ARTIGO

2965-6931 10.35699/2965-6931.2023.46940

REVISTA DA UNIVERSIDADE FEDERAL DE MINAS GERAIS

Heuristic proposal for generation of valid solutions to a forest production planning problem

Isabella Alkmim Barral
Universidade Estadual de Montes Claros (Unimontes)
https://orcid.org/0009-0004-3045-3809
isabellabarral@hotmail.com

Luciana Balieiro Cosme
Instituto Federal do Norte de Minas Gerais (IFNMG)
https://orcid.org/0000-0002-3927-0329
luciana.balieiro@ifnmg.edu.br

Allysson Steve Mota Lacerda
Universidade Estadual de Montes Claros (Unimontes)
https://orcid.org/0000-0002-1647-3916
steve.lacerda@unimontes.br

ABSTRACT

In the forestry sector, efficient planning of activities is considered essential for companies to achieve their goals and remain competitive in the market. To assist in this process, this work proposes the development and evaluation of a heuristic for the generation of valid solutions for a forest production planning problem involving 120 stands and 81 management alternatives per field, totaling 9720 decision variables. In the tests carried out, such proposed heuristic presented promising results when compared to the literature, indicating that it is capable of providing good quality solutions with low computational cost. Results also indicate that the inclusion of solutions obtained by using the proposed heuristic in the set of initial individuals/antibodies of Genetic Algorithm and Clonal Selection

Algorithm can generate a significant improvement in the quality of final solutions and, consequently, in the performance of such meta-heuristics.

Keywords: forestry planning; heuristics; valid solution; metaheuristics.

Proposta de heurística para a geração de soluções válidas para um problema de planejamento da produção florestal

RESUMO

No setor florestal, o planejamento eficiente das atividades é considerado fundamental para que as empresas atinjam seus objetivos e permaneçam competitivas no mercado. Para auxiliar nesse processo, o presente trabalho propõe o desenvolvimento e avaliação de uma heurística para a geração de soluções válidas para um problema de planejamento da produção florestal envolvendo 120 talhões e 81 alternativas de manejo por talhão, totalizando 9720 variáveis de decisão. Nos testes realizados a heurística apresentou resultados promissores quando comparada com a literatura, indicando que é capaz de fornecer soluções de boa qualidade com um baixo custo computacional. Os resultados também apontam que a inclusão de soluções obtidas pela heurística proposta no conjunto de indivíduos/anticorpos iniciais do Algoritmo Genético e Algoritmo de Seleção Clonal pode gerar uma melhora significativa no desempenho dessas meta-heurísticas.

Palavras-chave: planejamento florestal; heurística; solução válida; meta-heurísticas.

Submissão em: 24/08/2023 | **Aprovação em:** 01/10/2023

1. INTRODUCTION

The Brazilian forestry sector, more specifically that of planted forests, plays a fundamental role in the socioeconomic scenario of the country, contributing to the generation of jobs, taxes, foreign exchange and income (Junior et al., 2012). In 2020, for example, companies in the segment were responsible for creating more than 536,000 direct jobs and 1.5 million indirect jobs, in addition to generating BRL 12.1 billion in federal taxes, which is equivalent to 0.9% of the country's total collection (IBÁ, 2021).

Due to its edaphoclimatic characteristics (soil and climate) and technological development achieved in the area of forestry, Brazil is highly competitive in the market for forest products (Juvenal; Mattos, 2002). However, increasingly globalized market pressures require companies to become increasingly competitive, providing high quality products at the lowest possible cost (Silva, 2001).

In the forestry sector, one of the most expensive steps is harvesting wood, which, together with transport, accounts for more than 40% of production costs (Machado; da Silva Lopes, 2000; Jaskiu, 2015; Chichorro et al., 2017). Due to the great impact of the harvest on the economic viability of forestry enterprises, it is essential to carry out efficient planning of this activity (Bredstrom et al., 2010; Fuentealba et al., 2019), since this allows reducing costs, increasing productivity, regulating the flow of wood and optimizing the use of machinery and equipment (Fidelis; Reis, 2019).

In general, harvest planning consists of determining the plots to be harvested in each period of time in order to meet the demand for wood, maximizing revenues (and/or minimizing costs) and satisfying any other restrictions then imposed (Werneburg, 2015; González-González et al., 2022). However, this can become a complex problem depending on the number of fields, due to the exponential increase in the number of variables (Gomide et al., 2009).

In solving this type of problem, traditional approaches, such as the use of linear programming (LP) and integer linear programming (ILP), have offered good results for the treatment of small dimensional problems (Nobre, 1999). However, for major problems, the computational time spent often makes the use of these methods technically unfeasible (Gomide et al., 2009). Since obtaining information with quality and speed is considered essential for the success of decision-making in forest management, heuristics and metaheuristics become interesting alternatives in these situations, as they make it possible to obtain satisfactory answers with a reasonable processing time (Pereira, 2004; Gomide et al., 2009).

Several studies have been carried out using metaheuristics to solve forestry planning related problems. The Clonal Selection Algorithm method (CSA) was used by Júnior et al. (2018b) in this type of problem and presented good results when compared to ILP. However, the authors point out that the choice of parameters is essential for this, since invalid solutions may be obtained depending on the configuration used. The same could be observed in the works developed by Ferreira et al. (2018), Júnior et al. (2018a) and Matos et al. (2019) using Simulated Annealing (SA), Variable Neighborhood Search (VNS) and Genetic Algorithm (GA), respectively.

In addition to the choice of parameters, the strategy used to generate initial solutions is another factor that can impact the performance of such methods. In the mentioned works (Ferreira et al. (2018), Júnior et al. (2018a), and Matos et al. (2019)), the initial solutions, submitted to the optimization methods, were randomly generated. However, given the complexity of such issues, the large number of possible solutions, and any restrictions imposed, there is a high probability this strategy generates low quality solutions, which can impact the performance of optimization methods. For that matter, an alternative is using other optimization methods to generate initial solutions. In the work carried out by Júnior et al. (2021) the inclusion, in the initial population, of a solution obtained by rounding the optimal solution of the LP for the relaxed problem was tested as an alternative to increase the performance of GA, CSA, VNS and SA. In this work, authors observed a substantial improvement in the performance of GA, CSA and VNS algorithms; however, no positive effects were observed for the SA metaheuristic.

Considering the importance of obtaining good quality solutions quickly for successful forestry enterprises, this work proposes the development of a heuristic for generating valid solutions for a production planning-related issue, aiming at providing solutions that meet the restrictions imposed by the planner with less dependence on parameters and low computational cost. Furthermore, considering the evidence that incorporating high-quality solutions into the initial population of metaheuristics can enhance their performance, we assessment the impact of including varying quantities of solutions generated by the proposed heuristic in the initial solution sets of GA, CSA, VNS and SA. The results obtained showed that the proposed heuristic can be used as a viable alternative for quick decision making in the forestry planning process. In addition, tests showed that the inclusion of valid solutions in the initial population of GA and CSA can generate a significant improvement in the performance of these metaheuristics.

