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VEHICLE ROUTING STRATEGIES AND OPTIMIZATION FOR WOOD TRANSPORTATION

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Resumo

Estratégias de sequenciamento de veículos na otimização da logística florestal. O transporte de madeira é uma atividade onerosa para as empresas do setor florestal. Há inúmeros esforços na redução e controle desses custos, a partir de equipamentos eficientes e ferramentas de otimização. Devido à natureza combinatória desses problemas, métodos determinísticos exigem um maior esforço computacional de processamento, o que geralmente inviabiliza o seu uso. Uma alternativa é a aplicação de algoritmos aproximativos, estratégias eficientes de busca para encontrar soluções factíveis. O presente estudo avaliou algoritmos na resolução de problema envolvendo o sequenciamento do transporte florestal. Cenários simulados foram criados compreendendo três instâncias de 10, 20 e 30 talhões com características realistas. Diante de opções operacionais, quatro estratégias de resolução foram propostas envolvendo ainda o uso de três algoritmos (*Simulated Annealing, Greedy, e Greedy-Simulated Annealing*). O código computacional, processamento e análise foram realizadas no software RStudio. Os resultados demonstram a existência de soluções factíveis testadas pelos algoritmos, dando destaque ao híbrido *Greedy-Simulated Annealing*. Com comprovada normalidade e homogeneidade da variância, os algoritmos foram testados com o teste de Tukey ao nível de 5%. A estratégia envolvendo blocos, seleção aleatória de talhões e fluxo múltiplo apresentou os melhores resultados nos cenários testados. Como conclusão, os algoritmos propostos são eficientes na resolução do problema de transporte florestal, podendo ser úteis no planejamento operacional da atividade.
Palavras-chave: Inteligência computacional, planejamento operacional, dimensionamento de frota.

Abstract

Timber transportation is a hard task for any forest company. There are several efforts to reduce and control these costs, considering efficient equipment and optimization frameworks. Due to the pattern of combinatorial problems, the deterministic methods have a high computational effort of processing time, which generally makes their use unfeasible. An alternative procedure is applying approximation algorithms, which have efficient searches for finding feasible solutions. The present study evaluated algorithms for solving the forest transport sequencing problem. The Simulated instances were designed to highlight three instances for 10, 20, and 30 stands with a realistic pattern. According to the operational set, four solving strategies were proposed, considering three algorithms (Simulated Annealing, Greedy, and Greedy-Simulated Annealing). The computational code, processing, and analysis of the data were performed using RStudio software. The results show feasible solutions from all tested algorithms, highlighting the hybrid Greedy-Simulated Annealing algorithm. With proven normality and homogeneity of variance, the algorithms were tested with the Tukey test at a level of 5%. The blocks, stand random selection, and multiple flow strategies produced the best results of the tested instances. As a conclusion, the proposed algorithms are efficient for solving the forest transportation problem and may be helpful at the operational planning level.
Keywords: computational intelligence, operational planning, fleet sizing.

INTRODUCTION

Timber transportation has a significant cost for biomass production and demands a series of controllers to guarantee the wood supply flow daily. This activity supplies the industry with plants to produce pulp, coal, and other products. Hence, logistics planning is a complex process responsible for maintaining service quality, safety, and low cost under environmental conditions. According to Lopes *et al*. (2016), forest transportation efficiency is often associated with the distance driven, traveling speed, log length, queues, the loading and unloading of wood, and inadequate fleet distribution. Generally, these goals are solved under the vehicular routing problem models, which have been widely studied in recent years (ALVAREZ & MUNARI 2016). These models may provide a reduction in transportation costs and truck fleet size (MONTI *et al*., 2020). On the other hand, it is consensus that optimization systems support decision-making for better strategies and low risks.

Nowadays, the economic relevance of optimization models is highlighted for their high industry performance. Operational research techniques have been applied to seek better operational procedures and strategic advantages. Surely, due to the large size of Brazil's forest companies, the use of these methods is strongly suggested to avoid risks, and several business cases are dedicated to this theme (WALTERS *et al*., 2001; MONTI *et al*., 2020). Epstein *et al.* (2007) suggest the use of optimization models for forest transportation to reduce accident risks, traffic jams, inefficiency, greenhouse gas emissions, and noise pollution. However, the operational planning of harvest and transportation tasks deals with short-term decision-making under limited resource availability (SANTOS *et al*., 2018).

The advances in mathematical methods for solving optimization problems have been designed in the fields of combinatorial problems and integer variables. The problem complexity accelerated a branch of computational procedures to reduce the time required for processing, and several algorithms have already been proposed recently. Haridass *et al.* (2014) proposed a simulated annealing method for solving the log truck scheduling problem, and they found a consistent solution at a compatible time. In addition, the author's findings suggested a reduced number of routes and trucks when compared with traditional decision-making. This meta-heuristic was also successful in the transport scheduling of woodchips, increasing operational efficiency and reducing the final cost (ACUNA *et al*., 2012). In this context, the present study aimed to solve the vehicle routing problem under forest transportation constraints and daily wood demand. We have tested three non-exact algorithms into four operational strategies. Besides, the vehicle route results were analyzed for their total cost and efficiency.

