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Gabriel Durães Guth

Exact and heuristic methods for the forest harvest planning problem

Dissertação de Mestrado

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Advisor: Prof. Luciana de Souza Pessôa

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I dedicate this dissertation to my parents, Avelange Pereira Durães and Guilherme Vitor Guth, who spared no effort in ensuring a quality education and encouraging me to pursue my dreams. I especially dedicate this to my father, who is no longer physically present with us but would have been immensely proud to see his child become a master in production engineering. I love you both, all of this was possible because of you.

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Abstract

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Brazil is one of the world's leading producers and exporters of pulp and paper, benefiting from favorable climatic and soil conditions, coupled with substantial investments in research. A significant challenge in this sector is the Forest Harvesting Planning Problem (FHPP), akin to a derivative of the Vehicle Routing Problem (VRP) featuring a heterogeneous fleet, periodic demand, and wood volume gain. This study addresses FHPP by employing Mixed Integer Linear Programming (MILP) modeling and the Greedy Randomized Adaptive Search Procedure (GRASP) metaheuristic across real and simulated scenarios to optimize the sequencing of harvesting teams among stands. The objective is to reduce operational costs and enhance volume growth over a 12-month planning horizon, while also considering time windows and scheduling constraints. A total of 12 instances were tested to evaluate GRASP's performance, with the metaheuristic matching or outperforming the MILP model in nine cases. Additionally, three instances reflect real scenarios from a major Brazilian pulp and paper company. When compared against the company's planning team results, GRASP achieved up to a 61.9% reduction in total costs. Furthermore, GRASP provides detailed harvesting plans within a short execution time, reducing planning team workload and enhancing decision-making flexibility.

Keywords

Forest Harvest Planning Problem; OR in Industry; GRASP Metaheuristic; Vehicle Routing Problem; Pulp and Paper Supply Chain.

Resumo

Guth, Gabriel Durães; Pessôa, Luciana de Souza. **Métodos exatos e heurísticas para o problema de planejamento da colheita florestal**. Rio de Janeiro, 2024. 63p. Dissertação de Mestrado – Departamento de Engenharia Industrial, Pontifícia Universidade Católica do Rio de Janeiro.

O Brasil é um dos principais produtores e exportadores de celulose e papel no mundo, beneficiando-se de condições climáticas e de solo favoráveis, além de investimentos substanciais em pesquisa. Um desafio significativo nesse setor é o Problema de Planejamento de Colheita Florestal (PPCF), semelhante a um derivado do Problema de Roteamento de Veículos (VRP), com uma frota heterogênea, demanda periódica e ganho de volume de madeira. Este estudo aborda o PPCF utilizando um modelo matemático de Programação Linear Inteira Mista (MILP) e a metaheurística *Greedy Randomized Adaptive Search Procedure* (GRASP) em cenários simulados e reais para otimizar o sequenciamento dos times de colheita entre as unidades produtivas. O objetivo é reduzir os custos operacionais e aumentar o crescimento do volume ao longo de um horizonte de planejamento de 12 meses, considerando também as restrições de janelas de tempo. Um total de 12 instâncias foram testadas para avaliar o desempenho do GRASP, sendo que a metaheurística superou o resultado do modelo MILP em nove casos. Além disso, três instâncias refletem cenários reais de uma grande empresa brasileira de celulose e papel. Quando comparado aos resultados da equipe de planejamento da empresa, o GRASP alcançou uma redução de até 61,9% nos custos totais. Além disso, o GRASP fornece planos de colheita detalhados em um curto tempo de execução, reduzindo a carga de trabalho da equipe de planejamento e aumentando a flexibilidade na tomada de decisões.

Palavras-chave

Problema de Planejamento da Colheita Florestal; PO na Indústria; Metaheurística GRASP; Problema de Roteamento de Veículos; Cadeia de Suprimentos de Papel e Celulose.

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1
Introduction

The pulp and paper industry plays a crucial role in the global economy, due to significant investments in research, technology, and employment, alongside the high revenue generated across all stages of the production chain. While digitization threatens the demand for printing and writing paper, the pulp market has grown substantially, with the production of packages and disposable products such as tissues, diapers, and sanitary pads. Additionally, there are cellulose applications in sustainable alternatives such as bio-fuels, adhesives, and pharmaceuticals [1].

In the context of the pulp and paper industries, the raw material for the processes are tree logs. Among these, certain species stand out due to characteristics such as wood quality, extractive content, density, time to maturity (rotation), required area, and soil for growth, among others. According to IBGE [2], in 2021, Brazil had a total planted area of 9.5 million hectares. Of these, 7.3 million hectares were eucalyptus and 1.8 million were pine trees, with both being major inputs for the pulp and paper industry.

According to data from the Energy Research Company (EPE) and the International Energy Agency (IEA) in collaboration with the Brazilian Tree Industry (IBA) [1], Brazil is one of the main producers and exporters of paper and cellulose globally, being highly competitive in cellulose production. This is primarily due to forestry factors, such as the country's climate and soil, and a focus on Research and Development (R&D) activities related to forest management techniques, genetic improvement, and sustainable practices. In 2020, Brazil ranked second globally in cellulose production, reaching 21 million tons per year (11.3% of the global output), trailing only behind the United States, which produces 50.9 million tons [3].

Additionally, wood fibers from eucalyptus (short fibers), the main fiber for cellulose in Brazil, take an average of 6 to 8 years to reach the ideal cutting point. In contrast, pine (long fibers), the main fiber in colder regions takes an average of 15 to 20 years. This favors Brazil with higher productivity and lower production costs for cellulose. Consequently, the country leads the ranking of the world's largest cellulose exporters, reaching a volume of 15.8 million tons (22.8% of global exports) [4].

Given this scenario, the size of the available productive area and the financial impact of the sector have led to increased proposals for optimization models to solve problems in the pulp and paper sector. These models consider studies on transport scheduling, distribution of physical areas, biodiversity, wood quality, and others [5]. One of the main challenges faced is the annual forest harvest planning, which directly impacts other processes in the pulp and paper production chain, such as forestry, road network construction, logistics, production, export, and more.

Furthermore, within the forest harvesting planning activity, there is the challenge of defining the routing of harvesting teams across various forest areas, impacted by base locations, harvesting capacity, forest growth, and climatic and contractual considerations. Therefore, this work aims to study and analyze the Forest Harvest Planning Problem (FHPP), which can be classified as an extension of the Vehicle Routing Problem (VRP) with a heterogeneous fleet, periodic demand, time windows, and volume growth by time.

The Vehicle Routing Problem (VRP) and its derivatives are considered NP-hard [6, 7]. Hence, instances with a large number of points to be visited become very complex or it is not possible to find a viable solution within a reasonable computational time using exact methods alone, necessitating the application of metaheuristics that have proven effective in solving this type of problem [8]. Thus, this study aims to solve the FHPP by developing exact and heuristic methods, comparing the results obtained between them on real instances from a Brazilian pulp and paper company. Therefore, the objectives of this work can be divided into present a variant of the forest harvest planning problem, emphasizing the sequencing of harvest teams, scheduling harvesting and the annual volume growth in forests; apply exact models and heuristic methods to solve the problem, contributing to the literature on Vehicle Routing Problem (VRP) and its derivatives.

This work is structured as follows. Section 2 describes the related literature articles with problems and applications similar to FHPP, common characteristics present in other standard optimization problems (TSP, VRP, Scheduling), and the use of MILP and metaheuristic techniques like GRASP resolving these problems. In Section 3, the Forest Harvest Planning Problem (FHPP) is presented. Section 4 details the mathematical model for performing forest harvest planning. In Section 5, the GRASP metaheuristic is developed to obtain good-quality solutions for the mathematical model. Section 6 covers the results and tests conducted using the MILP model and GRASP on instances of the FHPP. In Section 7, a case study is presented comparing the GRASP algorithm and the plan executed by the planning team of a big Brazilian pulp and paper company in real-world instances. Finally, in Section 8 the main conclusions of this study and the next steps of the research are established.

2
Related literature

The studies related to tactical planning in the pulp and paper industry present various Operational Research (OR) models applied to support decision-making. Those deal with activities such as harvesting and forwarding, location of harvesting machines, road construction, delineation of harvesting areas, integration between harvesting and transportation, wood supply to factories, and others [9].

Audy et al. [10] provide a review of various applications of Timber Transportation Vehicle Routing Problems (TTVRPs). The authors highlight that VRP problems in wood transportation differ from general routing problems due to the specific characteristics of the sector, such as large forest areas, industrial context, type of transportation, and fleet ownership.

A well-explored problem in the literature involves examining numerous road configurations to select the most cost-effective construction option, considering the return on wood volume while meeting the needs of harvesting, forestry, and wood transportation operations. Road construction decisions for transportation systems are guided by economic factors and physical, geographical, and topographical constraints of forest areas. Murray and Church [11] provide a solution based on three approaches for operational forest planning problems. They developed algorithms based on Interchange, Simulated Annealing, and Tabu Search to maximize the return from monthly wood harvesting minus road construction costs.

Guignard et al. [12] addressed the problem of optimizing the net present value of profit in forest harvest planning, considering budget constraints and road building costs. The objective is to explore different budget models and constraints to improve the efficiency and outcomes of forest management. The solution involves using advanced mathematical programming techniques and metaheuristic approaches, such as trigger constraints and branch-and-bound methods, to achieve practical and optimal results within reasonable computational times.

Quintero-Méndez and Jerez-Rico [13] worked on optimizing tactical forest planning to maximize profit and carbon sequestration while considering constraints like harvesting and transportation costs. The objective is to develop a metaheuristic-based model to improve the decision-making process for forest management. The solution presented utilizes a Tabu Search algorithm to effectively handle the complexity of the optimization problem. Ferrari et al.

[14] presented the problem of scheduling forest harvest operations to minimize harvest costs taking into account investments in wood purchase, freight and production cost. The objective is to develop an effective scheduling strategy that can handle the constraints and variabilities inherent in forest management. The authors propose a metaheuristic approach combining simulated annealing and genetic algorithms, demonstrating its efficiency and robustness through computational experiments.

Meignan et al. [15] presented the optimization problem of locating new access roads for forest harvesting operations to minimize construction road and harvesting costs. The objective is to develop an efficient road network using a P-forest problem model and solve it with a Greedy Randomized Adaptive Search Procedure (GRASP) with Variable Neighborhood Descent (VND). Computational experiments on both simulated and real instances demonstrate the effectiveness of the proposed method in comparison to manually designed networks.