2. MATERIALS AND METHODS

In this section, the definition of the studied problem is carried out, as well as description of the heuristic developed and the metaheuristics Genetic Algorithm (GA), Clonal Selection Algorithm (CSA), Variable Neighborhood Search (VNS) and Simulated Annealing (SA) implemented and, finally, the presentation of those methods used for evaluations.

2.1. DEFINITION OF THE PROBLEM

In this work, the database presented by Matos et al. (2019) referring to a eucalyptus forest (Eucalyptus) with ages varying between 1 and 6 years old and a total area equal to 4,210 hectares was used. According to the authors, this forest was divided into 120 stands (management units) and 81 different prescriptions (management alternatives) were generated for each stand, defining the sequence of harvesting and planting to be carried out during a planning horizon of 16 years. The definition of prescriptions took into account the cutting of management units aged between 5 and 7 years old and immediate planting after cutting.

Assigning a certain prescription to a stand defines the age of the forest stand in each period of the planning horizon, each period being equal to one year. The volume of wood produced and related silvicultural costs vary according to the age of the stand. In this sense, the choice of prescription affects not only when the harvest will be carried out, but also the amount of wood harvested and the Net Present Value (NPV) obtained. The production and NPV values corresponding to the application of each management alternative in each stand are contained in the database, composed of 20 columns and 9720 rows. Columns 1, 2 and 3 contain the stand number, current age and applied prescription, respectively. Columns 4 to 19, the volumetric production of wood for each year of the planning horizon and column 20, the NPV (Figure 1).

Figure 1 - Database representation. The columns contain the number of the plot, age of the forest stand, applied prescription, production in each year of the planning horizon and NPV.

	1	**2**	**3**	**4**	**...**	**19**	**20**
1	1	1	1	0	...	0	14703
2	1	1	2	0	...	0	14703
...	...	...	...	...	...	...	...
9719	120	6	80	8960	...	8960	442508
9720	120	6	81	8960	...	8960	442508

Font: Author (2022).

The forestry production planning problem studied consists of determining which of the 81 prescriptions should be assigned to each of the 120 stands to maximize the NPV and meet the minimum and maximum annual demand for wood. For this, each solution was represented as a vector with 120 positions, where each position can assume an integer value between 1 and 81. In this representation, the positions correspond to the stands and the assigned values, to prescriptions. The mathematical optimization model used considered the structure proposed by Johnson and Scheurman (1977), represented by Equation 1.

$$MAX\ NPV = \sum_{i=1}^{M}\sum_{j=1}^{p} NPV_{ij}.X_{ij} \quad (1)$$

Subject to:

$$\sum_{j=1}^{P} X_{ij} = 1\ \forall\ i \in \{1,\ \dots,\ M\} \quad (2)$$

$$\sum_{i=1}^{M}\sum_{j=1}^{P} V_{ijk}.X_{ij} \geq Dmin_k\ \forall\ k \in \{1,\ 2,\ \dots,\ 16\} \quad (3)$$

$$\sum_{i=1}^{M}\sum_{j=1}^{P} V_{ijk}.X_{ij} \leq Dmax_k\ \forall\ k \in \{1,\ 2,\ \dots,\ 16\} \quad (4)$$

$$X_{ij} \in \{0,\ 1\} \quad (5)$$

Where: NPV_{ij} is the NPV of the management unit i according to the management regime j; X_{ij} is the binary decision variable, receiving value 1 when the management alternative j is assigned to the management unit i or 0; otherwise; M is the total number of management units; P is the total number of management alternatives for the management unit i; V_{ijk} is the total volume of wood(m^3) of the management unit i according to the management regime j in a period k of the planning horizon; $Dmin_k$ and $Dmax_k$ are, respectively, the minimum and maximum wood demand (m^3) k in the planning horizon period.

The objective function (Eq. 1) seeks to maximize the financial return and is subject to binary (Eq. 5), integrity (Eq. 2) and production (Eq. 3 and Eq. 4) constraints. he integrity constraint guarantees the choice of only one prescription for each management unit, and the production constraints ensure the supply of the forest product at the desired levels in each period of the planning horizon (Pereira, 2004).

In this work, the objective function took into account the method of penalties, reducing the calculation value of the function (Eq. 1) by R$ 500,00 (five hundred Brazilian Reais) per volume of wood produced, exceeding or lacking in relation to $Dmin$ e $Dmax$. The minimum and maximum wood demands stipulated by Matos et al. (2019) are 140,000 m³ and 160,000m³, respectively.

$$MAX\ NPV = \sum_{i=1}^{M} \sum_{j=1}^{p} NPV_{ij} . X_{ij} - P \sum_{k=1}^{T} dk \tag{6}$$

Where: P represents the penalty (R$); dk is the absolute value of the volumetric deviation of wood in m³ in a period k of the planning horizon.

The dk value is calculated through the absolute difference between the total production of the solution and $Dmin$ e $Dmax$. In order to obtain the total production, the amount of wood harvested in each year of the planning horizon in each stand is searched in the database and stored in the production history. Finally, the sum of the production history is carried out for determining total production.

Figure 2 illustrates the process used to calculate the total production, in which (a) represents a solution, (b) database, (c) production history and (d) total production. The solution has prescription 66 assigned to the first stand; therefore, the row containing number 1 in the first column, referring to the stand, and the number 66 (prescription) in the third column is spotted in the database. From the searched row, the values contained in columns 4 to 19 (production in each year of the planning horizon) are stored in the production history (c). This process is carried out for all stands and, subsequently, the sum of the production history is performed, so that total production (d) is obtained. From total production, it is possible to identify whether a given year of the planning horizon has production outside the established limits and calculate the absolute value of the wood volumetric deviation.

Figure 2 - Representation of the production calculation, where (a) represents a solution, (b) database, (c) production history, and (d) total production. In (d), the years in red (1, 2, 14, 15 and 16) had production

outside the established limits, so for each cubic meter of wood in excess or lack of these, the defined penalty applies.

a)

1	2	3	4	...	119	120
66	74	11	74	...	7	36

b)

	1	2	3	4	...	19	20
1	1	1	1	0	...	0	14703
...	...	...	...	...	...	...	...
66	1	1	66	0	...	0	15257
...	...	...	...	...	...	...	...
155	2	1	74	0	...	0	-1051
...	...	...	...	...	...	...	...
9720	120	6	81	8960	...	8960	442508

c)

	1	2	3	4	...	14	15	16
1	0	0	0	0	...	0	0	0
2	0	0	0	0	0	8151	0	0
3	0	0	0	0		0	0	6192
4	0	0	0	0		6970	0	0
...	...	...	...	...	...	...	...	...
119	4140	0	0	0		0	0	0
120	8190	0	0	0		0	0	0

d)

1	2	3	4	...	14	15	16
123711	179452	145609	145125	...	180281	170059	137684

Font: Author (2022).

2.2. PROPOSED APPROACH

Description of the proposed heuristic

The proposed heuristic aims at finding valid initial solutions for the studied forestry planning problem, a solution considered valid when all years of the planning horizon have production within the minimum and maximum limits established. For this, the algorithm developed was based on the idea of defining, at each iteration, the years with the highest and lowest production, and seeking to reduce such differences by changing prescriptions in certain stands.