MATERIAL AND METHODS

Forest transportation problem

The forest transportation problem has started in the industry, and the vehicle fleet must have to drive between vertices (v), returning to the initial point loaded with wood logs. This simple state problem also involves a complex combinatorial graph G = {v, a}, load/unload tasks by crane, minimal demand for wood, type of vehicle and capacity, cost, and the stand volume offer (Table 1). This wood transition flow is potentially large enough to increase operational inefficiency. The instance tests were designed for the charcoal project. The land area covers almost 30 carbonization units, and the vehicle fleet needs to supply wood within ten days. The working time of the vehicle fleet is 6 hours on a single shift day. There are three problem instances defined by changing the stand set (10, 20, and 30) to expand the algorithm analysis to deal with n problem size (MONTI, 2020).

Table 1. The vehicle fleet data and simulated instances used to assess the vehicle sequencing strategies and algorithms.
Tabela 1. Características dos veículos e instâncias usados para testar as estratégias de sequenciamento.

Instances	Stands		Minimal demand (ton)
	N	Volume (Mg)	
1	10	64,875	6,500
2	20	114,629	12,000
3	30	149,300	15,000

Vehicle characteristic sets	Types of vehicles with semi-trailers	
	T_2	T_3
Available vehicles (*pcs*)	100.0	100.0
Capacity (*ton*)	33.0	46.5
Fixed Cost (*BRL.day^{-1}*)	1,471.0	1,572
Variable cost (*BRL.Km^{-1}*)	5.06	6.08
Average velocity (*Km.h^{-1}*)	33.0	41.0
Loading Time (*h*)	0.27	0.39
Unloading time (*h*)	0.68	0.87

Vehicle sequencing strategies (VSS)

Solving any optimization problem is a state of the art under mathematical view and challenge (LI *et al*., 2010). Therefore, dealing with meta-heuristics is also a wide-open case for formulating a real problem into a programming code (FALCÃO *et al*., 2020). Instead of method performance, the approaches to solving the problem consider given strategies of thinking previously. Beyond vehicle fleet efficiency, vehicle sequencing strategies should ensure only feasible solutions. After the initial foreword, the vehicle's route is driven according to only two options (single or multiple access). They have a slight difference related to the number of stand access to load the wood logs. The multiple access visits a set of stands to complete the vehicle capacity, otherwise, it is single access. However, the vehicle fleet duty is to ensure continued wood supply within 10 days. The next further strategies are associated with spatial clustering, and this arrangement may affect the final performance. Initially,

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the spatial block defines a set of stand adjacencies that offer the equal volume requested by the industry daily. This proposal idea only makes sense due to the remaining volume left on day *n-1* and available for the next day. The second option is to randomly select for wood supply daily. Finally, the activity executions are the combination of vehicle drive access (single or multiple) and stand (block or random).

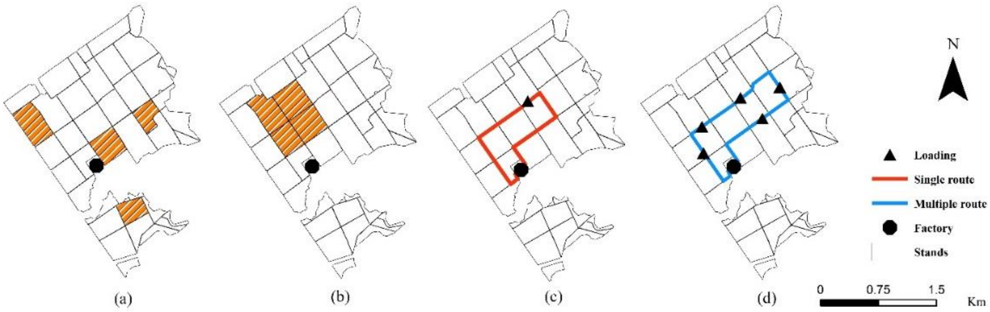

Figure 1. Vehicle sequencing strategies for wood transportation. (a) Random selection and Single Route access - RSSR, (b) Spatial Block and Single Route access – SBSR; (c) Random selection and multiple route access - RSMR; and (d) Spatial Block and Multiple Route access – SBMR.

Figura 1. Estratégias de sequenciamento de veículo para o transporte de madeira. (a) Seleção aleatória e rotas simples, (b) Bloco espacial e rotas simples, (c) Seleção aleatória e rotas múltiplas, (d) Bloco espacial e rotas múltiplas.

Stochastic algorithms

The nature of the problem under analysis has high complexity and binary variables, which usually compromises the computational run-time processing. An available option is to apply heuristics to overcome the time consumption. An efficient randomized heuristics is often desirable to solve a range of optimization problems. Their nature is stochastic, and there is a wealth of practical application and performance in the literature (FALCÃO *et al*., 2020). The probabilistic component is the key point of deep searches over the space, and this choice allowed different solutions at each time of execution. Hence, heuristic adaptation for solving an optimization problem is a state of the art. Therefore, novel methods are introduced to overcome the new challenges. Hybrid algorithms have also been tested in recent decades, and several gaps are still open in forest science (DONG *et al*., 2016; FALCÃO *et al*., 2020). Many published papers deal with single algorithms or exact methods for solving the vehicle routing problem associated with forest transportation (MONTI *et al*., 2020), and numerous studies have been carried out within various application domains (LI *et al*., 2010; MALIK *et al*., 2015; DONG *et al*., 2016; FERREIRA *et al*., 2017). Furthermore, the vehicle routing problem derives from the traveling salesman problem, which is one of the most studied optimization problems (ZUNIC *et al*., 2020).