Karlsson et al. [16] showed a MILP mathematical model for annual tactical harvest planning aiming to minimize total cost. This model considers harvesting costs (machine-dependent), displacement, road construction, wood purchase, factory logistics, and storage, with demand and capacity constraints. Naderializadeh et al. [17] represented a problem integrating the definition of harvesting blocks, road construction, and wood transportation costs. This problem is known to be NP-hard due to the use of binary decision variables, so the authors developed a new solution procedure with metaheuristic algorithms, specifically Simulated Annealing (SA), to solve this integrated model on a large scale, something not feasible with exact methods in reasonable computational times.

A model for forest harvesting and wood transportation planning was developed by Shabaev et al. [18], presenting a formulation to maximize harvested volume and revenue from sold products minus transportation costs. A linear programming model with Dantzig-Wolfe decomposition and column generation method is implemented in the Opti-Wood software. The author also proposes a constructive algorithm combined with Simulated Annealing for scheduling harvesting machines monthly to meet volume demands [19].

Pais et al. [20] addressed the challenge of managing timber production in a forest divided into harvest cells over a planning horizon, incorporating the complexities of road construction and uncertainty in market conditions and tree growth. The problem was formulated as a multi-stage stochastic programming model with scenarios representing different values of uncertain parameters. The authors used the Progressive Hedging (PH) algorithm to decompose the problem by scenarios and enhance it with various improvements for better performance. The results show that this method can handle the complexities and uncertainties inherent in real-world forestry planning, leading to robust and efficient solutions.

Søvde et al. [21] presented a problem of optimizing machine trail layout in forest harvesting, aiming to minimize the overall cost of forwarding operations in varied terrain. The challenge is modeled as a NP-hard problem, similar to the Steiner minimal tree problem, using a grid-based terrain representation with cost factors for terrain steepness and roughness. The objective function maximizes net profit by accounting for revenue from timber and costs of harvesting and forwarding. The results indicate that the Greedy Randomized Adaptive Search Procedure (GRASP) metaheuristic significantly improves the efficiency of trail layout design compared to the greedy heuristic, demonstrating its potential applicability in operational forest management.

Another type of application frequently addressed in the literature involves scheduling the harvesting operation with the aim of minimizing the total harvesting cost and maximizing the net present value of the harvesting areas, without considering the construction of roads for factory supply and machine access. Chauhan et al. [22] approached the short-term procurement planning problem in the forest supply chain, focusing on synchronizing harvesting, bucking, and transportation operations. The goal is to optimize the entire process by integrating bucking decisions into the procurement model. A two-tier column generation-based approach with a heuristic is introduced, showing significant improvements in operational efficiency.

Frisk et al. [23] addressed a forest harvest scheduling and robust utilization of harvest and transportation resources. They present a Mixed-Integer Programming (MIP) model that integrates detailed operational decisions with higher-level tactical planning, using a rolling horizon approach. Their solution involves a three-phase heuristic to decompose and aggregate the problem, balancing detailed short-term scheduling with more aggregated long-term planning.

Augustynczik et al. [24] aim to optimize forest harvesting planning and improve machine operational efficiency in a study conducted in southern Brazil. The authors propose a two-step approach to solve the problem: the first step involves a model based on the Minimum Spanning Tree Problem (MST) to determine connections between harvest areas to maximize Net Present Value (NPV), and the second step employs a Simulated Annealing (SA) heuristic to improve connectivity between areas. SA is also used by Crowe and Nelson [25] to solve the Area Restricted Model (ARM), which defines the areas to be harvested each year in a strategic planning framework with the goal of maximizing profits.

Bagaram et al. [26] addressed the challenge of incorporating climate uncertainty into forest harvest scheduling, aiming to improve the handling of large stochastic mixed integer programs. The proposed solution is a new heuristic algorithm that uses a parallelized variable fixing process within the progressive hedging framework, allowing efficient decomposition and solution of complex multistage stochastic harvest scheduling problems.

Alternatively, Bettinger et al. [27] apply a Tabu Search metaheuristic with 1-opt and 2-opt moves to maximize harvested wood volume over a time horizon, considering forest growth. Falcão and Borges [28] presented a large timber harvest scheduling problem in Portugal, encompassing a significant number of binary integer variables and constraints. The large size of the model lead to the use of genetic algorithm techniques to obtain optimized solutions within reasonable computational times.

Ríos-Mercado et al. [29] presented a different approach, based on Unit Restriction Model (URM), to address a forest harvesting problem with adjacency and environmental constraints to protect wildlife habitat and minimize infrastructure cost. The model was formulated as an Integer Programming (IP) and the parameters evaluated included the distance value between pairs of units harvested in the same period, the distance value between those considered natural reserve units, the timber volume to be harvested, the green-up period, and the minimum forest reserve area.

Pecora et al. [30] present a model that aims to decide which available wood should be transported to each processing unit in the factory (where the wood is cooked) to minimize wood density variability. The strategy was to develop a hybrid collaborative approach in two stages: the first stage consists of two iterative heuristic methods to reduce the solution search space, and the second stage involves a mathematical model for a thorough search. As a result, the study found good results, reducing solution time by 90% using hybrid methods, highlighting the advantage of these techniques.

Another important application in forest harvesting planning problems is in defining the routing of harvesting teams through stands during the planning horizon. Santos et al. [31] proposed an optimization model to minimize costs related to forest harvesting and wood transportation on a weekly/daily horizon. The developed Pure Integer Linear Problem (PILP) model considers factors such as forest production capacity, transportation capacity, time constraints, and distances. The test instances were small, with up to 30 stands and a 15-day horizon. The authors suggest implementing heuristics and metaheuristics techniques for performe larger instances.

Hansson et al. [32] present a Vehicle Routing Problem (VRP) model for routing forwarder trucks to haul wood in harvesting units. An MILP solution is proposed to solve small instances with five stands. Bordon et al. [33] presents a solution to integrate harvesting and transportation decisions in a weekly planning horizon. The problem considers the routes of the trucks and the scheduling of the harvesting crews, and an MILP solution is used to solve the problem with three machines, three production units and a five-day planning horizon. An application to define the route for the inventory team to map stand information is presented by Meneguzzi et al. [34]. The article develops a Vehicle Routing Problem (VRP) mathematical model where the concept of vehicles is replaced by "months of work.

Viana et al. [35] addressed a logistical problem involving the allocation and routing of harvesting equipment. Their study focuses on optimizing the transfer of machinery to various forest sites, considering numerous technical constraints inherent to the forestry industry. The problem is formulated as a generalization of the Travelling Salesman Problem (TSP), making it particularly challenging to solve. The proposed optimization model integrates both allocation and routing problems, aiming to minimize the total cost of equipment movement between different harvesting fronts. In a case study in Uruguay, their approach demonstrates significant potential in enhancing the economic efficiency of forest harvesting and log transport by ensuring optimal equipment planning and reducing overall operational costs.

Bredström et al. [36] developed a model for annual harvest planning considering the number of machines (harvesters, forwarders, and harwarders) and seek to minimize the total operation cost, which involves production, travelling, and movement costs of the machines. The study presents a two-step model: the first is an assignment model defining machines associated with harvesting areas, and the second is a scheduling model for machines in harvesting areas over the planning horizon.

Viana et al. [37] addressed the problem of optimizing the logistics of forest harvesting operations in Uruguay, which is crucial due to its significant impact on production costs. The authors proposed a combinatorial optimization model based on the Multi Depot Multiple Traveling Salesman Problem (MmTSP) to enhance the scheduling and routing of contractors harvesting equipment. This model is designed to minimize the costs associated with relocating equipment between different harvest sites, thereby improving the efficiency of the annual harvest plans. The results demonstrated that the proposed model can effectively reduce equipment transfer costs, thus providing a practical tool for contractor companies to develop better quality and more cost-effective harvest plans. Bredström and Rönnqvist [38] classify the harvesting operation problem, defining machine sequences and wood supply problems as Vehicle Routing Problems with Time Windows (VRPTW). They develop a solution based on a mathematical model and a heuristic to compare performance in some real instances, considering time constraints and achieving better results with the heuristic within a certain time limit.

Moura and Scaraficci [39] developed a complex planning and scheduling forest harvest and transportation involves creating daily plans over a one-year horizon, specifying the areas to be harvested, the volume of wood to be harvested and transported, while adhering to numerous constraints such as team productivity, transportation conditions and wood quality. The proposed solution is a hybrid heuristic approach that leverages the Greedy Randomized Adaptive Search Procedure (GRASP) enhanced with memory-based construction, path-relinking, and solution recombination methods. The solution involves generating an initial pool of elite solutions, followed by refining these solutions using relaxed linear models.

Gómez-Lagos et al. [8] study a problem related to forest harvesting, involving the optimization of the tactical harvest plan for fruit orchards. The decision involves considering harvest types, number of workers, harvest productivity, time windows, minimum and maximum demand, among others, over a 60-day planning horizon. The authors propose an approach with a mathematical model and the GRASP metaheuristic to minimize harvest costs, temporary and permanent worker hiring, early and late harvesting, and unharvested fruits. The mathematical model and GRASP are compared, with results showing the heuristic approach produces better outcomes in shorter computational times than the exact approach.

The literature shows a variety of problems in the context of forest planning, involving the pulp and paper industry, focusing on the forest harvesting stage. However, to the best of our knowledge, no work was found that presents the Forest Harvest Planning Problem (FHPP) to determine the sequencing of harvest teams in forest areas, aiming to minimize displacement costs and maximize forest volume growth, assuming large instances and time windows constraints.

Table 2 presents a consolidation of the works discussed in this section and the identified characteristics related to forest harvesting planning problems. In most problems evaluated in real instances, the literature points to the use of exact methods for small scenarios and hybrid solutions with heuristics for larger instances due to the complexity of the scenarios, the number of variables, and because they are mostly NP-Hard problems [6].

Therefore, this work seeks to present a exact model and metaheuristic approach to solve the FHPP with the sequence of farms harvested by each harvesting team over a 1-year planning horizon. The problem definition is described in Section 3.