Algorithm 1 presents the proposed heuristic, in which the variable $numSolutions$ is the number of valid solutions to be generated, DB is the database, and DBr is the reorganized database (detailed in section 2.2.1). The generated solutions are stored in the variable $setSolutions$. $StopCrit$is the maximum limit of objective function calculations per run, $PrunningCrit$ is the interval at which the pruning function will be performed. $Dmin$ and $Dmax$ the defined minimum and maximum limits of annual production, the $NumPrescriptions$ and $NumStands$ represent the total number of prescriptions and plots, respectively.

Algorithm 1 [setSolutions] = Initial heuristic (numSolutions, DB, DBr)

1. Constants: StopCrit = 1000; PruningCrit = 16; Dmin = 140.000; Dmax = 160.000; NumPrescriptions = 81; NumStands = 120
2. **for** i = 1:qSoluções **do**
3. StopCounter = 0;
4. PruningCounter = 0;
5. [solution] = Generate a random solution (NumStands, NumPrescriptions);
6. [prodHist, totalProd] = Calculate production (solution, DB, Dmin, Dmax, NumStands);
7. [numIrregulars] = Define the number of years with irregular production (totalProd, Dmin, Dmax);
8. **while** numIrregulars > 0 **do**
9. **if** StopCounter >= StopCrit **then**
10. Break;
11. **else**
12. [lowYear, highYear] = Select the years (totalProd);
13. [stand] = Choose a stand (prodHist, lowYear, highYear);
14. [prescription] = Define the new prescription for the selected stand (stand,lowYear, highYear, DBr);
15. [solution$_{aux}$] = Modify the stand prescription (solution, stand, prescription);
16. [prodHist$_{aux}$, totalProd$_{aux}$] = Calculate the production of the new solution (solution$_{aux}$, DB, Dmin, Dmax, NumStands);
17. [numIrregulars$_{aux}$] = Define the number of years with irregular production (totalProd$_{aux}$, Dmin, Dmax);
18. **if** numIrregulars$_{aux}$ <= numIrregulars **then**
19. solution = solution$_{aux}$;
20. prodHist = prodHist$_{aux}$;
21. totalProd = totalProd$_{aux}$;
22. numIrregulars = numIrregulars$_{aux}$;
23. **end if**
24. StopCounter = StopCounter + 1;
25. PruningCounter = PruningCounter + 1;
26. **if** PruningCounter >= PruningCrit **and** numIrregulars > 0 **then**
27. [solution] = perform the pruning (solution, prodHist, totalProd, NumStands, NumPrescriptions, Dmin, Dmax);
28. [prodHist, totalProd] = Calculate production (solution, DB, Dmin, Dmax, NumStands);
29. [numIrregulars] = Define the number of years with irregular production (totalProd, Dmin, Dmax);
30. PruningCounter= 0;
31. **end if**
32. **end if**
33. **end while**
34. setSolutions(i, :) = solution;
35. **end for**

To obtain a valid solution, the proposed heuristic generates a random solution and calculates the production, storing the production history and total production. With total production, it is possible to determine the number of years with irregular production (less than 140,000 m³ or greater than 160,000 m³). If all years have regular production, the solution is saved and the heuristic is closed. As long as this criterion is not met or until the maximum number of objective function calculations is exceeded, the algorithm sorts the production of all years and selects those with the highest and lowest production. The year with the highest production is stored in variable $highYear$ and the one with the lowest production, in $lowYear$.

Variables and production history are used to select a stand to have the prescription modified. For this, the criterion used is that, if possible, the plot selected under the current prescription has production greater than zero in $highYear$ and equal to zero in $lowYear$. These requirements were defined taking into account that changing the prescription can modify the years in which the plot will be harvested and, therefore, the total production of the solution. In this sense, the first requirement was adopted in order to increase the probability that the modification will reduce production in $highYear$, and the second requirement is intended to prevent this modification from also reducing production in $lowYear$.

Figure 3 illustrates the selection of stands subject to modification in a solution that, as shown in the total production, has as $highYear$ (highlighted in red) and $lowYear$ (highlighted in blue) the first and thirteenth years of the planning horizon, respectively. In the first column of the production history, which consists of the production of all stands in $highYear$, stands 118, 119 and 120 are selected because their productions are greater than zero. Subsequently, evaluating in column 13, stand 120 is excluded from the alternatives because it has a production different from zero in $lowYear$. Therefore, 118 and 119 would be alternative stands to be modified.

Figure 3 - Representation of production history and selection of plots subject to modification

	1	2	3	4	5	...	12	13	14	15	16
1	0	0	0	0	0	...	0	0	5632	0	0
2	0	0	0	0	0	...	6468	0	0	0	0
...	...	...	...	...	...	...	...		...	...	...
118	8190	0	0	0	0	...	8190	0	0	0	0
119	4140	0	0	0	0	...	0	0	0	0	0
120	8190	0	0	0	0	...	0	8960	0	0	0
Total Production	178542	131494	172975	129274	130838	...	153757	124962	165986	141769	130159

Font: Author (2022).

The choice of the new prescription is carried out aiming at increasing the production of $lowYear$, maintaining the production of $highYear$. For this, a reorganization of the database was proposed, evaluating, for each year of the planning horizon, which prescriptions could be assigned to each of the stands so that the harvest could occur in that year. For example, if stand 118 of the solution shown in Figure 3, were selected for alteration, the reorganized database would apply to define which prescriptions could be assigned to this plot so that there would be a harvest in the thirteenth year ($lowYear$) and not in the first one ($highYear$).

The method used to reorganize the database was to filter, for each stand and year of the planning horizon, prescriptions with production other than zero and copy them to a new file. Figure 4 shows the reorganized database, in which the first column refers to the stand and the second to the year of the planning horizon. The remaining columns contain the prescriptions that, if assigned to a stand, will generate production in the year in question. A zero value is assigned when no prescription will result in a harvest during the year under evaluation.

Figure 4 - Database reorganization. Prescriptions stored in columns 3 to 56, if assigned to column 1 plot, will generate harvest in column 2 year. In the example mentioned, prescriptions 7, 8 and 66 could be assigned to plot 118 (row 1558), so that this plot would have production in the thirteenth year. However,

the application of prescriptions between 1 and 54 (row 118) generates a harvest in the first year. In this situation, an alternative would be prescription 66, as if applied it would generate a harvest in $lowYear$ and not in $highYear$.

	Stand	Year	Prescriptions					
1	1	1	0	0	...	0	...	0
2	2	1	0	0	...	0	...	0
...	...	...	...	...	...	...	...	...
118	118	1	1	2	...	24	...	54
...	...	...	...	...	...	...	...	...
1558	118	13	7	8	...	66	...	0
...	...	...	...	...	...	...	...	...
1919	119	16	28	79	...	0	...	0
1920	120	16	28	79	...	0	...	0
	1	**2**	**3**	**4**		**26**		**56**

Font: Author (2022).