Based on the forewords, the present study tested three algorithms for solving the study case. In optimization literature, two of them are known as simulated annealing (SA) and greedy algorithms (G). The last one is a hybrid algorithm combining the first two methods and is defined as GSA (greedy + simulated annealing). The combination of algorithms is common and may allow for finding solutions. Usually, there still exist additional improvements in search efficiency in some heuristic algorithms. According to Li *et al*. (2010), the decision criteria for switching algorithms procedures are relatively simple and determined by the expertise of the researchers. In this sense, the algorithms were performed in their natural form, and the hybrid algorithm GSA considers the first stage of a greedy search procedure, and the SA runs at the end. This means that the initial solution of SA derives from the best solution acquired from the G algorithm. The meta-heuristic SA parameters were initial temperature (40,000 °C), cooling rate (0,725%), 25% exchange rate of bases, and final temperature of 25°C. These parameters were obtained after initial tests. The Greedy algorithm is a simple set of rules accepting only better solutions; otherwise they are refused. The search procedure of exchanging bases was equal for all tested methods at 25% of the rate and 1,000 iterations of stop criteria. The pseudocode of the general procedure was provided in Table 2.

Table 2. Pseudocode of the main hybrid and individual procedures
Tabela 2. Pseudocódigo para os principais procedimentos híbridos e individuais

```
Step 1 Begin:
  for x in strategy ϵ {RSSR, SBSR, RSMR, SBMR} do:
    G (arguments: x;
          random initial feasible solution-obtained by the internal procedure of G without the enhancing factor,
          Pr (vehicle fleet size),
     Return: outputG – best solution to the Greedy algorithm
```

```
    ) End step 1;
  Step 2 Begin:
    SA (arguments: x;
        initial SA set of parameters,
        random initial feasible solution-likewise in G but using the SA internal procedure,
        outputG,
     Return1: outputSA – best solution of Simulated annealing algorithm
     Return2: outputGSA – best solution of Simulated annealing algorithm derived from G
     ) End Step 2;
 End Procedure
```

The initial solution of the tested algorithms identifies the set of stands and vehicle fleets available for wood supply daily. There is a probabilistic procedure under uniform distribution to select a vehicle n to pick up and deliver the wood service. The loading constraint defines the maximum use of the available n vehicle, and so on for the next selected vehicles. The stop criteria sequence is associated with the minimum bound of wood demands and the working hour limit daily. The final set of vehicle displacements within 10 days is the complete solution. The four-vehicle sequencing strategies are strongly respected for solving the problem in any instance. Finally, the assessment of the candidate solution (x) is carried out according to the total cost [1], which is the sum of the costs related to the vehicle's use on the day and its respective displacement. The meta-heuristics performance states at their principles and new candidate solution are evaluated properly. Therefore, the new change occurrence starts over vehicles and stands until the stop criteria are met.

$$\mathrm{CT} = \sum_{\mathrm{h}}^{\mathrm{HP}} \sum_{\mathrm{v}}^{\mathrm{V}} \mathrm{D}_{\mathrm{hv}}\, \mathrm{CV}_{\mathrm{v}} + \sum_{\mathrm{h}}^{\mathrm{HP}} \sum_{\mathrm{v}}^{\mathrm{V}} \mathrm{CF}_{\mathrm{hv}} \qquad [1]$$

where: HP: days; CT: the total of operation cost (BRL); CV: the variable cost of vehicle *v* on day *h*, the price of the kilometer driven (BRL); D: vehicle displacement v (Km); CF: the fixed cost, maintenance cost, and depreciation of the vehicle v (BRL).

Experiment analysis

Usually, the best solution is always highlighted to describe the desirable strategy with high performance. However, all tested algorithms are stochastic and should not present a real search performance to find better solutions (DONG *et al.*, 2015). Therefore, the solution performance was evaluated, considering a statistical experiment with three factors and 36 treatments (algorithms-3, instances-3, and vehicle sequencing strategies-4) at 10 independent runs. Considering the initial solution as stochastic, the final solution for analysis may be assumed as an independent sample from a larger population. Then, the performed statistical tests may be acceptable (DONG *et al.*, 2015); therefore, normality is calculated by the Shapiro-Wilk test, and homogeneity of variance is calculated by the Bartlett test. Given all the assumptions, Tukey's parametric mean test was performed with a confidence level of 5%. The additional information measured was the cost of wood transportation at unity cargo [2]. Where: C - the cost of wood transported at unit scale (BRL.ton-1); MT - the amount of wood transported (ton); and CT - the total cost of transportation (BRL).