Table 2.1: Classification of all related work and problems characteristics

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Murray and Church [11]	Maximize discounted net revenue minus cost of road construction	Interchange, Simulated Annealing and Tabu Search	3	-	45		✓	✓				✓
Guignard et al. [12]	Maximize net present value of timber revenues minus road building and transportation costs	MILP with branching strategies	3	-	28 - 350		✓	✓		✓		✓
Quintero-Méndez and Jerez-Rico [13]	Maximize the Net Present Value of timber production and carbon sequestration	Metaheuristic (Genetic Algorithms and Simulated Annealing)	40	-	200		✓	✓		✓	✓	✓

Table 2 (Continued)

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Ferrari et al. [14]	Minimize harvest costs taking into account investments in wood purchase, freight and production cost	MILP	4	-	-		✓	✓		✓		✓
Meignan et al. [15]	Minimize harvesting and road construction cost	GRASP with variable neighborhood descent	6-12	-	25 - 100		✓			✓		✓
Karlsson et al. [16]	Minimize the harvesting, forwarding, travelling, road construction, purchase logs and transportation costs	MILP and heuristic techniques	12	5	437		✓			✓		✓

Table 2 (Continued)

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Naderializadeh et al. [17]	Maximize net present value of revenue minus costs of road construction and transportation	MILP and Metaheuristic	-	-	400 - 900		✓			✓		✓
Shabaev et al. [18]	Maximize net revenue from sale of products minus harverting and transportations costs	Column Generation within Dantzig-Wolfe decomposition	-	14	198		✓		✓	✓		✓
Shabaev et al. [19]	Minimize the costs of logging and transport opperations, and machinery set relocating	Metaheuristic with Simulated Annealing	-	20	1000		✓		✓	✓		✓

Table 2 (Continued)

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Pais et al. [20]	Minimize the harvesting, production, transportation, road construction cost minus benefits from product sales	Multi stage stochastic programming with Progressive Hedging (PH) algorithm	4	-	118		✓			✓		✓
Søvde et al. [21]	Maximize the net profit of timber revenue minus harvesting and forwarding cost	GRASP	-	-	-		✓					✓
Chauhan et al. [22]	Minimize harvesting, transportation and outsourcing costs	MIP-based heuristic	7	-	30		✓			✓		

Table 2 (Continued)

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Frisk et al. [23]	Minimize production, tranportation, inventory costs minus net present value of not selected harvested areas	MILP and three-phase heuristic approach	9 - 12	14 - 26	285 - 584		✓			✓		
Augustynczik et al. [24]	Maximize net present value of harverst minus penaltys of wood volume and harvest blocks	Simulated Annealing	5	-	236		✓	✓				
Crowe and Nelson [25]	Maximize net present value	Simulated Annealing	3	-	50 - 100		✓	✓			✓	
Bagaram et al. [26]	Maximize the profit from timber harvest from all scenarios weigthed by probabilities	Stochastic MILP and heuristic	-	-	32 - 1363		✓	✓				

Table 2 (Continued)

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Bettinger et al. [27]	Maximize total harvest volume	Tabu Search with 1-opt and 2-opt moves	5	-	40-700		✓	✓				
Falcão and Borges [28]	Maximize net present value	Genetic Algorithm	70	-	696		✓	✓				
Ríos-Mercado et al. [29]	Maximize the harvesting profit	MILP	5 - 12	-	56		✓				✓	
Pecora et al. [30]	Minimize the difference between the target density and the average density of wood assigned to each cooker	Hybrid algorithm with heuristic methods and a exact model for a thorough search	16 - 52	-	400 - 1000				✓	✓		

Table 2 (Continued)

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Meneguzzi et al. [34]	Minime the total distance covered to visit all plots monthly	MILP	-	2	13	✓						
Santos et al. [31]	Minimize harvesting cost by transportation, operation and routing	Pure Integer Linear Programming (PILP)	7 - 12	3	12 - 50	✓	✓					
Hansson et al. [32]	Minimize routing cost	MILP	-	1	5	✓						
Bordon et al. [33]	Minimize the transportation, raw material loss and log stock cost	MILP	5	3	3	✓	✓			✓		
Viana et al. [35]	Minimize the costof harvest operation and movement between locations	MILP	12	12	77	✓	✓					

Table 2 (Continued)

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Bredström et al. [36]	Minimize production, traveling and moving cost of harvest	MILP	4	23	968	✓	✓					
Viana et al. [37]	Minimize the moving cost of equipment between harvest blocks and the base of operations	MILP	12	2 - 11	12 - 27	✓	✓		✓			
Bredström and Rönnqvist [38]	Minimize travelling time and balancing fleet variation	MILP and branching heuristic	9	4 - 16	20 - 80	✓	✓		✓			
Moura and Scaraficci [39]	Minimize the violation of constraints like demand not satisfied, volume of logs not delivered in time, wood quality, total kilometers by the teams	GRASP	-	-	-	✓	✓			✓		✓

Table 2 (Continued)

Reference	Objective Function	Methodology	Planning Horizon	Harvest Teams	Number of Stands	Harvest Routing	Harvest Scheduling	Wood Growth	Time Windows	Transportation	Spatial Area	Road Network
Gómez-Lagos et al. [8]	Minimize the costs of mechanical harvesting, hiring and dismissing permanent and temporary workers, idle time, unharvested fruits*	GRASP	60	41	67	✓	✓		✓			
FHPP (This work)	Minimize the harvesting teams routing cost minus net present value of stands wood growth	GRASP	2 - 12	2 - 10	20 - 576	✓	✓	✓	✓			

3
Problem Definition

Every year, the pulp and paper industry forecasts the volume of wood needed to obtain an estimated production volume. The strategic planning areas define which stand will be harvested in the next 5, 10, and 20 years. Various factors influence this decision, including soil composition, planting clones, age, growth rate, wood density, and quality. These factors also impact tactical planning for a one-year harvest. Therefore, to sequence the harvest, the planning team develops a monthly plan with a twelve-month horizon to meet both factory expectations and contract constraints, and that reaches the lowest possible cost.

Advance harvest planning is necessary for harvest teams to be prepared, for the factory to be informed about the wood it will receive, and for other processes such as forestry and forest management to be ready to act after the harvest stage. However, this activity can become quite complex when there are many harvest teams and stands to be sequenced, which is a common situation in large pulp and paper companies. For that reason, this study aims to present a tactical–operational level problem, denoted as the Forest Harvest Planning Problem (FHPP).

The data for the primary problem comprises a list of stands or blocks, which have been defined by the strategic area for harvesting over the next one-year planning horizon. Each block or stand corresponds to an extensive area of eucalyptus trees with similar characteristics of wood volume, average tree size, wood density, and other quality factors. Data pertaining to the stands include their geographical location, the average volume of a tree (with and without bark), areas susceptible to damage (from pests, fires, diseases, storms, and theft, among other factors), the number of trees, monthly volume growth, age of trees, distance to the harvesting team bases, distance to factories, and inter-stands distances.

For each stand, there is a route that provides access for trucks and machinery, facilitating the subsequent transportation of harvested wood to the factory. The proposed model does not consider the creation of new roads for transportation and assumes that they are already constructed.

As the stands are living assets with different characteristics, a determining factor in the FHPP is the monthly growth rate of each stand. Therefore, the volume considered for harvesting depends on the month in which the harvesting of that area will start, demanding the inclusion of scheduling characteristics in the model, thus increasing its complexity. Additionally, there are time window constraints related to the availability of the area for harvesting and the harvested volume must meet the minimum monthly demand of the processing unit without exceeding the maximum production demand.

In forest harvesting, several factors are crucial to consider and understand. A harvest team consists of a set of machines (Harvester or Feller Buncher) that perform the harvesting, workers who operate and support the harvesting, and a mobile base installed in the stand to support the operation, equipped with restrooms, rooms, water and food supply, and spaces with spare parts and repair equipment. Harvest teams typically operate in regions close to the fixed bases of residence for the workers and maintenance workshops. When the team must move to a more distant region, it is referred to as an off-base relocation, which includes additional operational costs such as accommodation, meals, and transportation.

The types of machines used in harvesting are the Harvester (Figure 3.1a), which employs the Cut-to-Length (CTL) method (cutting the wood to a specific length with the bark removed), and the Feller Buncher (Figure 3.1b), which employs the Full Tree (FT) method (cutting the entire tree with bark). These different cutting methods directly impact the productivity of the harvesting team, i.e., the time required to harvest a productive area. The CTL method is less efficient than the FT method, but as the wood is already debarked and cut, it advances a process that typically would need to be performed at some later stage, often at the mill. Another factor that impacts productivity is the type of wood, as different stands have varying characteristics in trunk circumference and wood size, affecting the volume and harvest time.

(a) Harvester.

(b) Feller Buncher.

Figure 3.1: Harvest machine types.

The harvest team's operating capacity is influenced by the parameters mechanical availability and operational efficiency, which vary from 0 to 100%.

The former pertains to the time machines are available for operation, i.e. when a machine needs to be halted for maintenance, this downtime is deducted from the total available operational time. Operational efficiency follows the same reduction concept but accounts for the decrease in operational hours due to shift changes, meal breaks, machine relocation, and other activities that impact the operation.

To relocate the harvest team's machines, a specific type of truck known as a low loader trailer is required, equipped with a ramp allowing the machines to be driven onto the platform. In some instances, certain harvest teams own their trucks, but it is more common for there to be a supplier of low–loader trailers, who is paid per relocation performed by the vehicle. Consequently, the FHPP considers the relocation cost of the low–loader from the supplier's base to the stand, between units, and its return to the base.

The FHPP objective is to produce a monthly harvest plan, which involves determining the optimal route for each of the m harvest teams, minimizing transportation costs, and maximizing wood growth, which depends on the month of choice of harvest for the stand. The plan needs to detail when the harvest team arrives and leaves from a stand f for a 12-month period. The FHPP needs to address metrics such as distance traveled, travel time, the volume of harvested wood, harvesting duration, and idle hours for each stand, while also accounting for operational nuances and the constraints outlined below. Additionally, the following assumptions are considered:

1. The harvest teams are heterogeneous and always available (deducting mechanical availability and operational efficiency). Each team can harvest only one stand at a time and must complete the harvest before moving to another stand;

2. Each stand can be harvested by only one harvest team m, and it must be entirely harvested;

3. The set-up time is defined by the time spent on traveling between different stands;

4. The initial stand for each harvest team is predefined;

5. The harvest teams must operate within a radius of no more than 100 kilometers from their respective bases, except for off-base stands;

6. Each harvest team has a maximum harvest completion deadline of 12 months. However, early completion is permitted in cases of idle machines;

7. Harvesting must adhere to stands' specific operational time windows, if they have, accounting for weather conditions, contractual obligations, road networks, and other factors;

8. Monthly wood demand at the factories must be met and fulfilled;

9. The wood volume of each stand exhibits distinct monthly growth rates over the course of a year. In this modeling approach, the harvested volume of each stand is considered relative to the initial volume plus the wood growth of stands at the start time of the harvesting process.

Figure 3.2 provides an overview of the FHPP, highlighting the sequence of stands to be harvested by a harvest team throughout the year. During each segment of travel between the stands, it is necessary to request low-loader trucks from suppliers, which make a round trip. Additionally, an operation can be observed at an off-base stand when the team exceeds the operation radius.

