the relation is linear, although in the latter case it is a bit steeper, meaning that variations in demand have more impact on costs at higher than at lower levels of demand.

The impact of the level of demand on the three strategies is reported in Table 3. The deterministic solution has a very poor performance. For instances where the demand is considerably lower than 100% of the actual demand, the deterministic approach provides a feasible solution for only two of the eight possible scenarios. This indicates how sensitive to the demand this form of planning is. In specific scenarios, the deterministic solutions have a higher cost than stochastic ones, with differences ranging from 31.5% to 50%. For the Flexible case, these costs increase, starting at 48% and rising up to 67%. This increment obeys to the fact that the flexible strategy is more dependent on external supply. However, this larger external supply enlargement allows meeting the demand in 6 of the 8 possible scenarios (the deterministic plan is feasible only in 2 scenarios).

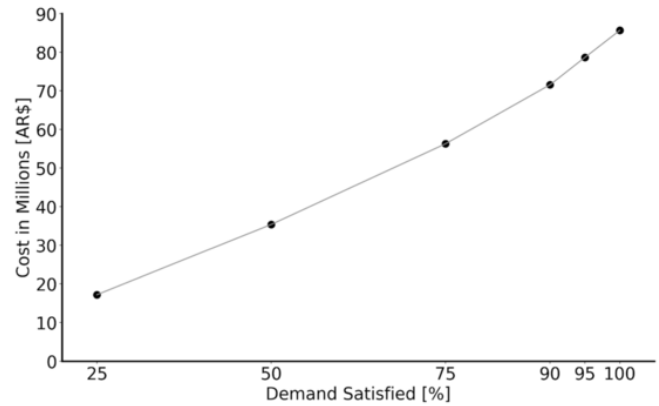

Fig. 4. Sensitivity of the costs of the stochastic plan to variations of total demand in the monthly planning periods.

Table 3
Solutions at different levels of demand at the monthly planning periods. The ***% difference in cost*** is the average percentage on feasible scenarios, with respect to the corresponding stochastic solution.

Demand satisfied	Stochastic	Deterministic		Flex	
	Expected cost	% difference in cost	Number of infeasible scen	% difference of cost	Number of feasible scen
25	$ 17,229,210	34.7%	6	69.8%	0
50	$ 35,372,994	50.9%	6	67.4%	0
75	$ 56,292,781	40.0%	6	61.2%	0
90	$ 71,586,575	37.7%	6	56.8%	0
95	$ 78,729,296	32.1%	6	51.3%	0
100	$ 85,690,150	31.5%	4	48.4%	0

5.2.3. Biweekly time representation

Biweekly planning procedures duplicate the number of periods, which is why the PH algorithm is used to calculate the production plans. The solutions obtained by means of PH do not ensure, in general, the optimal solution to discrete problems. However, PH yields an annual planning for this more realistic and difficult problem. In our case, we can verify the quality of the solutions by comparing them with the solutions obtained with the deterministic and/or flexible approach.

In Table 4 (in the Appendix), we present the results with stochastic, deterministic, and flexible plans for the 64 scenarios. We can see that the deterministic plan is not able to generate a feasible solution to the problem. This shows that the solutions obtained with the tools used by managers are very unreliable (this is why they limit themselves to the monthly representation). We can see that only by resorting to the flexible strategy, it may be possible to use a more atomized representation of time periods. In turn, the stochastic approach generates feasible production plans for all possible scenarios, with a total expected cost just over AR $ 96 million. Comparing the costs of the plans obtained with the stochastic solution to those obtained with the flexible strategy (column "gap"), we find that they can be considerably different, ranging from 62% on scenario 29 to a negative 9% (Scenario 2). On average, the stochastic approach achieves a 23% improvement over flexible plans. However, when looking at specific scenarios, we observe that there are cases where the flexible strategy yields better results than the stochastic strategy (those in which the gap is negative). This happens because there are scenarios that have parameters similar to those of the expected scenario. Therefore, since the flexible strategy uses the deterministic solution as a basis (calculated on the expected scenario), it yields better results than the stochastic solution when scenarios are similar to the expected one. On the other hand, it is possible to see that the cost of the stochastic solution tends to be lower than the cost of flexible plans.