The prescription to be assigned to the defined stand is selected by searching the reorganized database for alternatives that result in harvest in the $lowYear$. Of these alternatives, those that generate harvest in the $highYear$ are excluded. Then, a prescription is randomly selected from the remaining options. If no prescriptions meet the criteria or all are equal to zero, the selection is made randomly among all prescriptions.

By changing the prescription in the chosen stand, the calculation of the number of years with irregular production is performed again. If the modified solution has an equal or lesser number of violations, it becomes the current solution, otherwise it is discarded. This process runs until the algorithm reaches the maximum number of objective function calculations or the solution has no years with uneven production.

In the proposed heuristic, the choice of stand and prescription were developed with the objective of performing a local search, in order to improve the current solution.

However, to prevent the algorithm from getting stuck in local optima, it was necessary to implement the pruning function in order to make changes in the neighborhood. The pruning function applies when the algorithm executes the described procedure $PruningCrit$ 16 times and the solution remain invalid. This function resets the production and assigns random prescriptions to the plots that have harvested in years with excess production until total production of these years approaches $Dmin$. If there are no years with excess production, the function uses the year with the highest production.

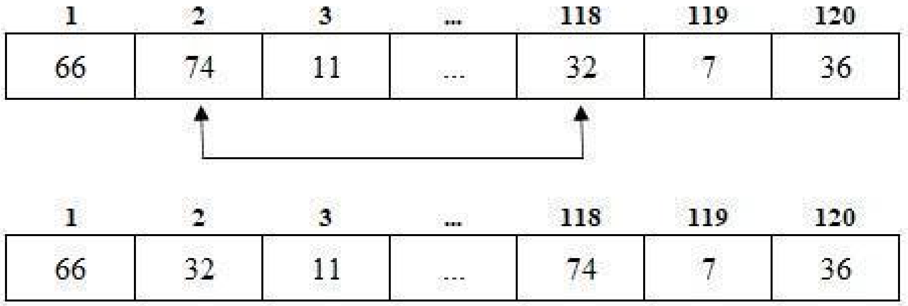
Description of metaheuristics

The implemented metaheuristics Genetic Algorithm (GA), Clonal Selection Algorithm (CSA), Variable Neighborhood Search (VNS), and Simulated Annealing (SA) followed the definitions proposed by Gaspar-Cunha et al. (2012), Souza and Romero (2014), Júnior et al. (2018a), Rodrigues et al. (2004), respectively. On GA and CSA, all tests were performed using 50 initial solutions. These solutions were generated randomly or using the developed heuristic. The number of solutions generated by the heuristic is defined by the $numSolutions$ variable (Algorithm 1). The remaining amount, to reach 50 solutions, is generated randomly. The Variable Neighborhood Search (VNS) and Simulated Annealing (SA) metaheuristics use only a current solution that, in this work was randomly generated or through the proposed heuristic ($numSolutions$ = 1).

The GA uses the tournament selection method to select the parents for mating, and the mating of individuals was performed with a break point at a probability of 80%. The mutation carried out consisted of exchanging prescriptions of two randomly selected plots with a probability of 1%. This mutation was called swap and is shown in Figure 5. The tournament was also used as a method of replacing individuals in the population; however, elitism was adopted to avoid losing the best individuals. In the elitism used, the 10 best individuals among the parents and generated children are selected for the next generation.

Figure 5 - Swap-type mutation in which prescriptions of two random plots are exchanged. The first and second images represent the solution before and after mutation, respectively.

Font: Author (2022).



In the Clonal Selection Algorithm (CSA), the selection rate for cloning adopted was 20% and the number of clones generated for each antibody was determined using Equation 7 (Batista, 2010). The generated clones were submitted to the hypermutation process, which consists of assigning random prescriptions to a number of plots inversely proportional to NPV (affinity). The mutation rate was obtained using Equations 8, 9 (Batista, 2010; Júnior et al., 2018b). The worst antibodies generated were replaced by the best clones in an elitist manner. Then, the antibody with the lowest affinity was replaced with a randomly generated solution in order to maintain diversity.

$$Nc = \sum round(TC\,.\,\frac{N}{i}) \tag{7}$$

$$\rho = 5(1 - TH) \tag{8}$$

$$\alpha = exp(-\,\rho\,.\,D^{*}) \tag{9}$$

Where: where TC is the cloning rate (25%), N is the total amount of antibodies and round is the operator that rounds the value in parentheses to the nearest integer, TH is the hypermutation rate (10%), D* is the normalized NPV.

In VNS, the set of neighborhood structures implemented consisted of randomly modifying 1, 2, 3, and 4% of prescriptions (Júnior et al., 2018a). In SA, the initial temperature adopted was 10^{6} and the temperature reduction rate was 0.01 (Ferreira et al., 2018). In both cases, the Local Search procedure applied was swap, which involves exchanging the position of two random prescriptions. In VNS, 200 neighbors were used, while in SA, there were 30.

2.3. ASSESSMENT METHODS

To assess the performance of the proposed heuristic and the studied metaheuristics, two more restrictive scenarios were generated, in addition to the scenario described in section 2.1. The first scenario generated, called Scenario 2, has a minimum demand ($Dmin$) equal to 140,000 m³ and a maximum demand ($Dmax$) of 150,000 m³. The second scenario generated, Scenario 3, has $Dmin$ same 150.000 m³ e $Dmax$ 160.000 m³. As shown in Table 1.

Table 1 - Description of the evaluated scenarios. Scenario 1 contains the original constraints of the forestry planning problem and Scenarios 2 and 3 were generated by modifying the minimum and maximum production constraints, in order to evaluate the performance of the proposed heuristic.

Scenario	**Minimum demand (m³)**	**Maximum demand (m³)**
1	140,000	160,000
2	140,000	150,000
3	150,000	160,000

Font: Author (2022).

The proposed heuristic was tested in each scenario, verifying the amount of objective function calculations necessary to obtain viable solutions. For this, 1,000 runs of the heuristic were performed, storing the number of calculations of the objective function, the solution obtained and the run time. Metaheuristics were implemented as presented adopting 5,000 objective function calculations as a stopping criterion, present in the works developed by Júnior et al. (2018a) and Matos et al. (2019). For each scenario, the proposed heuristic and metaheuristics were run 30 times, storing the maximum NPV and the number of valid solutions at the end of each run.

Subsequently, the performance of GA and CSA metaheuristics was evaluated using 1, 5, 10 and 15 individuals generated by the heuristic proposed in the set of initial solutions in the resolution of the first scenario studied (original). For VNS and SA, which uses only one current solution, the use of $numSolutions$ equal to 1 was evaluated. In these tests, the stopping criterion of 5,000 objective function calculations was adopted, considering the calculations used to generate the initial individuals, running 30 times for each value of $numSolutions$ and storing the maximum value of NPV obtained in each run. The results obtained by the metaheuristics using the randomly generated set of solutions and using the solutions generated by the proposed heuristics were submitted to statistical analysis at a significance level of 5%.