$$\mathrm{C} = \frac{\mathrm{CT}}{\mathrm{MT}} \qquad [2]$$

RESULTS

Initially, to validate the Tukey test, the data was analyzed to determine whether it was adequate according to the assumptions. The homogeneity of the variance was calculated with the Bartlett test, where the p-value was assumed to be 0.24, which confirms the homogeneity of the variance since the p-value is greater than the confidence level of 0.05. In addition, the Shapiro-Wilk normality test was also performed, and the normality value was 0.36. The experiment results present a high degree of detail that incorporates significant values for the method tests. According to variance analysis, the treatments have strong differences compared to the transportation cost (Table 3). This trustable finding derives from a low variation of all the algorithms' solutions within instances and strategies. This positive aspect points out that no outliers and the mean are not affected by those values. As expected, the studied instances suggested a considerable difference in the final cost due to the problem size. The number of stands increases the vehicle fleet size and the traveling flux.

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Table 3. The experimental solutions to the forest transportation problem rely on algorithms, vehicle sequencing strategies, and the instance size.
Tabela 3. Resultados do experimento do problema de transporte florestal relacionado aos algoritmos, estratégias de sequenciamento de veículos e o tamanho de instância.

Instances	VSS	Algorithms	runtime Processing (s)	Best solution (BRL)	Average Cost (BRL)	CV (%)
1	RBMR	G	56.72	575,318.96	578,007.33	0.26
		GSA	92.69	573,567.01	575,935.10	0.22
		SA	68.85	573,686.74	576,737.02	0.33
	RBSR	G	58.01	576,804.85	578,780.48	0.18
		GSA	96.05	575,050.29	577,754.04	0.19
		SA	69.24	575,642.96	578,860.02	0.32
	SBMR	G	58.04	578,113.46	581,077.09	0.24
		GSA	95.09	577,966.73	580,321.33	0.23
		SA	71.64	577,953.85	578,941.51	0.25
	SBSR	G	56.26	581,917.20	582,848.16	0.08
		GSA	95.18	580,347.72	582,471.66	0.15
		SA	69.44	581,191.53	582,494.03	0.13
2	RBMR	G	117.92	989,293.60	995,247.78	0.28
		GSA	200.56	992,423.78	994,073.15	0.11
		SA	143.71	991,614.28	994,526.74	0.19
	RBSR	G	116.91	991,939.65	995,973.59	0.25
		GSA	197.91	989,879.86	994,342.22	0.29
		SA	145.44	993,975.49	997,013.13	0.19
	SBMR	G	116.92	998,794.81	1,001,712.13	0.18
		GSA	198.59	997,872.69	999,892.21	0.15
		SA	144.13	996,841.87	999,911.73	0.15
	SBSR	G	114.82	999,940.29	1,001,552.22	0.14
		GSA	201	997,715.46	1,001,493.35	0.18
		SA	145.2	999,163.21	1,001,943.58	0.14
3	RBMR	G	186.98	1,305,392.69	1,309,923.15	0.19
		GSA	304.98	1,309,155.29	1,310,767.32	0.07
		SA	214.02	1,306,364.12	1,311,414.60	0.22
	RBSR	G	185.79	1,310,921.70	1,315,558.44	0.23
		GSA	307.86	1,310,391.78	1,314,597.92	0.21
		SA	212.53	1,309,680.57	1,313,359.21	0.15
	SBMR	G	186.7	1,312,113.48	1,315,788.52	0.13
		GSA	305.13	1,309,822.98	1,313,244.01	0.11
		SA	213.83	1,310,328.97	1,314,370.21	0.19
	SBSR	G	185.54	1,315,431.35	1,318,768.70	0.13
		GSA	304.34	1,316,102.05	1,318,247.19	0.08
		SA	212.58	1,317,059.35	1,319,326.77	0.11

Legend: G: Greedy; SA: Simulated Annealing; GSA: G and SA algorithm hybridization, SBSR: Spatial block and a single route; SBMR: Spatial block and multiple routes; RBSR: Random block and a single route; RBMR: Random block and multiple routes.

The analysis of the variance of the experiment shows the existence of a significant difference between treatments (Table 4). The analysis shows a disruption between the algorithms (p-value = 0.0001), strategies (p-value = 0), and instances (p-value = 0). Interactions between strategy and scenario also differ significantly (p-value = 0). In this study, the solver methods were not similar for solving the state problem, and the final solutions differed from the searching strategies. Instead of vehicle sequencing strategies or instance size effects, it was possible to confirm the high performance of the algorithms GSA, SA, and G solutions in this decreasing order by Tukey's test (Table 4). The meta-heuristic SA is almost like GSA and G algorithms, and the strategy of previously using a greedy algorithm to explore the space solution was positive. Seeking to understand the solver's behavior in all instances, the factor was unfolded regarding the instance's subgroup. The analysis of variance highlighted a significant difference between the algorithms in instances 1 and 2. In contrast, this tendency was not observed in instance 3 or the algorithms. An overview of these interaction effects shows that the GSA has superior performance for instances of sizes 1 and 2. On the other hand, there are no differences between this algorithm and SA. The size and dimension of the problem may affect the algorithm's performance and convergence. The last analysis suggests a similar performance of all tested algorithms on the large problem. Hence, this finding is strongly associated with algorithm tuning and should differ from other studies. The independent runs of all algorithms validate the solutions, and the low values of the coefficient of variation were consistent enough.