We can analyze the behavior of the proposed resolution method at different conditions of the problem, running the same sensitivity analysis to the demand as for the monthly planning periods. For this, we set the demand at 95%, 90%, 75%, 50% and 25% of the demand used to obtain the results in Table 4. The deterministic approach again does not yield feasible solutions. Table 4 presents a comparative summary of the results under the stochastic and the flexible approaches. The number of infeasible scenarios as well as the gap between the stochastic solutions and the flexible solution is shown according to the type of strategy. To characterize the gap, we show the maximum, minimum and average improvements due to the adoption of stochastic planning instead of flexible planning.

In Table 4 the number of infeasible scenarios indicates that the stochastic approach is clearly superior to the deterministic approach since the latter is unfeasible at all the scenarios. On the other hand, with respect to the flexible approach, in all cases, the stochastic solution reduces the average cost of the flexible solution. The stochastic solution yields a production plan saving more than 17%. In turn, as the demand to be satisfied decreases, the average improvements of the stochastic solution tend to increase, reaching peaks of 51% for the 50% of real demand. The largest improvements of the stochastic plan obtain with lower levels of demand. This can be explained by noting that, as the demand to be satisfied decreases, the stochastic plan satisfies it with a higher proportion of its own production. The satisfaction of demand by increasing purchases from third parties proper of the flexible strategy is much more expensive.

Fig. 5 depicts the relationship between the costs of the expected stochastic solution and the percentage of demand to be met. The relationship tends to be fairly linear: the higher the level of demand, the higher the cost of the production plan. In turn, unlike the monthly case, when demand levels approach 100% the slope of the line tends to decrease.

5.2.4. Comparison of the monthly and biweekly time representations

Before comparing and discussing the results of the previous sections it is worth to mention that the costs calculated in the two models, monthly and biweekly, do not represent exhaustively all the costs and expenses that the company must face. However, this is not the main objective when deciding the management plan. The crucial element is not

Table 4
Comparison of solutions for different demand levels in the biweekly approach.

Demand Percentage	Stochastic solution	Based on Deterministic Model				
		No. Infeasible scenarios		GAP		
		Deterministic	Flexible	Max	Min	Average
25%	$ 19,294,138	64	0	108%	−13%	44%
50%	$ 36,991,199	64	0	113%	0%	51%
75%	$ 61,059,206	64	0	79%	−3%	34%
90%	$ 79,790,729	64	0	83%	−17%	26%
95%	$ 91,352,349	64	0	89%	−8%	18%
100%	$ 96,891,656	64	0	62%	−9%	23%

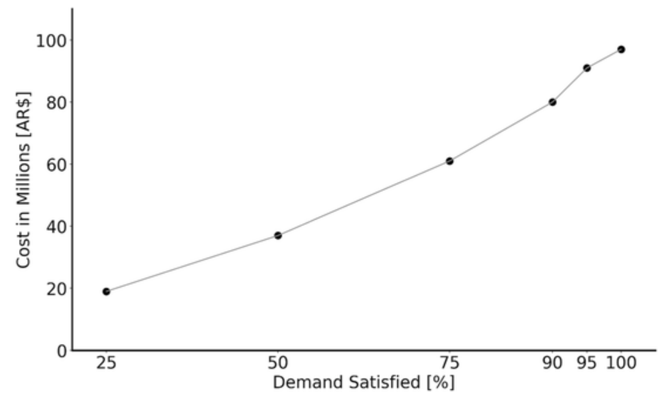

Fig. 5. Sensitivity of the costs of the stochastic plan against variation of the total demand in the biweekly approach.

the final cost obtained by each plan, but the sequence of decisions associated to the plans. In this sense, the main difference between the monthly and biweekly model is that the latter allows improving our ability to represent the real problem faced by the managers. This is due to the possibility of capturing the higher variability within a month, with periods at which we are or not able to harvest. This can be captured by the biweekly model, but not by the monthly one. Therefore, the biweekly model allows decisions to be made that more faithfully represent the situations that managers may face, thus improving their decision-making capacity, which will result in lower real costs.