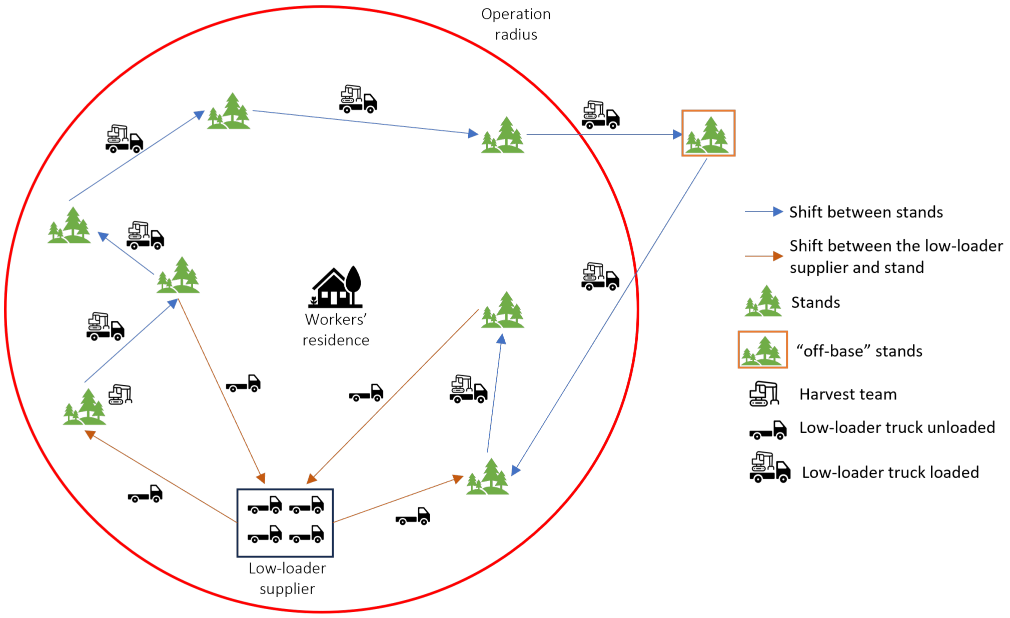

Figure 3.2: Forest Harvest Planning Problem (FHPP)

Given the data and requirements presented in this section, a wide variety of information and characteristics are simultaneously necessary for the development and execution of a forest harvest plan involving multiple harvest teams and stands. This complexity renders the planning process both critical and challenging. Therefore, the following sections will present a mathematical formulation and an approach using the GRASP metaheuristic to address this problem.

4
Formulation

The tactical forest harvest planning model developed in this work considers all of the details described in Section 3 and it is formulated as a Mixed Integer Linear Programming (MILP) model. Table 4.2 details the sets and parameters used in the exact model while Table 4.1 describes the decision variables.

Table 4.1: Definition of variables used in forest harvest planning model

Variables	
$v_{m,f,t}$	Volume harvested by harvest team m, on stand f, at month t
$y_{m,f,t}$	$y_{m,f,t} \in \{0,1\}$, where $y_{m,f,t} = 1$ if harvest team m harvest stand f at month t, 0 otherwise
$s_{m,f,t}$	$s_{m,f,t} \in \{0,1\}$, where $s_{m,f,t} = 1$ if harvest team m started the harvesting the stand f at period t, 0 otherwise
$w_{m,f,f',t}$	$w_{m,f,f',t} \in \{0,1\}$, where $w_{m,f,f',t} = 1$ if harvest team m moves from stand f to f' at period t, 0 otherwise
$z_{m,f}$	$z_{m,f} \in \{0,1\}$, where $z_{m,f} = 1$ if harvest team m harvests stand f, 0 otherwise
g_f	Indicates the volume growth of stand f
$art\_v_{d,t}^{max}$	Artificial wood volume at pulp mill d at month t that exceeded the maximum demand
$art\_v_{d,t}^{min}$	Artificial wood volume at pulp mill d at month t that did not reach the minimum demand
$art\_t_{m,t}$	The number of hours that the stand f harvest exceeded the planning horizon
$art\_tw_f^{end}$	Indicates the number of days that the harvesting of stand f exceeded the time window
$art\_tw_f^{int}$	Indicates the number of days that the harvesting of stand f was before the operating window
$art\_it_{m,t}$	Indicates the number of idle hours (without harvesting or shifting) of the harvest team m at period t

The objective function can be decomposed into seven terms to increase comprehension. The first four (Equations (4-1)–(4-4)) refer to the real costs of the planning process and the last three (Equations (4-5)–(4-7)) to the penalties of the artificial variables belonging to the model.

Table 4.2: Definition of sets and parameters used in forest harvest planning model

Sets	
$f, f' \in F$	Set of stands
$m \in M$	Set of harvest teams
$t \in T$	Set of the months for harvesting the stands
$d \in D$	Set of pulp mills destinations to send the harvested wood
Parameters	
$WG_{f,t}$	Wood growth of stand f in period t, expressed in m^3
OC_m	Cost per hour for harvest team harvesting stands f "off-base"
C_m	Cost per kilometer of harvest team m for displacement between stands
SC_m	Cost per kilometer of displacement between the low loader supplier's base of harvest team m and stand f
WP	Value of wood in market, expressed in R$/m^3
$K_{m,t}$	Number of hours available for harvest team m in period t
$V_{t,d}^{min}$	Minimum factory demand d in month t
$V_{t,d}^{max}$	Maximum factory demand d in month t
$DF_{f,f'}$	Distance between stands f and f'
$DM_{m,f}$	Distance between the base of harvest team m and the stand f
$DS_{m,f}$	Distance between the base of low loader supplier of harvest team m and the stand f
$DD_{f,d}$	Distance between the stand f and pulp mill d
$\gamma_1, \gamma_2, \gamma_3$	Artificial cost penalties for failing to comply with some constraints
IF_m	Initial stand f for harvest team m
$P_{m,f,t}$	Volume of wood that one machine of harvest team m harvest per hour in stand f, in month t
$N_{m,t}$	Number of machines of harvest team m in period t
$DT_{f,f'}$	Displacement time between stands f e f'
$V0_f$	Initial volume of stand f, expressed in m^3
FD_f	Destination pulp mill for harvested wood from the stand f
TW_f^{int}	Minimum mandatory time window for harvesting the stand f
TW_f^{end}	Maximum mandatory time window for harvesting the stand f
$OB_{m,f}$	$OB_{m,f} \in \{0,1\}$, where $OB_{m,f}$ takes value 1 if stand f is "off-base" for harvest team m, and 0 otherwise
$I0_d$	Indicates the initial wood stock volume at the pulp mill d
TH	The end of the time horizon
T_0	The first month of horizon

$$\mathcal{Z}_1 = \sum_{(m,f,f',t)\in MFFT} N_{m,t} \cdot C_m \cdot DF_{f,f'} \cdot w_{m,f,f',t} \tag{4-1}$$

$$\mathcal{Z}_2 = \sum_{(m,f,t)\in MFT} N_{m,t} \cdot SC_m \cdot 2 \cdot DS_{m,f} \cdot s_{m,f,t} \tag{4-2}$$

$$\mathcal{Z}_3 = \sum_{(m,f,t)\in MFT} N_{m,t} \cdot OC_m \cdot OB_{m,f} \cdot y_{m,f,t} \tag{4-3}$$

$$\mathcal{Z}_4 = \sum_{f} WP \cdot g_f \tag{4-4}$$

$$\mathcal{Z}_5 = \sum_{d,t} \gamma_1 \cdot art\_v^{max}_{d,t} + \gamma_2 \cdot art\_v^{min}_{d,t} \tag{4-5}$$

$$\mathcal{Z}_6 = \sum_{f} \gamma_3 \cdot (art\_tw^{int}_{f} + art\_tw^{end}_{f}) \tag{4-6}$$

$$\mathcal{Z}_7 = \sum_{m,t} \gamma_4 \cdot 0.9^t \cdot art\_it_{m,t} \tag{4-7}$$

Eq. (4-1) represents the cost of displacing all harvesting machines between stands. Eq. (4-2) depicts the cost of moving the low loader trailer between its supplier's base and the stand. Eq. (4-3) represents the cost incurred when a harvest team is assigned to off-base farms. Eq. (4-4) has a negative sign as it represents the consequent money gained from the growth of trees over the periods. Eq. (4-5) corresponds to the artificial costs of not meeting the specified demand in the period. Eq. (4-6) represents the penalty for not respecting the time window constraints of the stands. Eq. (4-7) corresponds to the penalty associated with idle hours of the harvest teams in each period, being multiplied by the factor 0.9^t to penalize non-compliance more at the beginning of the period than at the end.

$$\min \quad \mathcal{Z}_1 + \mathcal{Z}_2 + \mathcal{Z}_3 - \mathcal{Z}_4 + \mathcal{Z}_5 + \mathcal{Z}_6 + \mathcal{Z}_7 \tag{4-8}$$

s.t.

$$\sum_{(m,f,t)\in MFT} w_{m,f,f',t} = 0 \qquad \forall\ f' \in F | f' = IF_m \tag{4-9}$$

$$\sum_{(m,f,t)\in MFT} w_{m,f,f',t} = 1 \qquad \forall\ f' \in F | f' \neq IF_m \tag{4-10}$$

$$\sum_{(m,f,t)\in MFT} w_{m,f',f,t} = 1 \qquad \forall\ f' \in F \tag{4-11}$$

$$\sum_{m\in M} z_{m,f} = 1 \qquad \forall\ f \in F \tag{4-12}$$

$$\sum_{(f',t)\in FT} w_{m,f,f',t} \leq z_{m,f} \qquad \forall\ (m,f) \in MF \tag{4-13}$$

$$\sum_{(f,t)\in FT} w_{m,f,f',t} \leq z_{m,f'} \qquad \forall\ (m,f') \in MF \tag{4-14}$$

$$y_{m,f,t} \leq z_{m,f} \qquad \forall\ (m,f,t) \in MFT \tag{4-15}$$

$$\sum_{t\in T} y_{m,f,t} \geq z_{m,f} \qquad \forall\ (m,f) \in MF \tag{4-16}$$

$$y_{m,f,t} = s_{m,f,t} + y_{m,f,t-1} - \sum_{f'\in F} w_{m,f,f',t-1} \qquad \forall\ (m,f,t) \in MFT \tag{4-17}$$

$$\sum_{(m,t)\in MT} s_{m,f,t} = 1 \qquad \forall\ f \in F \tag{4-18}$$

$$s_{m,IF_m,T_0} = 1 \qquad \forall\ m \in M \tag{4-19}$$

$$s_{m,f,t} \leq \sum_{f'\in F} w_{m,f',f,t} \qquad \forall\ (m,f,t) \in MFT \tag{4-20}$$

$$\sum_{(m,t)\in MT} v_{m,f,t} = \sum_{m\in M} (V0_f \cdot z_{m,f}) + g_f \qquad \forall\ f \in F \tag{4-21}$$

$$g_f \leq \sum_{(m,t)\in MT} WG_{f,t} \cdot s_{m,f,t} \qquad \forall\ f \in F \tag{4-22}$$

$$v_{m,f,t} \leq 2 \cdot V0_f \cdot y_{m,f,t} \qquad \forall\ (m,f,t) \in MFT \tag{4-23}$$

$$\begin{aligned}\sum_{f\in F} \frac{v_{m,f,t}}{P_{m,f,t}} + art\_it_{m,t} = K_{m,t} \cdot N_{m,t}& \\ - \sum_{(f,f')\in F} DT_{f,f'} \cdot w_{m,f,f',t}& \qquad \forall\ m \in M, t \in T\end{aligned} \tag{4-24}$$

$$q_f - q_{f'} + (NF+1) \cdot \sum_{t\in T} w_{m,f,f',t} \leq NF \qquad \forall\ (m,f,f') \in MFF \tag{4-25}$$

$$\sum_{(m,f)\in MF, d\in FD_f} v_{m,f,t} \geq V^{min}_{s,d} - art\_v^{min}_{s,d} \qquad \forall\ t \in T \tag{4-26}$$

$$\sum_{(m,f)\in MF, d\in FD_f} v_{m,f,t} \leq V^{max}_{s,d} + art\_v^{max}_{s,d} \qquad \forall\ t \in T \tag{4-27}$$

$$art\_tw^{int}_f = \sum_{m\in M, t<TW^{int}_f} y_{m,f,t} \qquad \forall\ f \in F \tag{4-28}$$

$$art\_tw^{end}_f = \sum_{m\in M, t>TW^{end}_f} y_{m,f,t} \qquad \forall\ f \in F \tag{4-29}$$