The implementation and experiments were performed using MATLAB R2020b, on a computer with an Intel® Core™ i5-7400 3.0 GHz processor with 4 GB RAM. For statistical analysis, Excel 2019 was used, initially verifying the assumptions for using the one-way analysis of variance (Anova one-way). The assumptions analyzed were normality, using the Shapiro-Wilk test, and homoscedasticity, applying the Levene test. In cases where these assumptions were met, Anova was performed, applying the Tukey mean comparison test when necessary. In cases where the assumptions were not met, the non-parametric Kruskal-Wallis test was used, followed by Dunn test.

3. RESULT AND DISCUSSION

3.1. EVALUATION OF THE PERFORMANCE OF HEURISTICS AND METAHEURISTICS IN THE SCENARIOS STUDIED

Results of evaluation of the proposed heuristic in the 3 scenarios studied are shown in Table 2. For the first scenario ($Dmin$ equal to 140.000 m² and $Dmax$ 160.000 m²), an average of approximately 82 objective function calculations and 0.026 seconds were required to obtain a valid solution, finding solutions with production within the established limits in all runs performed. In the second scenario ($Dmin$ equal to 140.000 m² and $Dmax$ 150.000 m²), an average of 1,006 objective function calculations and 0.22

seconds were required, obtaining valid solutions in 99.9% of runs. While in scenario 3 ($Dmin$ equal to 150.000 m^2 and $Dmax$ 160.000 m^2), no valid solutions were found in any of the 1,000 runs and the average time was 1.08 seconds.

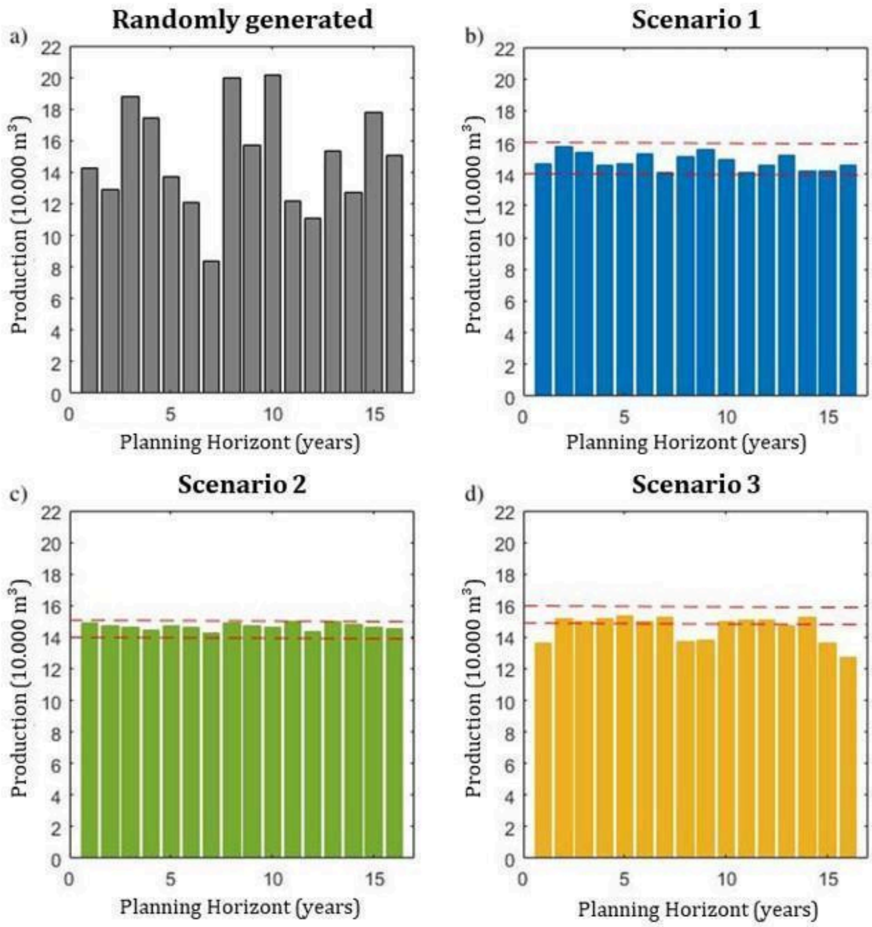
Table 2 - Evaluation of the proposed heuristic in the 3 scenarios in relation to the number of objective function calculations and the total number of valid solutions obtained

Scenario	**Average**	**Minimum**	**Maximum**	**Standard deviation**	**Valid solution**
1	81.86	15	371	48.82	1000
2	1005.81	51	5000	761.66	999
3	5000	5000	5000	0	0

Font: Author (2022).

Figure 6 illustrates the production in each year of the planning horizon of 4 solutions, the first randomly generated and the others obtained by the proposed heuristic in each scenario. In the randomly generated solution, it is possible to observe a large variation in the volume of wood produced, with 83,682 m^3 in the year with the lowest production, and 201,888 m^3 in the year with the highest production. The solutions obtained by the heuristic proposed in the first and second scenarios present productions within the established limits. The solution produced by the heuristic in the third scenario is invalid, since the production of 6 out of 16 years of the planning horizon are below the stipulated minimum demand. However, this solution presents greater regularity when compared to the random one. The presented results indicate that the developed heuristic is able to generate valid solutions with a low computational cost in Scenarios 1 and 2. However, Scenario 3 proved to be more restrictive, with the possibility that there are no valid solutions for this problem under these conditions.

Figure 6 - Figure (a) illustrates the production over the 16-year planning horizon of a randomly generated solution. Figures (b), (c) and (d) were generated by the heuristic proposed in the first, second and third scenarios, respectively. Red lines represent the maximum and minimum demand for each scenario.



Font: Author (2022).

Then, the performance of the proposed heuristic and metaheuristics Genetic Algorithm (GA), Clonal Selection Algorithm (CSA), Variable Neighborhood Search (VNS) and Simulated Annealing (SA) in solving the 3 scenarios of the forestry planning problem were evaluated (Table 3). By checking the number of runs with valid solutions (at the end of the run), it is possible to observe that in the first scenario, contrary to the proposed heuristic, all the studied metaheuristics had at least one run with invalid solutions. These results demonstrate that obtaining solutions with production within the established limits is not a trivial task in any of the scenarios, and indicate the potential of the heuristic for quick decision making in forest production planning. In the second scenario, the proposed heuristic, GA, CSA, VNS and SA obtained valid solutions in 100%, 20%, 6.66%, 10% and 36,7% of runs, respectively. In the third scenario, no valid solutions were found in any run.

Table 3 - Results of the 3 metaheuristics in each scenario studied using $numSolutions$ equal to 0, containing the evaluated metaheuristic, the average, minimum and maximum Net Present Value, the standard deviation and verification of the existence of valid solutions at the end of the 30 runs.