The RBMR strategy allows the loading of an unlimited number of instances per route, causing a reduction in transportation costs as evidenced by Tukey's test exclusively analyzing the strategy factor (Table 4). The assessment of the strategy factor regarding the instances showed that significant differences were observed in all instances according to the analysis of variance. As for the Tukey test by scenario (Table 4), it is possible to state that in instance 1, the best strategy is RBMR, followed by RBSR, SBMR, and SBSR. In instance 2, the strategies RBMR and RBSR proved to be the best and do not present statistical differences. There is also no difference between the SBMR and SBSR strategies. In instance 3, the best strategy is RBMR, with intermediate behavior from the SBMR and RBSR strategies, and the SBSM with the worst results.

On the unfolding test, we can say that scenario 1 has similar behavior to the strategy factor analysis without iteration. In instance 2, there is a different behavior where strategies that have random instance selection (RBMR and RBSR) emerge as the best ways to perform the task, making it clear that spatial selection is detrimental to the cost of transportation in similar instances. Regarding the use of multiple and single routes, this scenario is passive. In scenario 3, there is a change in the outcome order. Where the RBSR and SBMR strategies do not differ statistically, the use of multiple routes or spatial field selection has the same effect in instances of this proportion. However, RBMR remains the best and SBSR the worst.

Table 4. Tukey's tests analysis of the main set of studied factors and their interaction effects.
Tabela 4. Análise do teste de Tukey para os principais fatores de estudos e efeitos de interações.

Algorithms	
Treatments	Average of transportation cost (BRL)
GSA	963,595.0 a
SA	964,074.9 ab
G	964,603.1 b
Vehicle sequencing strategies	
Treatments	Average of transportation cost (BRL)
RBMR	960,736.9 a
RBSR	962,915.4 b
SBMR	965,028.7 c
SBSR	967,682.9 d
Instances x Algorithms	
Treatments	Average of transportation cost (BRL)
1 - GSA	579,120.5 a
1 -SA	579,258.1 ab
1 -G	580,178.3 b
2 - GSA	997,450.2 a
2 - SA	998,348.8 ab
2 - G	998,621.4 b

3 - GSA	1,314,214 a
3 - SA	1,314,618 a
3 - G	1,315,010 a
Instances x Vehicle sequencing strategies	
Treatments	Average of transportation cost (BRL)
1 - RBMR	576,893.2 a
1 - RBSR	578,464.8 b
1 - SBMR	580,113.3 c
1 - SBSR	582,604.6 d
2 - RBMR	994,615.9 a
2 - RBSR	995,776.3 a
2 - SBMR	1,000,505 b
2 - SBSR	1,001,663 b
3 - RBMR	1,310,702 a
3 - SBMR	1,314,468 b
3 - RBSR	1,314,505 b
3 - SBSR	1,318,781 c

Legend: G: Greedy; SA: Simulated Annealing; GSA: G and SA algorithm hybridization), Vehicle sequencing strategies – VSS (SBSR: Spatial block and a single route; SBMR: Spatial block and multiple routes; RBSR: Random block and a single route; RBMR: Random block and multiple route) and the instance size. Means assigned to different groups differ statistically at 5% probability.

The exact number of routes executed by the vehicles carrying logs with a loading capacity below the maximum limit was quantified (Figure 3). The multi-route strategies (RBMR and SBMR) significantly reduced the occurrence of half-load travels. An analysis of spatialization on the selected instances within each block formation was performed on the most complex scenario using the strategies RBMR and SBMR. To perform this analysis, the best search algorithm (GSA) in the first planning horizon was applied. In Figure 3, it is observed that the spatial block is formed with the SBMR strategy, and the instances are adjacent. While the RBMR strategy follows the proposed random selection pattern. The number of vehicles used for transportation varies according to the strategy adopted. For example, in scenario 3, the RBMR strategy enables a lower average number of vehicles per day (90.5 trucks), while the SBSR strategy enables a larger number of vehicles per day (93.1 trucks on average). As for the type of vehicle adopted, the T3 is used the most in all scenarios for any strategy. This fact demonstrates that larger capacity vehicles have better efficiency for transportation. Even though they are slower and more expensive, they have a better cost-benefit. The time frame of each vehicle was used rationally, not exceeding the daily limitation. The vehicles are continuously sent to the field until their use reaches infeasibility. The average time spent per vehicle on a business day is about 5.32 hours out of 8 hours, considering all search algorithms and strategies. Regarding the displacement of the fleet, it is not possible to identify a considerable difference between the strategies in the scenarios (Figure 3). However, it is possible to notice that the BARM strategy presents the smallest fleet displacement. Displacement accounts for a portion of the operating costs, but it is not the only factor involved.