Constraints (4-9)–(4-11) establish the basic conditions to allow only one transition between each stand in the planning. Constraint (4-9) states that the initial stand of each harvest will not have a predecessor. Constraint (4-10) ensures that each area, except the initial one of each harvest team, will have only one predecessor stand and Constraint (4-11) ensures that all forests will have exactly one successor.

Constraint (4-12) enforces each stand to be harvested by only one harvest team. Constraints (4-13) and (4-14) establish an upper bound limit so that each predecessor and successor farm can only transition if the harvest is allocated for that harvest team. Constraint (4-15) ensures that the stand can be harvested in any period only if the decision of harvest team was previously made for this stand. Constraint (4-16) ensures that the harvest of the stand by the harvest team must be performed in some period of the horizon if it is defined for the harvest team.

Constraint (4-17) ensure the balance of entry, exit, and operation of the harvest team in the stands. Constraint (4-18) guarantees only one entry into each stand, and (4-19) enforces the start of the initial stand of each harvest team. Constraint (4-20) ensures that the team can only begin harvesting the stand if it moves from another stand to the chosen one, except when it is the initial area of the harvest team.

Additionally, Constraint (4-21) ensures that the volume harvested in all periods for the forest equals its initial volume plus the amount the wood growth until the period it was harvested. Constraint (4-22) represents the volume growth of the forest at the time harvesting begins.

Constraint (4-23) ensures that the stand volume can only be harvested if the decision for harvesting the stand was previously made for that harvest team. Constraint (4-24) ensures that the harvest teams will operate with all available machines throughout the entire period, where the harvesting time is calculated by dividing the volume $v_{m,f,t}$ by the productivity $P_{m,f,t}$ and considering the travel time between forests. The available operating hours for each harvest team are given by the parameter $K_{m,t}$ and the variable $art\_it_{m,t}$ corresponds to the number of hours the harvest team did not operate during that period.

Finally, Constraint (4-25) ensures the elimination of sub-tours within the routes of each harvest team. The Constraints (4-26) and (4-27) ensure the harvest of the minimum and maximum volume demanded by the factory, with the creation of artificial variables if necessary. Constraints (4-28) and (4-29) ensure the transportation of stands in the periods defined in the time window.

As it will be detailed in Section 6, when this MILP model was applied to a real case it took such long time (>86400 seconds) and did not find an initial solution. Consequently, an heuristic algorithm was developed to reach near-optimal solutions and solve the problem for larger, real-world instances. This method is described in the next section.

5
Proposed GRASP for the FHPP

The meta-heuristic GRASP (Greedy Randomized Adaptive Search Procedure) is an iterative process where each iteration consists of two stages: a randomized semi-greedy constructive algorithm and a local search phase. This process continues until a stopping criterion is met, such as the maximum number of iterations, a target solution, or execution time. The structure of GRASP described by Resende and Ribeiro [40] is presented in Algorithm 1.

Algorithm 1: *Greedy Randomized Adaptive Search Procedure (GRASP)*

Input: *Data*
Output: Best Solution S^*

$f^* \leftarrow \infty$;
while *stop criterion not satisfied* **do**
    $S \leftarrow$ SemiGreedy();
    $S \leftarrow$ LocalSearch(S);
    if $f(S) < f^*$ **then**
        $S^* \leftarrow S$;
        $f^* \leftarrow f(S)$;
return S^*;

The algorithm takes the problem data as input (*Data*) and outputs the best solution (S^*). It begins by assigning an infinite cost to the variable (f^*). Then, while the stopping criterion is not met, an initial solution S is generated using the SemiGreedy() method, followed by the application of a local search on the obtained solution using the LocalSearch(S) method. If the local search yields a solution with a lower cost than the current f^* value, this solution is selected as the best, and f^* is updated with the cost of solution $f(S)$. At the end of the loop, the algorithm returns the lowest cost found among the generated solutions.

The GRASP algorithm has been explored in various practical vehicle routing problems, including general transportation applications [41], medical supply transportation [42], and waste collection [43]. As mentioned previously, GRASP algorithms for solving optimization models in harvest planning were presented by Moura and Scaraficci [39], Søvde et al. [21], and Gómez-Lagos et al. [8]. For this study, a GRASP was developed using the multi-start technique with parallel processors, which can obtain multiple solutions in shorter times [40].

The GRASP metaheuristic was selected to solve the tactical planning harvest model due to its demonstrated capability to find feasible solutions efficiently and its overall strong performance. This method tends to significantly reduce the execution time needed to obtain a high-quality solution for real-world cases similar to the FHPP. [8, 15, 21, 39]

In the following subsections, the phases of the proposed GRASP are detailed. First, the implementation of the constructive algorithm is presented in Subsection 5.1. Then, the local search methods customized for the problem are shown in Subsection 5.2.

5.1 Constructive algorithm

The Semi-Greedy Constructive Algorithm 2 aims to generate an initial solution for the Forest Harvest Planning Problem (FHPP) by creating routes for the harvest teams across all stands. The constructive algorithm customized for this problem is presented in Algorithm 2.

The algorithm begins by reading the FHPP $InstanceData$ and the "greediness" parameter α. The semi-greedy algorithm's solution S is initialized as an empty set (Line 1). The ls (Line 2) is a shuffled list constructed with all stands from the instance, and the lht (Line 3) is the shuffled list of harvest teams. Line 4 initializes an empty route for each harvest team in Solution S. The loop starting at Line 5 iterates through all the harvest teams, adding the initial stand, defined by the company, to each respective route within the solution set while concurrently removing it from ls.

Following this, the proposed method begins to explore the list ls until no more stands remain to be allocated (Line 8). The *costs* dictionary (Line 9) is initialized as empty but will be updated in each iteration to define the cost of each insertion evaluated in the semi-greedy algorithm. At Line 10 a check is performed to ensure that the list lht is not empty. If it is not, the first element of the list is selected; otherwise, a harvest team is randomly chosen.

Subsequently, the variable *cand* gets all possible stand candidates to insert in the route of harvest team *ht* (Line 14). If there are no candidate stands, the harvesting team *ht* is removed from the list lht (Line 16 and the loop restarts at Line 8. Otherwise, the cost of inserting each stand *ps* from the candidate list into the end of the harvesting team's route is calculated using the "CalculateOF" Function as described in Eq.(4-8), and added to dictionary *costs* (Line 19).

After constructing the *costs* dictionary with all candidate points and their respective costs, the restricted candidate list (RCL) is generated at Line

20, given by $RCL = \{C_i \mid C_i \leq C_{min} + (1-\alpha) \cdot (C_{max} - C_{min}) \; \forall \; i \in custos\}$, where C_{min} and C_{max} represent the minimum and maximum insertion costs of the stands ps in the *costs* dictionary, respectively. It can be noted that setting $\alpha = 1$ corresponds to implementing a purely greedy algorithm, as the lowest-cost element will always be selected at each iteration. Meanwhile, setting $\alpha = 0$ results in a completely random algorithm, where any new element may be added with equal probability at each iteration.

With the creation of the restricted candidate list (RCL), a stand is randomly selected (Line 21) and added to the route of the harvesting team (Line 22). At Line 23, the stand *selectedProdUnit* added to the solution is removed from the available stand list ls. If the harvest team has reached

Algorithm 2: Constructive: semi-greedy

Input: $\alpha, InstanceData$
Output: Initial Solution S

1 $S \leftarrow \emptyset$;
2 $ls \leftarrow$ GetAllStandsShuffled($\mathcal{F}$);
3 $lht \leftarrow$ GetAllHarvestTeamShuffled($\mathcal{M}$);
4 $routes \leftarrow$ InitializeRoutes(S);
5 **forall** $m \in \mathcal{M}$ **do**
6   AddFarmToRoute(routes, m, IF_m);
7   Remove IF_m from ls;
8 **while** $ls \neq \emptyset$ **do**
9     $costs \leftarrow \{\emptyset\}$;
10   **if** $lht \neq \emptyset$ **then**
11         $ht \leftarrow lht[0]$;
12   **else**
13         $ht \leftarrow$ RandomChoice($\mathcal{M}$);
14     $cand \leftarrow$ GetCandidateStand(ls, ht);
15   **if** $cand = \emptyset$ **then**
16   Remove ht from lht;
17   Return to Line 8;
18   **forall** $ps \in cand$ **do**
19         $costs[ps] \leftarrow$ CalculateOF($routes, ht, ps$);
20     $RCL \leftarrow$ BuildRCL($costs, \alpha$);
21     $selectedStand \leftarrow$ SelectFromRCL(RCL);
22   AddFarmToRoute(routes, ht, selectedStand);
23   Remove $selectedStand$ from ls;
24   **if** *FinishTimeHorizon*(ht) **then**
25   Remove ht from lht;
26 **return** S;

the time horizon limit, it is removed from *lht* (Line 24). After that, the loop restarts.

The constructive algorithm concludes by returning a solution containing each stand assigned to a harvest team. After completion, a local search phase is performed. In Subsection 5.2, the developed methods used in this phase are detailed.

5.2
Local search phase

Local search algorithms involve exploring the neighborhood of an initial solution with the aim of improving the solution at each iteration until reaching a local minimum. This process can be repeated until a stopping criterion is met and can be employed multiple times by changing neighborhoods and methods. In this study, five local search structures were tested: *exchange*, *relocate*, *swap-in*, *swap-out* and *2-opt*, which are among the main operators used in the implementation of local search algorithms [44]. In Section 6, more details of the local search process will be presented. However, each one was tested individually, and two new ones were created by combining all of them with different types of movements.