Method	Average	Minimum	Maximum	Standard deviation	Execution with valid solutions
			Scenario 1		
Heuristic	29990716	29593240	30392521	187132	30
GA	30431317	30153012	30681827	149990	29
CSA	30384715	30118383	30629176	129446	28
VNS	30560674	30357679	30819973	142232	29
SA	30755600	30497000	30970000	140324	28
			Scenario 2		
Heuristic	30296563	30073647	30641133	131356	30
GA	28766777	24272351	30409291	1931754	6
CSA	28271868	24276469	30379693	1417596	2
VNS	28521090	21255287	30453983	1993373	3
SA	28632600	20030000	30737000	2520334	11
			Scenario 3		
Heuristic	12558783	2173764	19499702	4539943	0
GA	15824019	8651377	21340680	3749860	0
CSA	17253809	11064146	22837152	2684917	0
VNS	15627888	6074459	21424824	3669773	0
SA	17046467	2288000	27674000	5152299	0

Font: Author (2022).

Regarding the Net Present Value (NPV), it is important to highlight that the proposed heuristic does not aim to maximize. In this sense, the results presented in Table 3 do not refer to the best NPVs found by the heuristic, but to the NPVs of the solutions found at the end of the heuristic execution, which occurs when a valid solution is found or when the stopping criterion of 5,000 objective function calculations is reached. In the first scenario, the proposed heuristic required an average of 67 objective function calculations to obtain valid solutions. These solutions had an average NPV of BRL 29,990,716.00, being the lowest among the methods evaluated. However, all metaheuristics required 5,000 function calculations.

Still in relation to Table 3, the proposed heuristic presented promising results for the second scenario. In addition to obtaining valid solutions in all runs, this method presented an average NPV greater than those of the evaluated metaheuristics, BRL 30,296,563.00, and a smaller standard deviation, BRL 131,356.00, using an average of 906 objective function calculations. In the third scenario, the proposed heuristic and the studied metaheuristics do not find valid solutions, demonstrating the complexity of the problem under these conditions.

3.2. EVALUATION OF THE FEASIBILITY OF APPLYING THE PROPOSED HEURISTIC FOR GENERATING INITIAL SOLUTIONS

Table 4 shows the comparison between results obtained by metaheuristics in solving the first (original) scenario of the forestry planning problem using different numbers of individuals generated by the proposed heuristic ($numSolutions$) in the set of initial solutions. Observing the results, it is possible to identify that the increase of valid solutions in the set of initial solutions generated an increase in the average NPV.

Table 4 - Average Net Present Value (NPV) and standard deviation of the Genetic Algorithm (GA), Clonal Selection Algorithm (CSA), Variable Neighborhood Search (VNS) and Simulated Annealing (SA) in the first scenario studied using 0, 1, 5, 10 and 15 $numSolutions$ in the set of initial solutions.

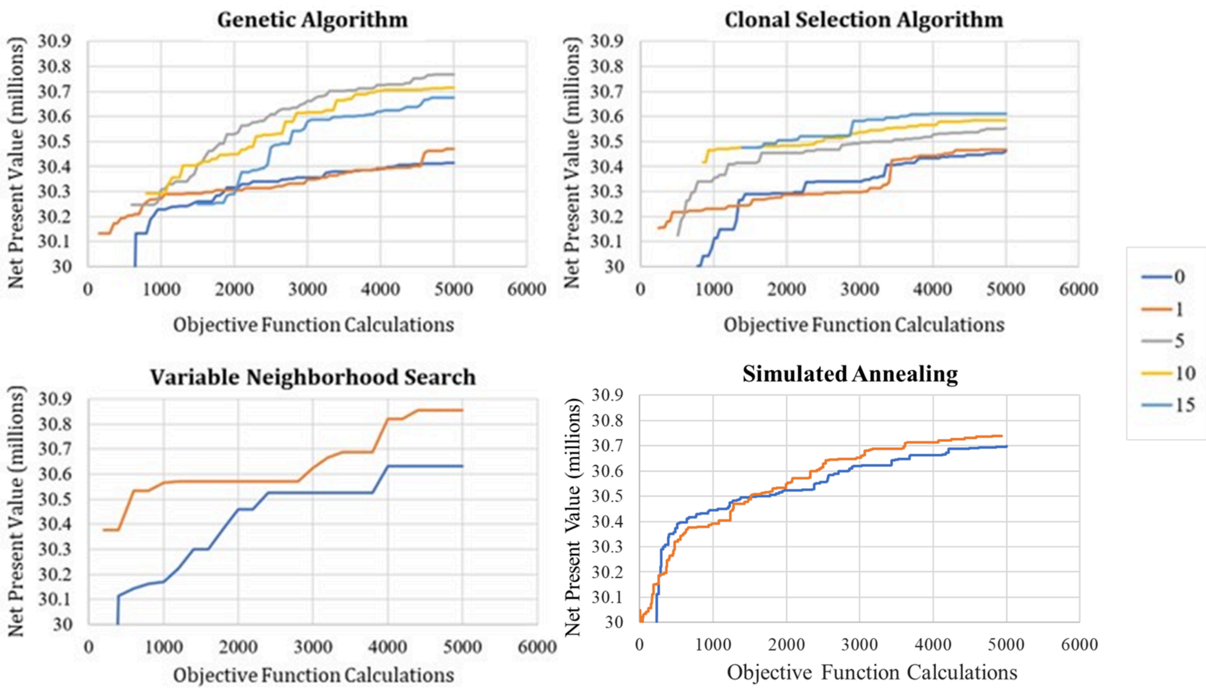
	Average/ Standard deviation			
$NumSolutions$	**GA**	**CSA**	**VNS**	**SA**
0	30431317 (149990)	30384715 (129446)	30560674 (142232)	30755600 (140324)
1	30500953 (147202)	30427883 (157953)	30615555 (160255)	30760167 (128353)
5	30624375 (96735)	30575246 (112913)	-	-
10	30667067 (98946)	30582604 (96385)	-	-
15	30644007 (93582)	30585436 (103619)	-	-

Font: Author (2022).

For better understanding the results, a statistical analysis of data presented in Table 4 was performed. For GA, considering the heterogeneity of variances verified by the Levene test (p − value = 2.02E-03), the analysis was performed using the non-parametric Kruskal-Wallis test (p – value = 5.08E-10), followed by the Dunn test. The Dunn test pointed out that there is no significant difference between the use of 0 and 1 initial individual. However, when increasing the amount of $numSolutions$, it was observed that $numSolutions$ equal to 0 and 5, 10 and 15 have statistically significant differences, indicating that the use of the heuristic can impact the convergence of this metaheuristic when using larger amounts of initial individuals. The comparison between 1 initial individual and 5, 10 and 15 reinforces this result, showing that there is a significant difference between the use of 1 and a larger number of individuals. Finally, no significant differences were identified between the use of 5, 10 or 15 initial individuals.

In the evaluation of CSA, the one-way analysis of variance indicated the presence of at least one statistical difference between the groups ($p - value$ = 1.47E-12) and the Tukey test performed showed a result similar to that of the GA. In the VNS and SA, the one-way analysis of variance revealed that there are no statistical differences between the groups ($p - value$ = 0.1660, 0.8958). That is, the use of only one valid solution did not generate statistical difference in the result. These results can also be seen in Figure 7, which illustrates the NPV throughout the execution of the GA, CSA, VNS and SA metaheuristics with different amounts of $numSolutions$.