The stochastic solutions can be compared for the two representations of the planning periods (monthly or biweekly). We find that the cost of the expected plan for the monthly stochastic solution (ES-M) is around AR $ 85 million, while for the biweekly stochastic solution (ES-F) it is of almost 97 million AR $. This indicates that ES-F is more expensive than ES-M. So, the move towards a better representation of the problem (the biweekly representation fits better the temporality of forestry operations) seems to imply a loss of planning efficiency. But a closer examination shows that the contrary happens.

The scenarios with rains will always be more expensive than the scenarios without rain, being in the latter the supply of the production of the firm at its maximum. Therefore, in the monthly representation there exists only one scenario at which it does not rain at any one of the months of the fall, representing 1 of 8 scenarios (12.5% of the scenarios). While in the biweekly representation there is also only one scenario in which it does not rain at any period (biweekly). Since the total number of scenarios is 64, this means that it does not rain only in 1.5% of them. Although it is true that these percentages are affected by the probabilities, we can notice the difference implies that the ES-F will incorporate purchases from third parties in more scenarios (in 98.5% of them), raising the cost of the expected stochastic solution. As an illustration, consider the scenario for the monthly representation in which it does not rain during one of the three critical months, implying that in three of the eight possible scenarios there will be a month in which the production of the firm is able to satisfy the demand. In the biweekly representation, instead, if there is no rain in a period, there will be a half month of full provision, but this will be the case of only 6 of the 64 possible scenarios. Even so, recall that the biweekly representation provides a more reliable characterization of the conditions of soil compaction.

However, the biweekly representation yields a better model of the harvesting dynamics (the duration of $N_{i,e}$ is more realistic at this frequency), as well as of the hydrological balance of the soil, and consequently, of the risk of soil compaction. As mentioned above, considering fifteen-day intervals allows a better representation of the harvesting operations, since the duration of these operations depends on the equipment that each contractor possesses, the size of the stand and the volume of wood, among other factors. Therefore, considering a time representation finer than a monthly one allows us to improve the representation of the impact of all these aspects in the definition of $N_{i,e}$. On the other hand, the biweekly periods also represent much better the hydrological balance of the soil, and therefore, the risk of compaction. As shown in Section 2.3, the risk of compaction depends on the humidity level, which is directly linked to the rainfall regime. Thus, considering "rainy" periods of a full month is less realistic than considering biweekly "rainy" periods. In other words, in the biweekly modeling, the occurrence of two consecutive “rainy” periods (i.e. a “rainy” month) is still possible, but it also incorporates the scenarios in which the whole month is not rainy, making harvest possible during part of that month. In turn, modeling the periods biweekly allows considering 2 consecutive periods of rain, actually belonging to different months. This last case gets lost in the monthly model, despite being equivalent to a rainy month. Therefore, biweekly modeling has several advantages over monthly modeling, other than the values of the objective function.

5.2.5. Discussion

This work is intended as a contribution to the literature that promotes stochastic programming as a valuable tool for forest planning. It is interesting to note that many of those studies have captured different uncertain features faced by planners, such as the price of products (Alonso-Ayuso et al., [2011]; Buongiorno & Zhou [2017]), the volume of wood to be harvested (Veliz et al., 2015) and variations in demand levels (Álvarez-Miranda et al., 2019). The risk of soil compaction, instead, has not been previously addressed in that literature. This work contributes to filling that gap by incorporating this critical factor in the harvesting operation. In this sense, the results of our research show that with an adequate approach it is possible to plan operations to be carried out even in the most unfavorable weather seasons. It is important to emphasize that advanced stochastic programming methods such as PH are required to find solutions modeling bi-weekly time intervals.

Although we found that stochastic programming is an effective approach to this planning problem, our future research agenda includes the development of weekly-based models. This is relevant because it seems to make more statistical sense to try to predict rainfall on a weekly basis using the historical record. But such level of detail could induce a very volatile behavior (for example, if it were possible to distinguish whether the first or the second week of April is rainier) or even affect the independence of the distribution of variables. On the other hand, an aspect that has become increasingly important in different economic activities is the impact of the carbon footprint. It indicates how economic activity affects the production of greenhouse gases. Forest harvesting uses heavy machinery, which requires large amounts of fuel. Then, it could be interesting to incorporate this factor into harvest plans to reduce those emissions. Another line of research could be to consider a version of the problem in which different objectives could be considered simultaneously, such as maximizing the monetary income and reducing the distances covered by trucks. In this case, a promising approach is Goal Programming (Díaz-Balteiro et al. al. 2017).