The first structure is the *exchange* procedure which aims to reposition the stand within the same route of the harvesting team by moving it forward and backward. In Figure 5.1, stand *e* is exchanged from their position and inserted into the same route after stand *c*.

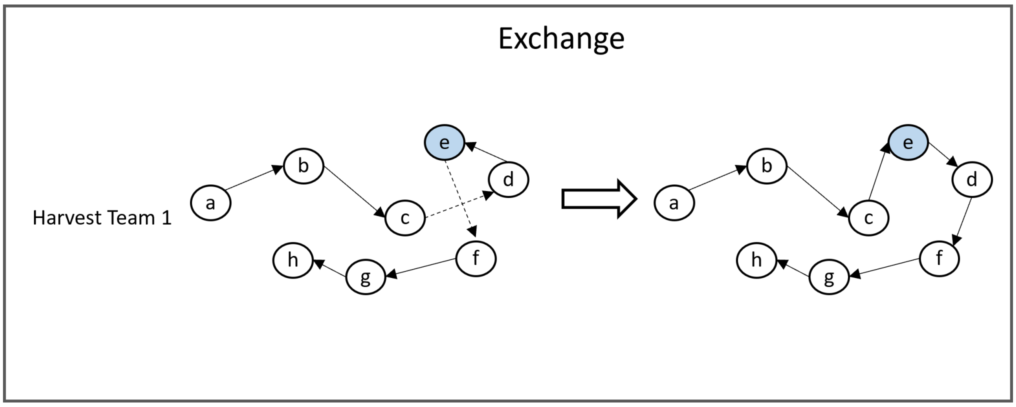

Figure 5.1: Exchange operator

The *relocate* operator (Figure 5.2) relocates a stand either within the same route or between routes of the harvesting teams when there is another position that will reduce the objective function cost. In the given example, the stand *g* from the route of harvesting team 2 is selected for the local search. Among the neighboring points, stand *b* from harvesting team 1 is the closest to it. In this case, stand g is removed from the route of harvesting team 2 and inserted into the route of harvesting team 1 after stand b.

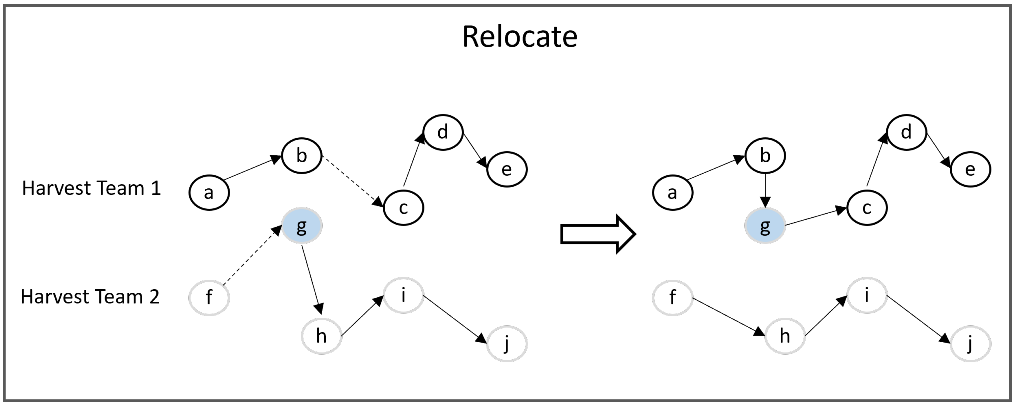

Figure 5.2: Relocate operator

The *swap-in* procedure involves swapping the positions of stands within the same route, while the *swap-out* procedure involves swapping between routes of different harvesting teams. In Figure 5.3, the *swap-in* operator is illustrated by the position changed between stands "c" and "g", with the rest of the route sequence remaining unchanged. The same logic applies to the *swap-out* operator shown in Figure 5.4, where the stands "b" and "g" are swapped between different routes.

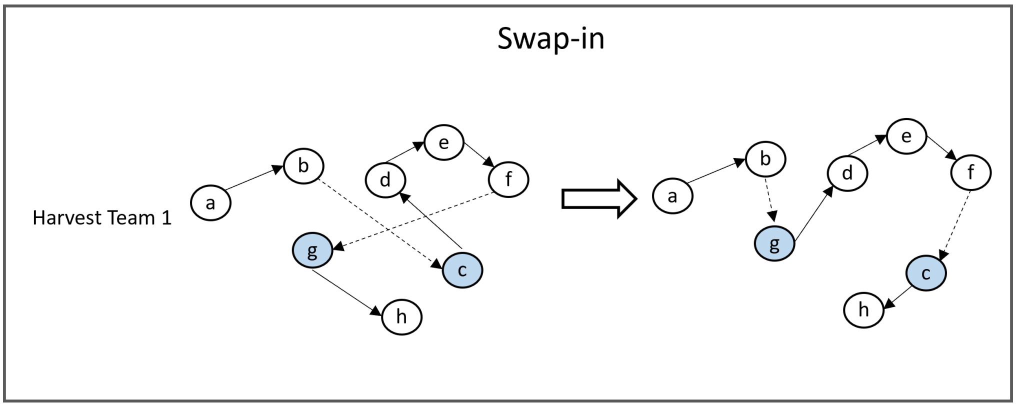

Figure 5.3: Swap-in operator

Finally, the last local search operator, commonly used in the literature, is the 2-opt. This involves removing two edges in the same route and adding two new edges by reversing the sequence direction to reduce route crossings. This operation can be seen in Figure 5.5, where edges $b \to c$ and $f \to g$ are selected to be swapped. Thus, the new order becomes $b \to f \to e \to d \to c \to g$.

In all movements performed by the local search, the cost of the scenario for each movement is calculated in the same way as given by the mathematical model (4-8). However, it must be updated for each stand from the earliest

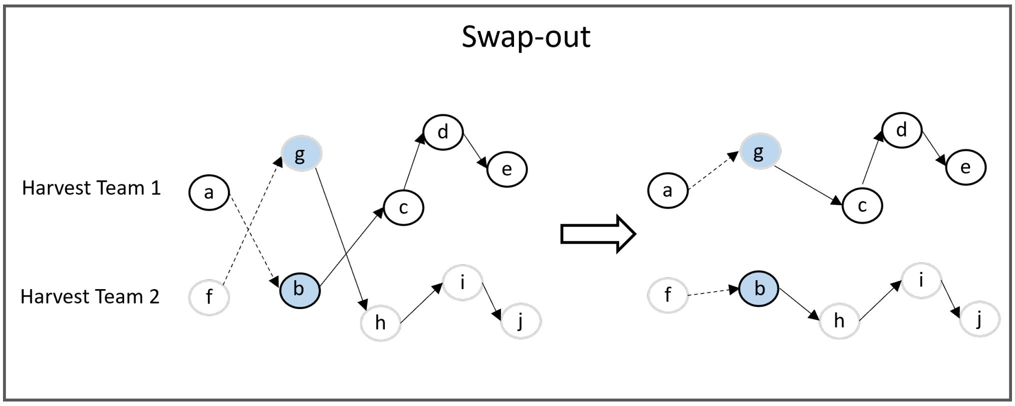

Figure 5.4: Swap-out operator

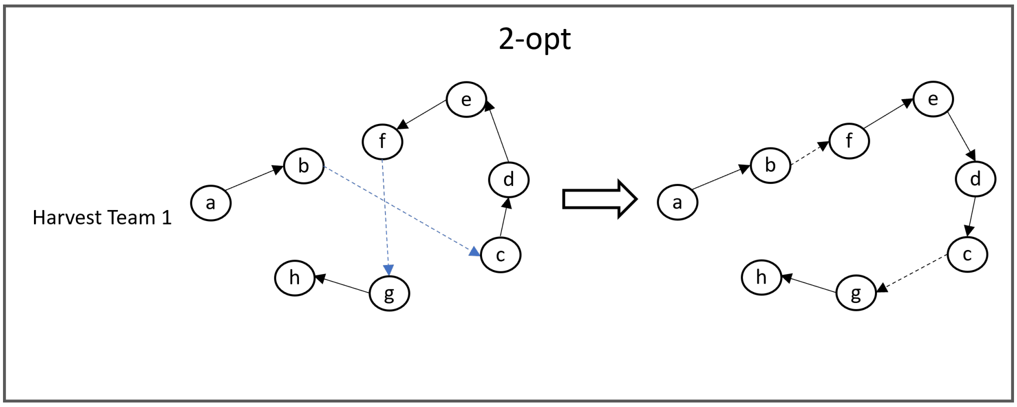

Figure 5.5: 2-opt operator

insertion position made in the harvest team's route. This is due to the cost impacts dependent on time (volume growth, harvesting productivity, time window constraints, idle time), making those operations computationally expensive.

6
Experiments

This section presents the detailed results of the execution of the MILP mathematical model (Section 4) and the GRASP metaheuristic (Section 5) on the 10 instances tested in this study. The details of the instances and the computational environment are described in Subsection 6.1. Subsection 6.2 provides a step-by-step account of the results obtained by the MILP model and the deterministic constructive algorithm, as well as the individual and combined local search methods. Finally, the results of GRASP with multiprocessing and the MILP model with a one-hour time limit are compared and discussed in Section 6.3.

6.1
Instances and computational environment

The mathematical model and the metaheuristic presented in Sections 4 and 5 were implemented in a computer with an Intel Core i7-12700 processor, 20 CPUs and 16 GB of RAM, running the Ubuntu Linux operational system. All the code was written in Python 3.11 and Gurobi 11.0 was used as the solver for exact models.

The experiments were conducted on instances provided by a large Brazilian pulp and paper company, and smaller artificial instances were created based on the original instances, varying factors such as the number of stands, harvest teams, and planning horizon. to validate the mathematical model and compare it with GRASP in solving the FHPP.

Table 6.1: Instance details

Instance	M	T	F	Binary	Continuous	Constraints
PPCF_1_6_36	1	6	36	9.245	311	2.102
PPCF_1_12_47	1	12	47	29.230	698	4.114
PPCF_2_2_20	2	2	20	2.680	279	1.364
PPCF_2_3_37	2	3	37	10.609	353	3.824
PPCF_2_6_47	2	6	47	30.211	729	6.906
PPCF_2_12_102	2	12	102	276.012	3.445	31.808
PPCF_3_2_49	3	2	49	7.296	591	3.452
PPCF_5_12_104	5	12	104	92.978	3.006	16.092
PPCF_6_6_168	6	6	168	155.612	3.559	31.408
PPCF_9_12_539	9	12	539	2.996.312	21.891	297.084
PPCF_10_12_524	10	12	524	2.781.188	18.195	281.069
PPCF_10_12_576	10	12	576	3.057.832	23.601	307.838

The 12 instances used in the experiment are described in Table 6.1. They vary in the number of harvest teams M, the planning horizon T, and the number of stands F, which consequently affects the number of variables and constraints in the model. The final three instances presented in this study represent real-world scenarios, which encompass a large number of stands to be sequenced and numerous binary variables, thereby significantly increasing the model's complexity. These instances illustrate the practical challenges faced in industrial applications, where the decision of when to harvest each stand adds to the complexity, requiring not only effective sequencing strategies but also the management of intricate timing constraints.