The best solution strategy for the chosen instance allocates a fleet of 39 vehicles (15 T2 and 24 T3) to carry 64,875.94 tons of logs. The fleet covered a total of 4,664.8 km of road length to completely meet the demand for the carbonization unit, generating a total cost of BRL 573,567.00. In the operational analysis proposed by Alves *et al*. (2013), time resource efficiency is 88.5%, with this work resulting in 88.46%. The cost-per-unit is found at BRL 8.84. This value is way below the one found by Alves *et al*. (2013) (between BRL 19.35 and BRL 31.24). In instance 2, the fleet used has a total of 70 vehicles (31 T2 and 39 T3). The total displacement of the fleet is 7,300.5 km and the efficiency of the time resource is 89.50%. The total cost was BRL 992,423.78, transporting 114,629.20 tons of logs from 20 stands, resulting in a cost of BRL 8.66 per ton of logs. The best solution obtained for instance 3 used a fleet of 90 vehicles (41 T2 and 49 T3). The fleet has a total displacement of 10,372.3 km. In the time resource analysis, no overtime payment was required. Thus, 6 hours per work shift was sufficient. According to the analysis of time consumed by the fleet, 4,944 hours were available for transportation, of which 4,402.75 hours were used, resulting in an efficiency of 89.05% regarding the use of available time per vehicle. With a total cost of BRL 1,309,155.29, transporting a total of 149,300.7 tons of logs from 30 instances, the cost per unit of wood tonnage was BRL 8.76. Per shift, the fleet meets the demand of the carbonization unit, except for the last day, when the wood contained in the instance was not sufficient to supply the target.

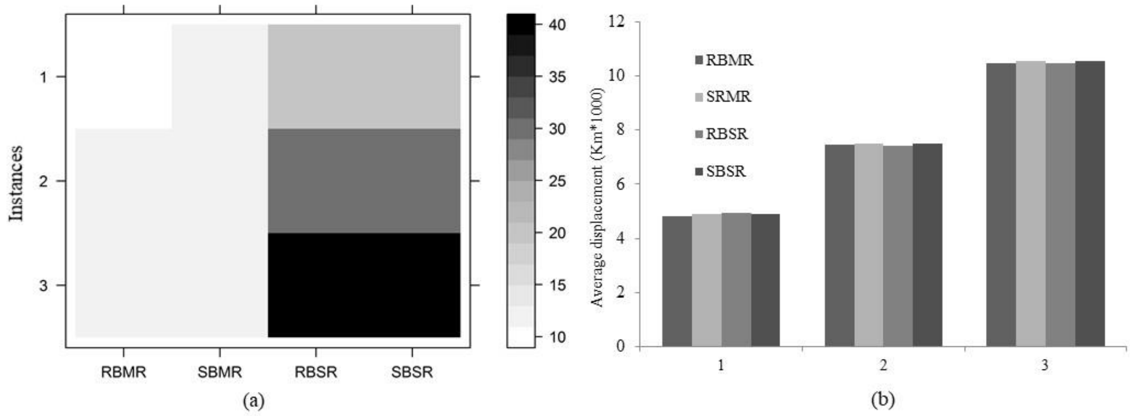

Figure 2. The algorithm solution considering (a) the frequency of a vehicle's route with incomplete loads and (b) the vehicle fleet drive distance (km). Where SBSR: Spatial block and single routes; SBMR: Spatial block and multiple routes; RBSR: Random block and a single route; RBMR: Random block and multiple routes.

Figura 2. Soluções dos algoritmos considerando (a) frequência de rotas com cargas incompletas e (b) deslocamento total dos veículos (Km). Onde SBSR: Bloco espacial e rotas simples; SBMR: Bloco espacial e rotas múltiplas; RBSR: Seleção aleatória e rotas simples; RBMR: Seleção aleatória rotas múltiplas.

DISCUSSION

The vehicle routing problem addressed is widely used in the economic sectors of agriculture (FLORENTINO *et al*., 2013; SANTORO *et al*., 2017) and industry (FERREIRA *et al*., 2017). However, in the forest sector, this problem has a peculiarity regarding the classic problem, with the vehicle's load capacity being smaller than the amount of product to be transported. Also note that these methods are recommended for complex problems as an alternative to exact methods (ABDALLAH *et al*., 2017). The solutions allowed generating a daily schedule per vehicle, which helps in the activity monitoring process. The potential of the logistics optimization process brings several advantages, not only economic but also operational (GOMES *et al*., 2019). Approximate methods have a disadvantage over the exact ones, as there is no guarantee of optimality. The use of mixed-integer linear programming presents high complexity in its formulation and high demand for processing time (LALLA-RUIZ *et al*., 2016). This fact is associated with the number of possible combinations (SOUZA *et al*., 2016). On the other hand, the algorithms tested in the present work have an applicable processing time, not exceeding 307.86 seconds. Malik *et al*. (2015) and Dong *et al*. (2016) corroborate the results found herein, with the hybrid algorithm being able to better explore the solution space, escaping local optima when compared with others. In addition, the quality of their initial solution distinguishes them as having the best convergence (DA CRUZ & PEREIRA, 2017). Under opposite conditions, the G algorithm is found to have great difficulty escaping from optimal locations due to purely value-constrained conditions of solution refinement.