6. Conclusions

This paper addresses the problem of planning annual forest harvests. The version of the planning problem addressed here is of special interest, since it seeks to incorporate the risk of soil compaction as a restriction to harvesting operations. The risk of compaction is a phenomenon closely related to the rainfall regime with its inherent uncertainty. The recommendation is not to harvest when soil moisture is very high, since the risk of severe compaction is also very high. In turn, when the humidity level is lower, the recommendation is to harvest. Then, a policy of good planning management is to take into account the level of soil moisture as an input of the decision-making process.

Currently, companies in the field solve the problem with a deterministic model using information from the expected scenario. If during the execution of the plan, the real scenario departs from the expected one, the managers adjust the plan by purchasing products from third parties to meet the demands of the clients. These adjustments force the companies to incur in higher costs than those of self-production. We developed a stochastic model that deals with the uncertainty derived from the risk of soil compaction. This stochastic model prevents the plan from being infeasible at any of the scenarios. In turn, the plan obtained by stochastic programming allows meeting customer demands at a considerably lower cost than the deterministic plan, reducing the costs in up to a 15%.

We also introduced a biweekly representation that allows to model in a more realistic way both the dynamics of the harvesting operations, as well as the hydric balance of the soil and its associated risk of compaction. This biweekly representation induces a considerably larger computational effort than the monthly one, since the planning periods become 24 instead of 12, and the number of possible scenarios is now 64 instead of 8. The deterministic strategy usually applied by forestry companies gets overwhelmed in this biweekly representation of the problem. Feasible solutions can then only be obtained using a flexible strategy. The stochastic programming model, instead, yields solutions for all the scenarios of the problem. To cope with the additional computational effort that biweekly representation requires, we applied a Progressive Hedging-based method. It allows obtaining high-quality solutions with a lower computational effort than the problem in the extended formulation. Although the solutions obtained with Progressive Hedging are not optimal, they improve by far those of the methods currently used by managers.

On the other hand, an analysis of the sensitivity of planning costs to the volume of demand shows that a piecewise almost linear relation exists between those two variables. In this sense, the deterministic strategy is very inefficient. As a future line of research, we aim to incorporate new uncertainties to the problem, as those associated to the projected demands.

Credit author statement

Daniel Alejandro Rossit: Conceptualization, Investigation, Software, Validation, Writing – original draft preparation, Funding acquisition, Writing- Reviewing and Editing. Cristobal Pais: Data curation, Investigation, Writing- Reviewing and Editing, Software, Validation. Diego Broz: Data curation, Conceptualization, Resources, Validation, Writing- Reviewing and Editing. Andrés Weintraub: Supervision, Investigation, Writing-Reviewing and Editing. Mariano Frutos: Funding acquisition, Writing- Reviewing and Editing. Fernando Tohmé: Supervision, Writing- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix.

Results of the Biweekly approach

Table 4
Costs of the stochastic, flexible and deterministic production plans for the sixty-four scenarios. The differences are reported with respect to the cost of the stochastic plan.