6.2 MILP, semi-greedy constructive and local search results

First, 10 instances to calibrate the GRASP metaheuristic were separated, evaluating the results of the semi-greedy constructive phase, each of the local search methods, and their combinations. For each of the 10 instances, the goal is to obtain the lower bound and objective values. To achieve this, the exact model was executed with a time limit of 86,400 seconds (24 hours). The obtained values will be used to estimate the GAP between the results of the MILP model, the semi-greedy constructive, and the local search methods. The results for each instance with all individual methods are shown in Table 6.2, which presents the average cost over five rounds with different seeds, and in Table 6.3, which shows the lowest cost found.

Table 6.2: GAPs from MILP, and average GAP from semi-greedy and local search methods

Instance	MILP (%)	Semi-greedy (%)	SG + Exchange (%)	SG + Relocate (%)	SG + Swap-in (%)	SG + Swap-out (%)	SG + 2-opt (%)	SG + Comb Full (%)	SG + Comb Sel (%)
PPCF_1_6_36	**0.29**	14.87	1.17	16.99	0.61	16.99	0.89	0.34	0.39
PPCF_1_12_47	**0.14**	12.89	1.32	14.86	0.46	14.58	0.79	0.22	0.28
PPCF_2_2_20	**0.00**	26.55	4.60	5.32	2.36	19.88	7.81	8.79	0.60
PPCF_2_3_37	**5.52**	85.79	17.29	86.93	13.16	71.9	19.29	15.72	11.54
PPCF_2_6_47	**0.90**	19.74	3.83	16.25	2.84	21.31	4.39	6.39	1.87
PPCF_2_12_102	Inf	22.38	2.99	6.65	2.00	22.58	2.52	16.33	**1.50**
PPCF_3_2_49	**0.01**	178.22	39.93	94.75	34.92	170.59	47.91	50.36	10.97
PPCF_5_12_104	5.20	61.06	8.67	28.68	7.47	57.90	24.40	2.50	**1.05**
PPCF_6_6_168	49.76	195.36	42.74	53.49	27.00	133.25	39.94	87.77	**20.09**
PPCF_10_12_524	Inf	96.35	84.32	72.78	82.61	87.62	89.97	76.19	**60.14**

Table 6.3: Lowest GAPs from MILP, semi-greedy and local search methods

Instance	MILP (%)	Semi-greedy (%)	SG + Exchange (%)	SG + Relocate (%)	SG + Swap-in (%)	SG + Swap-out (%)	SG + 2-opt (%)	SG + Comb Full (%)	SG + Comb Sel (%)
PPCF_1_6_36	**0.29**	10.92	0.87	14.86	0.53	14.86	0.75	0.30	0.37
PPCF_1_12_47	**0.14**	11.81	1.09	13.37	0.25	13.37	0.67	0.20	0.24
PPCF_2_2_20	**0.00**	25.06	3.07	3.59	0.78	17.13	5.87	6.42	**0.00**
PPCF_2_3_37	**5.52**	80.09	16.53	82.44	11.57	69.59	18.38	14.54	10.87
PPCF_2_6_47	**0.90**	17.47	3.06	14.78	2.57	19.76	3.44	5.77	1.51
PPCF_2_12_102	Inf	21.13	2.71	6.05	1.77	21.48	2.32	13.52	**1.34**
PPCF_3_2_49	**0.01**	155.43	34.97	78.95	29.26	156.56	34.54	43.24	8.26
PPCF_5_12_104	5.20	59.75	6.37	25.67	5.50	54.48	19.18	1.78	**0.64**
PPCF_6_6_168	49.76	185.64	37.73	45.75	24.80	129.13	32.91	82.13	**19.56**
PPCF_10_12_524	Inf	91.84	76.20	71.27	74.77	84.52	82.73	73.08	**59.84**

For most instances, the best solution objective found are negative due to the gain from the volume growth of the wood, a negative term in the objective function described in Eq. 4-4, being greater than all operational costs. The GAP for each result is calculated as $GAP = \mid ObjValue - LowerBound \mid / \mid LowerBound \mid$. In the MILP model, only instances *PPCF_2_2_20* and *PPCF_3_2_49* achieved the optimal solution value, while the others were stopped at the 86,400-second time limit. Among them, instances *PPCF_10_12_524* and *PPCF_2_12_102* did not find any incumbent solutions on the established time limit, resulting in an infeasible outcome, but the lower bound was used to estimate the performance of the metaheuristic. In three other instances, the GAP of the MILP model was less than 1%, which is a good result.

For the experiments with the semi-greedy constructive algorithm and the local searches, each instance was executed five times with different seeds and a time limit of 9,000 seconds. The parameter α for each iteration of GRASP is a randomly selected number between in the interval $[0, 1]$, because randomness in the process of choosing alpha and constructing the model facilitates convergence towards optimal results [40].

The GAP result represents the lowest cost obtained among the five different seeds executions for each method in Table 6.3 and the average of them in Table 6.2. The "Semi-Greedy" column shows the result of running only the constructive algorithm stage without any local search. Using only the constructive algorithm presented in Section 2 did not yield good solutions for the instances, with the smallest GAP being 10.92%. This highlights the need to use the local search phase.

Additionally, tests were conducted for each of the five local search methods detailed in Section 5.2. In these experiments, an initial solution was generated using the Semi-Greedy (SG) algorithm, followed by the application of local search techniques to enhance the solution. The algorithm iterated through the list of all stands in the solution and applied the best improvement strategy of the selected local search method to the entire neighborhood. If a movement reduce the solution cost, the stand was moved to the end of the list; otherwise, it was removed from the search. The local search phase ends when the list of stands is empty.

Among the local searches, the best performance was achieved by the *Swap-in* strategy, which attained GAPs below 1% in instances *PPCF_1_12_47*, *PPCF_1_6_36*, and *PPCF_2_2_20*, followed by *Exchange* and *2-opt*. However, individually executed local searches did not yield results better than or equivalent to the mathematical model, necessitating their combination. Therefore, two additional local search methods were added (*Comb Full, Comb Sel*), which refer to all combined local search movements.

The sequence of movements used in the combined methods included *swap-in, swap-out, exchange, relocate,* and *2-opt*. In the *Comb Full* method, all possible movements in the neighborhood were tested for each stand, selecting the movement that provided the greatest reduction in the objective function. However, testing all movements is computationally expensive; thus, the *Comb Sel* method was developed to limit the number of movements based on the performance of each local search.

The *Comb Sel* method was calibrated using the *relocate* movement with the five nearest neighbors, while the *exchange* movement involved advancing and retreating five positions. For *swap-out*, the five closest stands from a different harvest team sequence were selected, and finally, in the *swap-in* and *2-opt* methods, candidates were randomly selected based on half the total number of stands in that harvest team's sequence. After testing all these movements for each stand, if any improvement was found, the movement with the lowest cost was selected, and the stand was moved to the end of the list. If no improvement occurred, the stand was removed from the search.

The combined methods significantly improved the GRASP results. Notably, *Comb Sel* outperformed *Comb Full* due to the number of test movements performed in the local search. Since *Comb Full* combines all local searches and all possible movements, it requires substantial computational effort to calculate movements that do not necessarily improve the solution, resulting in fewer GRASP iterations within the limited time.

The GRASP executed with the semi-greedy algorithm and the *Comb Sel* local search achieved results superior to or equivalent to the MILP model in half of the instances, which is remarkable given that the model was run for 86,400 seconds and the metaheuristic for only 9,000 seconds. However, it should be emphasize that these are preliminary results used to assess the performance of each local search method and to calibrate the GRASP parameters.

6.3 Multistart GRASP with combined local search

After calibrating the GRASP metaheuristic with the best combination of local searches, defined as *Comb Sel* in Subsection 6.2, tests were conducted using the multi-start GRASP and the parallel processing in the MILP model with 10 threads and a 3,600-second time limit to validate their performance in a more realistic planning scenario. In this process, each thread executed an iteration of GRASP with a different seed until the stopping criterion was

Table 6.4: Multistart GRASP and MILP GAP results

Instance	MILP GAP (%)	GRASP GAP (%)
PPCF_1_6_36	**0.29**	0.33
PPCF_1_12_47	1.24	**0.23**
PPCF_2_2_20	**0.00**	**0.00**
PPCF_2_3_37	**7.94**	9.86
PPCF_2_6_47	2.30	**1.93**
PPCF_2_12_102	217.74	**1.32**
PPCF_3_2_49	**0.01**	8.58
PPCF_5_12_104	Inf	**0.85**
PPCF_6_6_168	996,31	**16.18**
PPCF_9_12_539	Inf	**55.15**
PPCF_10_12_524	Inf	**58.96**
PPCF_10_12_576	Inf	**72.54**

reached. At the end of all executions, the solution with the lowest objective function cost among all those executed across all threads was selected.

For the tests with the calibrated metaheuristic, two other real instances were added to verify the performance of the MILP and GRASP in solving the harvesting planning problem. In real-life applications, one hour is a reasonable amount of time to expect an optimized harvest plan. Table 6.4 presents the GAP results of the MILP and GRASP compared to the lower bound obtained by executing the model for 24 hours, as discussed in Subsection 6.2.

Under a more realistic execution scenario and with the same computational capacity allocated to both the MILP model and the GRASP method, it was observed that the metaheuristic demonstrated better performance, achieving a smaller GAP in 9 out of the 12 tested instances. In six instances, the GAP obtained was less than 2%, demonstrating an efficient result for GRASP. In the real instances *PPCF_10_12_524*, *PPCF_9_12_539* and *PPCF_10_12_576*, the GRASP achieved an average GAP of 62.22%, which is considered high. However, it is important to note that the exact model presented this value as the lower bound and failed to converge to an initial solution after 24 hours of execution. Therefore, the lower bound for a feasible solution is likely lower, which would reduce this GAP. This indicates a high level of efficiency of GRASP, especially in the real-world instances, where the mathematical model was unable to reach any feasible solutions within the execution time limit.

7
Case Study

After observing the capability of GRASP to efficiently solve the problem for real-world instances with short computational times, the metaheuristic results were compared to the plans created by the planning team of a large Brazilian pulp and paper company. This planning team currently constructs an annual harvesting plan and adjusts it month-by-month, with actions such as changing stands, adjusting the number of operating machines, and assessing available harvest volumes, among other factors.