Currently, the hybridization of searching algorithms has become a widely used technique for enhancing the quality of solutions. The combination of different methodologies is a useful tool for that matter, bringing gains in the quality of combinatorial optimization outcomes. In the study of stochastic algorithms, one of the main gains of this work is linked to a union between the characteristics of the traditional metaheuristics in a single hybrid algorithm where the SA has as input an already improved solution from G. Such an architecture allows the SA to start the iterative process with a reasonable quality solution. It increases the chances of finding the optimal solution to the problem. Even if the SA algorithm discards the initial solution via metropolis criteria, a generated candidate solution is considered the neighbor solution to the initial one. This fact ensures that G processing brings improvements to SA even at higher temperatures during the initial stage of its processing; thus, the best G solution can still be discarded.

In this work, as in Alvarez & Munuari (2016), in which vehicles travel several points of demand, the flow of vehicles that can serve multiple instances in a single route has a positive effect, reducing the number of vehicles arriving in the yard with partial load, making it clear that this kind of situation impairs the operational performance. According to Nelson (2003) and Augustynczik *et al*. (2015), the spatial approach in forest planning is important in management practices. Building spatial blocks is essential for performing tasks and improving the operational efficiency of the activity. However, in the present work, the strategies that use the spatial criteria for block formation (SBMR and SBSR) have the worst results. This type of management practice has an unwanted impact on the cost of transportation itself. In addition, only timber transportation does not fully represent logistic activity in forestry companies, and the integration of transportation and harvesting can enable block formation following spatial criteria.

According to the strategies developed, multiple flows improve the efficiency of the operation by creating new options for loading a vehicle. The random selection of plots for transport also shows operational gains. In a way, the selection of plots with the spatial criterion decreases the flexibility of selection for the algorithms. Possibly, in the optimal cost-based environment, the spatial criterion does not address combinations that are interesting from the point of view of cost optimization. The amplitude of the instances treated in this work presents a simple change in the behavior of the developed strategies, an intriguing fact that allows us to infer that in smaller environments it is possible to create an optimal environment with selection with spatial criteria. In addition, multiple flows are not recommended in these scenarios as they present a small set of alternatives for loading. The fact that the plots are dispersed in the study area potentially reduces the occurrence of queues and traffic jams, considering that this practice distributes the traffic of vehicles on several roads due to the dispersed location of the plots.

As observed, the number of vehicles used varies in days due to the distance from the instances to the factory, proving that large productive areas far from the factory lead to increased transportation costs, as reported by da Silva Lopes *et al*. (2018). This result indicates that for 88.6% of the active time, the vehicles are obligatorily in service (displacement, unloading, or loading). In the operational analysis proposed by Alves *et al*. (2013), the productive time of the fleet did not exceed 80% in any of the instances, highlighting that the use of algorithms can help in transport planning and increase the efficiency of the activity. The same happens with the cost per transported burden, even with the inflated costs for the present time, presenting satisfactory values. Transportation problems around the world are costly, and substantial investments in infrastructure produce small improvements in vehicle traffic (BAGLOEE *et al*., 2018). From a financial point of view, comparing the best results with the worst ones, the reduction in the cost of the operation is not practically significant. However, this work examined the planning of the operation, and the investment in management practices such as this has low value compared to building roads and buying vehicles for transportation.

CONCLUSION

- The GSA algorithm's performance for solving the transportation problem is plausible for the data set we applied in this study.
- This hybrid method explored the space solution efficiently, and the initial solution was improved significantly.
- The vehicle sequencing strategies (VSS) design provides feasible solutions for the routing feature and affects the performance of the algorithm.
- The random clustering of instances considers that the multiple routes (RBMR) strategy is the most suitable procedure for implementation in forest transportation modeling.

REFERENCES

ABDALLAH, A. M. F. M.; ESSAM, D. L.; SARKER, R. A. On solving periodic re-optimization dynamic vehicle routing problems. **Applied Soft Computing**, Amsterdam-Netherlands, v. 55, p. 1-12, 2017.

ACUNA, M.; MIROWSKI, L.; GHAFFARIYAN, M. R.; BROWN, M. Optimising transport efficiency and costs in Australian wood chipping operations. **Biomass And Bioenergy**, Amsterdam-Netherlands V. 46, P. 291-300, 2012.

ÁLVAREZ, A.; MUNARI, P. Metaheuristic approaches for the vehicle routing problem with time windows and multiple deliverymen. **Gestão & Produção**, São Carlos, v. 23, n. 2, p. 279-293, 2016.

ALVES, R. T.; ALVES, R. T., FIEDLER, N. C., SILVA, E. N. D., LOPES, E. D. S., & CARMO, F. C. D. A. D. Análise técnica e de custos do transporte de madeira com diferentes composições veiculares. **Revista Árvore**, Viçosa, v. 37, n. 5, p. 897-904, 2013.

AUGUSTYNCZIK, A. L. D.; ARCE, J. E.; SILVA, A. C. L. da. Spatial forest harvest planning considering maximum operational areas. **Cerne**, Lavras, v. 21, n. 4, p. 649-656, 2015.

BAGLOEE, S. A.; SARVI, M., PATRIKSSON, M., & ASADI, M. Optimization for Roads' Construction: Selection, Prioritization, and Scheduling. **Computer-Aided Civil and Infrastructure Engineering**, United Kingdom, v. 33, n. 10, p. 833-848, 2018.