Scenarios	Stochastic	Deterministic	Flex	
			Cost	Gap
1	$ 85,468,941	Infeasible	$ 122,355.136	43%
2	$ 129,281,757	Infeasible	$ 117,233,591	−9%
3	$ 118,287,590	Infeasible	$ 116,877,803	−1%
4	$ 102,246,024	Infeasible	$ 116,877,803	14%
5	$ 102,845,578	Infeasible	$ 118,343,364	15%
6	$ 118,680,040	Infeasible	$ 117,233,591	−1%
7	$ 99,357,895	Infeasible	$ 117,233,591	18%
8	$ 95,854,851	Infeasible	$ 116,877,803	22%
9	$ 104,970,622	Infeasible	$ 118,135,512	13%
10	$ 81,994,280	Infeasible	$ 117,233,591	43%
11	$ 102,445,922	Infeasible	$ 117,233,591	14%
12	$ 83,974,700	Infeasible	$ 116,877,803	39%
13	$ 100,312,924	Infeasible	$ 119,421,228	19%
14	$ 93,348,890	Infeasible	$ 117,233,591	26%
15	$ 97,181,094	Infeasible	$ 117,233,591	21%
16	$ 112,074,694	Infeasible	$ 116,877,803	4%
17	$ 89,994,859	Infeasible	$ 115,431,511	28%
18	$ 110,428,807	Infeasible	$ 117,233,591	6%
19	$ 105,243,207	Infeasible	$ 117,233,591	11%
20	$ 87,152,282	Infeasible	$ 116,877,803	34%
21	$ 94,715,857	Infeasible	$ 120,133,122	27%
22	$ 121,793,273	Infeasible	$ 116,877,803	−4%
23	$ 116,038,462	Infeasible	$ 116,877,803	1%
24	$ 89,397,903	Infeasible	$ 116,877,803	31%
25	$ 93,200,094	Infeasible	$ 121,119,887	30%
26	$ 96,324,497	Infeasible	$ 117,233,591	22%
27	$ 87,917,272	Infeasible	$ 116,877,803	33%
28	$ 123,400,305	Infeasible	$ 116,877,803	−5%
29	$ 76,521,126	Infeasible	$ 124,222,359	62%
30	$ 92,819,455	Infeasible	$ 117,233,591	26%
31	$ 85,688,603	Infeasible	$ 117,233,591	37%
32	$ 79,505,734	Infeasible	$ 116,877,803	47%
33	$ 77,214,800	Infeasible	$ 118,446,965	53%
34	$ 106,851,172	Infeasible	$ 117,233,591	10%
35	$ 106,034,868	Infeasible	$ 117,233,591	11%
36	$ 123,515,179	Infeasible	$ 116,877,803	−5%
37	$ 108,582,901	Infeasible	$ 118,446,965	9%
38	$ 99,866,701	Infeasible	$ 117,233,591	17%
39	$ 104,197,549	Infeasible	$ 117,233,591	13%
40	$ 87,288,358	Infeasible	$ 116,877,803	34%
41	$ 105,117,754	Infeasible	$ 121,119,887	15%
42	$ 105,102,529	Infeasible	$ 117,233,591	12%
43	$ 104,726,435	Infeasible	$ 116,877,803	12%
44	$ 96,239,351	Infeasible	$ 116,877,803	21%
45	$ 87,616,771	Infeasible	$ 121,119,887	38%
46	$ 94,245,901	Infeasible	$ 117,233,591	24%
47	$ 85,933,543	Infeasible	$ 117,233,591	36%
48	$ 96,771,065	Infeasible	$ 116,877,803	21%
49	$ 120,415,559	Infeasible	$ 121,119,887	1%
50	$ 125,778,497	Infeasible	$ 117,233,591	−7%
51	$ 86,943,430	Infeasible	$ 117,233,591	35%
52	$ 88,863,366	Infeasible	$ 116,877,803	32%
53	$ 99,461,316	Infeasible	$ 118,343,364	19%
54	$ 87,722,590	Infeasible	$ 117,233,591	34%
55	$ 81,841,358	Infeasible	$ 117,233,591	43%
56	$ 97,316,377	Infeasible	$ 116,877,803	20%
57	$ 102,439,968	Infeasible	$ 118,343,364	16%
58	$ 76,572,451	Infeasible	$ 117,233,591	53%
59	$ 79,988,282	Infeasible	$ 117,233,591	47%
60	$ 82,221,585	Infeasible	$ 116,877,803	42%
61	$ 75,632,443	Infeasible	$ 118,343,364	56%
62	$ 76,799,511	Infeasible	$ 117,233,591	53%
63	$ 82,567,121	Infeasible	$ 117,233,591	42%

Scenarios	Stochastic	Deterministic	Flex	
			Cost	Gap
64	$ 109,007,919	Infeasible	$ 116,877,803	7%
Expected	$ 96,891,656	–	–	**Average** 23%

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.113157.

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