The planning process typically takes between five and ten days to complete, occupies a significant portion of the planner's time, and consumes resources that could otherwise be used for more efficient plan critique and adjustment. With GRASP, it was possible to test the scenarios by setting a time limit of 3,600 seconds for each instance, representing a significant reduction in the time required to make a plan.

The last three instances mentioned in Section 6 represent data used by the planning team to create different plans. The sequence of stands defined for each harvesting team in these plans was considered, and the total cost of each scenario was calculated using the equation described in Section 4. The comparison between the result obtained by the planning team and the GRASP limited to one hour of execution is presented in Table 7.1.

Table 7.1: Planning Team vs GRASP results

Instance	$\mathcal{Z}_1 + \mathcal{Z}_2 + \mathcal{Z}_3$ (%)	$\mathcal{Z}_4$ (%)	$\mathcal{Z}_5 + \mathcal{Z}_6 + \mathcal{Z}_7$ (%)	$\mathcal{Z}_1 + \mathcal{Z}_2 + \mathcal{Z}_3 - \mathcal{Z}_4 + \mathcal{Z}_5 + \mathcal{Z}_6 + \mathcal{Z}_7$ (%)	$\mathcal{Z}_1 + \mathcal{Z}_2 + \mathcal{Z}_3 - \mathcal{Z}_4$ (%)
PPCF_9_12_539	17.3	23.7	-79.7	-137.4	-24.5
PPCF_10_12_524	19.1	48.3	-49.3	-282.2	-61.9
PPCF_10_12_576	37.3	35.9	-50.3	-721.5	-35.7
Mean	24.6	36.0	-59.8	-380.4	-40.7

All values are expressed as percentages and represent the difference between the results obtained by the GRASP method and the team's planned values. This difference was calculated using the equation $(GRASP - PLAN)/PLAN$, with positive values indicating an increase in cost (or gain) and negative values indicating a decrease. The results were presented as percentages to maintain confidentiality regarding the company's actual costs and gains. The terms presented were extracted from the rounds of each instance and were separated in a stage following execution to provide more detailed results. It is worth noting that the plan developed by the company's planning team focuses on reducing operational costs and does not account for the trade-off with the growth of the stands throughout the year.

The operational costs of the harvesting operation are represented by $\mathcal{Z}_1 + \mathcal{Z}_2 + \mathcal{Z}_3$ and correspond to the cost of travel between stands, the cost of transporting low loader trucks from suppliers, and the cost of the harvesting team operating outside their base, respectively. In all three instances, the operational costs calculated by the planning team were lower than those obtained by GRASP. In the instance *PPCF_10_12_576*, the cost associated with the operation increased by 37.3%. This tends to occur because minimizing these costs is the primary focus of the planning team, as manually evaluating the growth gain of each stand (represented by $\mathcal{Z}_4$) alongside other model constraints is nearly impossible.

Consequently, when examining the value of $\mathcal{Z}_4$, it is observed that GRASP yields a greater gain in wood growth across all instances, which is relatively higher than the additional operational cost. The instance *PPCF_10_12_524* showed a 48.3% increase in the gain from forest growth in the results obtained by GRASP. It is important to note that the gain from forest growth $\mathcal{Z}_4$ is subtracted in the objective function and is the most significant component, leading to a greater difference in the total costs of the plan. Therefore, the harvesting teams should travel further to select the optimal stands for harvesting throughout the planning horizon, allowing the more stands to grow for a longer period.

The costs associated with the artificial variables $(\mathcal{Z}_5 + \mathcal{Z}_6 + \mathcal{Z}_7)$ mainly involved the $\mathcal{Z}_7$ value, which is the penalty for idle hours of harvesting teams. This reflects a poor assignment of stands made available for harvesting throughout the year or a too large number of harvesting machines, indicating that some harvesting teams will finish their operations before the 12-month planning horizon ends. Both the plan created by the planning team and the GRASP metaheuristic solution generated this artificial variable, although the cost obtained by GRASP was lower. For comparison purposes of the final results obtained by GRASP and the planning team, all artificial cost was excluded from the total cost consolidation.

Therefore, to evaluate the final result of GRASP compared to the planning team, the following terms were considered $\mathcal{Z}_1 + \mathcal{Z}_2 + \mathcal{Z}_3 - \mathcal{Z}_4$. The cost reduction percentage ranged between -24.5% and -61.9%. In the smallest instance, *PPCF_9_12_539*, the operational cost increased by 17.3%, but this was offset by a 23.7% gain in forest growth. This gain resulted in a total cost reduction of -24.5% for that scenario. In instance *PPCF_10_12_576*, the result was even more significant: the operational cost increased by 37.3%, but the productivity gain percentage was higher than in the previous instance, representing an increase of 35.9%. Since the forest growth gain was much higher than the operational cost, the total cost difference between the planning team and GRASP was -35.7% in this scenario. Finally, scenario *PPCF_10_12_524* showed the largest total plan cost difference with a reduction of -61.9%, mainly driven by the forest growth gain, which jumped by 48.3%. This instance also saw an increase in operational cost by 19.15%, which was offset by the gain from timber growth.

The results obtained by GRASP demonstrate the efficiency of using optimization methods to aid decision-making in the forest harvesting planning problem for paper and cellulose companies. These results were presented to the company's planning team, who were impressed with the outcomes achieved in just one hour of execution and the potential solutions provided. They highlighted that the annual base plan is prepared well in advance for the next year, usually three months ahead, to define contracts with suppliers, fleet and machinery requirements, production forecasts, and available harvest areas. These definitions impact the harvesting plan and often change until a final decision is made by the company. Therefore, having a robust harvesting plan allows for early analysis of changes, reducing harvesting costs for the company and improving coordination with subsequent stages in the supply chain for the paper and cellulose industry.

The impact of using an optimization tool in this process enables the creation of a harvesting plan in a much shorter time. This is a significant improvement over the current process, which takes around five to ten days to construct a plan and often does not account for all operational constraints or potential gains, as observed in the examples with forest growth gains.

Furthermore, the GRASP metaheuristic can satisfy all operational constraints and minimize the total cost of the process in just a few minutes. Another advantage of using GRASP is the ability to create and test various scenarios with just changes to the input data, allowing for the evaluation of different hypothetical situations and configurations, such as the composition of harvesting teams, available areas, supplier setups, and other characteristics. This enables the assessment of the impact on harvesting planning for each change due to the speed of the metaheuristic.

8
Conclusions

In this study, an optimization model was proposed to support a new category of Forest Harvest Planning Problem (FHPP) that uniquely considers the sequencing of harvesting teams between stands and the volume growth of these areas depending on the timing of the harvest in the paper and pulp industry. To solve this problem, a MILP model was developed to minimize the operational harvesting cost minus the gain from the forest growth of the stands over a 12-month tactical planning horizon.

Several artificial and real instances were used to validate the model. When solved by an exact method using the Gurobi solver on large instances (10 harvesting teams, 12 months, and over 500 stands), no feasible solution was found before the 86,400 seconds (24-hour) time limit. Additionally, the complexity of obtaining optimal solutions increased with the number of stands, harvesting teams, and planning months. For this reason, a GRASP metaheuristic was developed to solve the problem in real-world harvesting planning scenarios in the paper and pulp industry.

To calibrate GRASP, it was executed for 9,000 seconds using only the constructive algorithm stage and individually with each of the local searches proposed in Subsection 5.2 — *exchange*, *relocate*, *swap-in*, *swap-out*, *2-opt* and their combinations — to determine which had the best performance. Among the tests conducted, the best results were achieved by combining local searches with restricted neighborhoods at each constructed solution, a strategy which was named *"Comb Sel"*. Based on this calibration, GRASP was executed using a multi-start procedure, allowing parallel processing with 10 threads and achieving higher numbers of iterations within the one-hour execution time limit. As a result, GRASP outperformed the exact MILP model, obtaining a lower GAP in 9 of the 12 instances tested. In six instances, GRASP achieved a GAP of less than 2%, and in the real instances, GRASP was the only method capable of finding a good solution, whereas the MILP model did not find any initial solution.

After evaluating the performance of GRASP in solving the initial instances, a case study was conducted on a real-world example from a large paper and cellulose company in Brazil. The study assessed the plan created by the company's planning team across three instances. Both scenarios involved 12-month planning with 9 or 10 harvesting teams and more than 500 stands. The objective function described in Section 4 was used to compare the sequences given by the planning team and 1-hour GRASP.

A significant portion of the cost was attributed to the model's artificial variables, particularly those representing the cost of idle operation hours for the harvesting teams. This indicates that the harvest teams can complete operations before the 12-month planning horizon ends, reflecting poor allocation of machines in harvest teams or selection of the to-be-harvested stands.

Nevertheless, when considering only the operational costs and the gain from the volume growth of the stands, GRASP was able to reduce the harvesting planning cost by up to 61.9%, with an average reduction of 40.7% across the three scenarios compared to the plan created by the company's planning team. This demonstrates the efficiency of the metaheuristic in solving the FHPP in real-world instances.

Additionally, the results obtained by GRASP were presented to the company's planning team, highlighting how using a decision-support tool can significantly enhance the annual harvest planning process. Each year, the consolidated harvest planning procedure is prepared three months in advance and is responsible for defining contracts with suppliers, purchasing and selling machinery, production decisions, and selecting areas to be harvested. Therefore, having a robust plan in advance is crucial for reducing harvesting costs and directly impacts subsequent activities in the paper and cellulose supply chain.

Furthermore, this manual process takes around five to ten days to create a plan and additional time for final validation. This makes it very challenging to test different configurations and scenarios while adhering to all operational constraints imposed on the problem. GRASP, as an auxiliary tool, significantly improves the planning process by generating an optimized plan that respects all mapped operational constraints and minimizes total harvesting costs. Moreover, with GRASP, it is possible to generate various scenarios and test configurations with just a few changes in the input data, allowing the evaluation of different problem compositions and obtaining good solutions in just a few minutes of execution. Finally, the proposed solution provides all the necessary information for harvest planning over the 12-month horizon. It allows for the evaluation of when each stand will be harvested, how long it will take, the distances traveled, the total operation cost, and the volume of forest growth, among other factors. This enables the harvest planning team to conduct a proper and detailed follow-up of the operation and also facilitates communication with other stakeholders in the supply chain.

For future research, it would be interesting to apply and test the GRASP solution on other real instances of the harvest planning problem in different operational scenarios. This would allow for an evaluation of its performance in various contexts and companies. Moreover, the decision-making process of GRASP could be integrated with forecasting models and stochastic scenarios to estimate different growth values for each stand and the market sale price ($R\$/m^3$) of the wood, which would directly impact the decision.

9
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