Figure 7 - Illustration of the convergence of the metaheuristics under study, using different amounts of $numSolutions$. A run was performed for each amount of $numSolutions$.



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In this figure it is possible to observe the consumption of the objective function calculations by the proposed heuristic, identified by the NPV starting point, and also the impact of the inclusion of valid solutions on the convergence of the metaheuristics. When using 0 or 1, it is possible to observe the approximation or overlap of the NPVs at some moments of the execution. With a greater number of valid solutions, a difference in convergence is visible, especially in GA.

Still in relation to Figure 7, the reduction in the NPV at the beginning of the SA execution, equal to 1, indicates that the solution generated by the heuristic was replaced by another of lower quality, accepted due to the high temperature at the beginning of the optimization process. The same behavior of the SA method was described by Júnior et al. (2021), concluding that the use of good initial solutions did not affect the performance of this meta-heuristic. However, the inclusion of the solution generated by rounding the optimal linear programming solution in the initial CSA, GA, and VNS solutions significantly impacted the performance of these algorithms, generating a 3.93% increase in the average NPV in CSA (algorithm that had the greatest impact on average NPV). This result disregards, however, the computational cost necessary to obtain the solution generated by the PL.

3.3. CONSIDERATIONS ABOUT THE PROPOSED HEURISTIC AND LITERATURE

The proposed heuristic was developed to generate good initial solutions for other optimization methods. However, the results presented by the literature (JÚNIOR et al., 2018a, b; MATOS et al., 2019) and the metaheuristics evaluated indicate the possibility of applying this method for rapid decision-making in planning forestry production. In the study carried out by Matos et al. (2019), for example, the solution found by the entire programming (branch and bound), after 96 hours of processing, presented an NPV equal to BRL 31,964,100 and the GA with 2.74 minutes (using 50 individuals and 100 generations), obtaining an average NPV of BRL 30,336,526. If compared with these results, the NPV of the proposed heuristic (obtained with an average time of 0.026 seconds) corresponds to 93.83% and 98.86%. Compared to SA (the studied meta-heuristic that showed better performance), the proposed heuristic obtained an NPV corresponding to 97.51% using an average of 1.34% of the objective function calculations. To illustrate, the same SA executed with the stopping criterion of 67 objective function calculations presents an average NPV of BRL 5,003,598.00.

Considering the ability to provide good quality, valid solutions with a low computational cost, the proposed heuristic can be an interesting alternative for making quick decisions. However, as this method does not aim to maximize the NPV, a longer processing time or more objective function calculations would not generate an improvement in performance. This is because the heuristic generates random valid solutions. In this sense, in situations where the decision maker has more time available, the use of heuristics alone may not be interesting.

To maximize the NPV, the proposed heuristic can be used in conjunction with other optimization methods, such as GA and CSA, to improve its performance. However, the use of valid solutions at the beginning of the optimization process does not guarantee that the final solutions will also be valid. This occurs because meta-heuristics prioritize maximizing the NPV, and invalid solutions may have a high NPV depending on the penalty applied. Several works (Rodrigues et al., 2004; Gomide et al.; 2009; Nascimento et al., 2012; Matos et al., 2019) use the penalty method to implement these restrictions, however, the penalty values differ between the authors. For example, in the work of Júnior et al. (2021), Gomide et al. (2009), and Nascimento et al. (2012) the fine for each cubic meter of wood outside the production range is BRL 100.00, BRL 500.00 and BRL 100,000.00, respectively. Although maintaining a constant flow of production allows meeting market demands and also promotes benefits such as the regular employment of labor and the balance between annual income and expenses (Davis, 1996; Rodrigues et al., 1998), the tolerance for production variation depends on the analysis conducted by the decision maker.

4. CONCLUSION

In this work, it was proposed the development of a heuristic to obtain valid solutions for a forestry planning problem. The performance of the proposed heuristic was evaluated in 3 scenarios and compared with the GA, CSA, VNS and SA meta-heuristics. Then, different amounts of solutions generated by the proposed heuristic were inserted into the set of initial solutions of the studied metaheuristics and the impact on the performance of these methods was evaluated. Results indicate that the developed heuristic can be a viable alternative for quick decision making in forestry production planning, since it obtained valid solutions in 100% of the runs of the first scenario (original) and in 99.9% of the second scenario, demanding an average of 82 and 1006 objective function calculations, respectively. In addition, the results also indicate that the solutions generated by this heuristic can be used in the initial population of metaheuristics such as the Genetic Algorithm (GA) and Clonal Selection Algorithm (CSA), in order to improve their performance.

In future work, we intend to compare the impact of including solutions generated by the proposed heuristic and the relaxed PL in the set of initial solutions of the GA and CSA meta-heuristics.

5. ACKNOWLEDGMENT

The authors are grateful to Fundação de Amparo à Pesquisa do Estado de Minas Gerais - FAPEMIG for financial support.

REFERENCES

BATISTA, Lucas de Souza,. **Investigação de novas abordagens em sistemas imunes artificiais para otimização**. Dissertação (Mestrado em Engenharia Elétrica) —Universidade Federal de Minas Gerais, 2010..

BREDSTROM, David; JÖNSSON, Petrus; RÖNNQVIST, Mikael. **Annual planning of harvesting resources in the forest industry**. International transactions in operational research, v. 17, n. 2, p. 155-177, 2010. DOI: https://doi.org/10.1111/j.1475-3995.2009.00749.x

CHICHORRO, José Franklim; DA SILVA, André Luiz Pinheiro; ANDRADE, Wendel Sandro de Paula; HEGEDUS, Clovis Eduardo Nunes; KUBOYAMA, Filipe Quirino Aquira. **Custos e índices econômicos de povoamentos de eucalipto do Programa Produtor Florestal no Espírito Santo**. Pesquisa Florestal Brasileira, v. 37, n. 92, p. 447-456, 2017. doi: https://doi.org/10.4336/2017.pfb.37.92.1232

DAVIS, K. P. **Forest management: regulation and valuation**. 2.ed. New York: McGraw-Hill, 1966. 519 p.

GASPAR-CUNHA, António; TAKAHASHI, Ricardo; ANTUNES, Carlos Henggeler. **Manual de computação evolutiva e metaheurística**. Imprensa da Universidade de Coimbra, Coimbra, 2012. DOI: http://dx.doi.org/10.14195/978-989-26-0583-8.

DE CASTRO, L. Nunes; VON ZUBEN, Fernando J. **The clonal selection algorithm with engineering applications**. Proceedings of GECCO. 2000. p. 36-39.

FERREIRA, Paulo Henrique Batista; MATOS, Lisandra Maria; DE ASSIS, Adriana Leandra; CABACINHA, Christian Dias; JÚNIOR, Carlos Alberto Araújo. **Influência dos parâmetros da metaheurística simulated annealing em um problema de planejamento da produção florestal**. Caderno de Ciências Agrárias-UFMG, 2018.

FIDELIS, Alessandro Cruvinel; REIS, Ricardo Pereira. **Decisão no planejamento bianual da colheita florestal**: o uso da programação inteira mista. Revista de Economia e Sociologia Rural, v. 39, n. 2, p. 9-26, 2019.