DA CRUZ, V. F.; PEREIRA, F. H. Estudo da influência da estimativa inicial na qualidade da solução no algoritmo genético binário em problemas de sequenciamento da produção em ambiente job shop. **Exacta**, São Paulo, v. 15, n. 4, p. 1-11, 2017.

DA SILVA LOPES, E.; VIEIRA, T. P.; RODRIGUES, C. K. Avaliação técnica e de custos do transporte rodoviário com diferentes espécies e sortimentos de madeira. **Floresta**, Curitiba, v. 46, n. 3, p. 297-306, 2016.

DONG, L. BETTINGER, P., LIU, Z., QIN, H., & ZHAO, Y. Evaluating the neighborhood, hybrid and reversion search techniques of a simulated annealing algorithm in solving forest spatial harvest scheduling problems. **Silva Fennica**, Helsinki-Finland, v. 50, n. 4, p. 1-20, 2016.

EPSTEIN, R.; RÖNNQVIST, M.; WEINTRAUB, A. Forest transportation. In: **Handbook of operations research in natural resources**. Boston-USA, 2007. p. 391-403.

FALCÃO, A.O., BORGES, J.G., 2002. Combining random and systematic search heuristic procedures for solving spatially constrained forest management scheduling models. **For. Sci**., Switzerland, v.48, p.608–621.

FERREIRA, J. C.; STEINER, M. T. A.; GUERSOLA, M. S. A Vehicle Routing Problem Solved Through Some Metaheuristics Procedures: A Case Study. **IEEE Latin America** Transactions, New York-USA v. 15, n. 5, p. 943-949, 2017.

FLORENTINO, H. O. ISLER, P. R., RAMOS, P. R., NERVIS, J. J., & HOMEM, T. P. D. Modelo Matemático para plantio e colheita da cana-de-açúcar. **CMAC**, Bauru, p. 21-26, 2013.

GOMES, J. A. C. SANTOS, J. R. T., BARBOSA, G. V. D., & DE CARVALHO, G. B. Application of computational tool in the optimization and mitigation of costs in routing of charge transport logistics. **Brazilian Journal of Development**, Curitiba, v. 5, n. 7, p. 7703-7716, 2019.

HARIDASS, K., VALENZUELA, J., YUCEKAYA, A. D., & MCDONALD, T.. Scheduling a log transport system using simulated annealing. **Information Sciences**, Amsterdam-Netherlands, V. 264, P. 302-316, 2014.

LALLA-RUIZ, E. E., EXPÓSITO-IZQUIERDO, C., TAHERIPOUR, S., & VOß, S. An improved formulation for the multi-depot open vehicle routing problem. **OR spectrum**, Switzerland,v. 38, n. 1, p. 175-187, 2016.

LI, R., BETTINGER, P., BOSTON, K., 2010. Informed development of meta heuristic for spatial forest planning problems. **Open Oper. Res.,** Switzerland, J. 4, 1–11.

LOPES, E.S.; VIEIRA ,T.P.; RODRIGUES, C.K. Avaliação técnica e de custos do transporte rodoviário com diferentes espécies e sortimentos de madeira. **Floresta,** Curitiba, V. 46, N. 3, P. 297 - 305, 2016.

MALIK, A. J.; SHAHZAD, W.; KHAN, F. A. Network intrusion detection using hybrid binary PSO and random forests algorithm. **Security and Communication Networks**, London-UK, v. 8, n. 16, p. 2646-2660, 2015.

MONTI, C. A. U.; GOMIDE, L. R.; OLIVEIRA, R. M.; FRANÇA, L. C. J. Optimization of wood supply: the forestry routing optimization model. **Anais Da Academia Brasileira De Ciências,** Rio de Janeiro, V. 92, P. 1-17, 2020.

NELSON, J. Forest-level models and challenges for their successful application. **Canadian Journal of Forest Research**, Ottawa-Canada, v. 33, n. 3, p. 422-429, 2003.

SANTORO, E.; SOLER, E. M.; CHERRI, A. C.. Route optimization in mechanized sugarcane harvesting. **Computers and Electronics in Agriculture**, Amsterdam-Netherlands, v. 141, p. 140-146, 2017.

SANTOS, P. A. V. H. ; SILVA, ARINEI LINDBECK DA ; ARCE, J.E. ; AUGUSTYNCZIK, A.L.D. . A mathematical model for the integrated optimization of harvest and transport scheduling of forest products. **Forests**, Basel-Switzerland,V. 10, P. 1-13, 2019.

SOUZA, R. O.; CREMASCO, C. P.; GABRIEL FILHO, L. R. A.. Análise dos valores de frete da soja a granel nos sistemas unimodal e multimodal de transporte. **Revista em Agronegócio e Meio Ambiente**, Maringá, v. 9, n. 4, p. 819-837, 2016.

WALTERS, K. R.; COX, E. S. An empirical evaluation of spatial restrictions in industrial harvest scheduling: the SFI planning problem. **Southern Journal of Applied Forestry**, v. 25, n. 2, p. 60-68, 2001.