FUENTEALBA, Sebastián; PRADENAS, Lorena; LINFATI, Rodrigo; FERLAND, Jacques A.. **Forest harvest and sawmills**: An integrated tactical planning model**.** Computers and Electronics in Agriculture, v. 156, p. 275-281, 2019. DOI: https://doi.org/10.1016/j.compag.2018.11.011.

GOMIDE, Lucas Rezende; ARCE, Julio Eduardo; DA SILVA, Arinei Carlos Lindbeck. **Uso do algoritmo genético no planejamento florestal considerando seus operadores de seleção**. Cerne, v. 15, n. 4, p. 460-467, 2009.

GONZÁLEZ-GONZÁLEZ, José Mario; VÁZQUEZ-MÉNDEZ, Miguel Ernesto; DIÉGUEZ-ARANDA, Ulises. **Multi-objective models for the forest harvest scheduling problem in a continuous-time framework**. Forest Policy and Economics, v. 136, p. 102687, 2022. doi: https://doi.org/10.1016/j.forpol.2021.102687.

IBÁ . Indústria Brasileira de Árvores. **Relatório Anual 2020**. Disponível em: https://iba.org/ publicacoes/relatorios; 2021. Acesso em: 31 dez. 2021.

JASKIU, Eldemar. **Planejamento florestal espacial atendendo exigências de áreas máximas e mínimas contínuas de colheita. 63 p.** Dissertação (Mestrado em Ciências Florestais) —Universidade Federal do Paraná, Curitiba, 2015.

JOHNSON, K. Norman; SCHEURMAN, H. Lynn. **Techniques for prescribing optimal timber harvest and investment under different objectives-discussion and synthesis**. Forest Science, v. 23, n. suppl_1, p. a0001-z0001, 1977. DOI: https://doi.org/10.1093/forestscience/23.s1.a0001.

JUNIOR, Antonio Almeida de Barros; DA SILVA, Gilson Fernandes; PEREIRA, Gustavo Willam; MELO, Robson. **Aplicações de heuristicas para a solução de um problema de planejamento florestal**.: Simpósio Brasileiro de Pesquisa Operacional. Rio de Janeiro, Brazil; 2012. p. 2430–241.

JÚNIOR, Carlos Alberto Araújo; CASTRO, Renato Vinícius Oliveira; MENDES, João Batista; LEITE, Helio Garcia. **Can linear programming assist metaheuristics in forest production planning problem?** FLORESTA, v. 51, n. 3, p. 751-759, 2021. DOI: http://dx.doi.org/10. 5380/rf.v51i3.72612.

JÚNIOR, Carlos Alberto Araújo; MENDES, João Batista; CABACINHA, Christian Dias; DE ASSIS, Adriana Leandra; MATOS, Lisandra Maria Alves; LEITE, Helio Garcia. **Meta-heuristic clonal selection algorithm for optimization of forest planning**. Revista Árvore, v. 41, 2018b. DOI: https://doi.org/10.1590/1806-90882017000600007.

JÚNIOR, Carlos Alberto Araújo; MENDES, João Batista; DE ASSIS, Adriana Leandra; CABACINHA, Christian Dias; STOCKS, Jonathan James; DA SILVA, Liniker Fernandes; LEITE, Helio Garcia. **Tuning of the metaheuristic variable neighborhood search for a forest planning problem**. **Cerne**, v. 24, p. 259-268, 2018a. DOI: https://doi.org/10.1590/01047760201824032538.

JUVENAL, Thais Linhares; MATTOS, René Luiz Grion. **O setor florestal no Brasil e a importância do reflorestamento**. Banco Nacional de Desenvolvimento Econômico e Social. Acesso em: http://web.bndes.gov.br/bib/ jspui/handle/1408/3142; 2002. Acesso em: 15 nov de 2021.

MACHADO, Carlos Cardoso; DA SILVA LOPES, Eduardo. **Análise da influência do comprimento de toras de eucalipto na produtividade e custo da colheita e transporte florestal**. Cerne, v. 6, n. 2, p. 124-129, 2000.

MATOS, Lisandra Maria Alves; JÚNIOR, Carlos Alberto Araújo; DE ASSIS, Adriana Leandra; CABACINHA, Christian Dias; FERREIRA, Paulo Henrique Batista; MAGALHÃES, Emanuelly Canabrava. **Influência dos parâmetros da metaheurística algoritmo genético em um problema de planejamento florestal**. Advances in Forestry Science, v. 6, n. 4, p. 767-774, 2019. DOI: 10.34062/afs.v6i4.6197.

NASCIMENTO, Flavio Augusto Ferreira; DIAS, Andrea Nogueira; FILHO, Afonso Figueiredo; ARCE, Julio Eduardo; MIRANDA, Gabriel de Magalhães. **Use of Metaheuristics particle swarm optimization in Forest planning**. Scientia Forestalis, Vol.40 No.96 pp.557-565, 2012.

NOBRE, Silvana Ribeiro. **A heurística da Razão-R aplicada a problemas de gestão florestal**. Dissertação (Mestrado em Administração da Empresa Rural) —Universidade Federal de Lavras, Lavras, 1999.

PEREIRA, Gustavo Willam. **Aplicação da técnica de recozimento simulado em problemas de planejamento florestal multiobjetivo**. Dissertação (Mestrado em Ciência da Computação) —Universidade Federal de Minas Gerais, Belo Horizonte, 2004.

RODRIGUES, Flávio Lopes, LEITE, Helio Garcia, SANTOS, Heleno do Nascimentos, SOUZA, Agostinho Lopes, RIBEIRO, Carlos Antônio Álvares Soares. **Metaheurística simulated annealing para solução de problemas de planejamento florestal com restrições de integridade**. Revista Árvore, v. 28, p. 247-256, 2004. doi: https://doi.org/10.1590/S0100-67622004000200011.

RODRIGUES, Flávio Lopes, LEITE, Helio Garcia, SOUZA, Agostinho Lopes, RIBEIRO, Carlos Antônio Álvares Soares, SILVA, Márcio Lopes**. Regulação de florestas eqüiâneas utilizando programação linear: uma aplicação da teoria do modelo II**. Revista Árvore, v. 22, n. 2, p. 193-213, 1998.

SILVA, Gilson Fernandes da. **Problemas no uso de programação matemática e simulação em regulação florestal**. Tese (Mestrado em Engenharia) — Universidade de São Paulo, São Paulo, 2001.

SOUZA, Simone SF; ROMERO, Ruben. **Algoritmo Imunológico Artificial CLONALG e Algoritmo Genético Aplicados ao Problema do Caixeiro Viajante**. Proceeding Series of the Brazilian Society of Computational and Applied Mathematics, v. 2, n. 1, 2014. DOI: https://doi.org/10.5540/03.2014.002.01.0106.

WERNEBURG, Mauro Antônio Pereira. **Planejamento em grandes empresas florestais no Brasil**. Dissertação (Mestrado em Ciência Florestal) — Universidade Federal dos Vales do Jequitinhonha e Mucuri; Diamantina; 2015.