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LOGISTICS EFFICIENCY IN MILITARY AIR TRANSPORT: A CASE STUDY ON SUPPLY LOGISTICS IN THE AMAZON

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ABSTRACT

To maintain Brazil's sovereignty in the Amazon, the Brazilian Army maintains Special Border Platoons (PEF) in remote locations, where the supply of basic materials is primarily conducted via air transport, supported by the Brazilian Air Force. Using concepts from Packing Problems in Operational Research, this work presents a proposal to increase the efficiency of support operations for the PEFs through a mathematical model for loading aircraft during missions. The proposed model demonstrated a significant reduction in the number of necessary trips, optimizing load distribution and operation time. The study highlights the efficiency achieved by applying a process that considers the use of an exact optimization model and a high-performance hybrid algorithm in a case study applied to the PEFs in Surucucu and Auaris, contributing to the reduction of operational costs.

Keywords: Operational Research, Packing Problems, Mathematical Modeling.

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1. INTRODUCTION

To maintain integration and safeguard the defense of national territory, the Brazilian Army (EB) deploys platoons at strategic border points known as Special Border Platoons (PEF). The mission of the Amazon Military Command (CMA) of the EB is to secure the Amazonian border. To fulfill this mission, the CMA relies on Jungle Infantry Battalions (BIS), which are strategically located throughout the Amazon region of the country. Each BIS commands the necessary number of PEFs, ensuring territorial control of the area under its responsibility (Moraes 2021). Isolated in the midst of the Amazon jungle, the survival of the soldiers in these platoons directly depends on the joint work of the EB with the Brazilian Air Force (FAB), as, in some cases, the only way to access the platoon is by air. Through C-98A Grand-Caravan and C-105 Amazonas aircraft, the FAB provides most of the supplies sent to these locations, utilizing the Amazon Support Plan (PAA) (Dantas and Silvestre 2020). The flights originate from the corresponding BIS, which serves as the central distribution point for rations and essential items. In many locations, due to the limited space available to construct a runway, the only aircraft capable of landing and taking off is the C-98A.

Due to the aircraft's loading limitations and the large amount of cargo destined for the PEFs, multiple trips are necessary to deliver all the cargo to its destination. Another relevant point in this process is the calculation of cargo distribution for loading the aircraft, which is currently done empirically. There is no existing study focused on maximizing the amount of material to be loaded, discriminating by weight, and relating it to the aircraft's capacity. As a result, the aircraft makes a large number of trips, generating high operational costs. In the scientific literature, vehicle loading problems have been studied for a long time and are known as the Bin-Packing Problem (BPP). The BPP involves accommodating the maximum amount of cargo in a minimum number of packages or bins (Nakano et al. 2018), in this case, aircraft. However, BPPs can be intractable or unfeasible to solve exactly. For these cases, heuristics or metaheuristics are used to obtain satisfactory results (Fan et al. 2020).

Based on the Aeronautics Strategic Military Plan (PMAER), which aims to seek efficiency in the use of available resources (Brasil 2018), this work offers, as a tool for fulfilling the PAA missions (Moraes 2021), a mathematical model to increase the efficiency of supply transport to the PEFs, carried out by the C-98A aircraft. Initially, an exact model is used to optimize the means of transport; however, if it is not possible to obtain a result in a reasonable time, an adaptation of a heuristic model is presented as an option. The goal is to transport all the necessary cargo through a minimal or nearly minimal number of trips. This study also explores how the granularity of items impacts the efficiency of the proposed algorithm. This article contains five sections. The next section provides the foundation of the BPP in the context of the mentioned missions. Section III shows the application of the BPP in support of the PEFs. The results are presented in section IV and discussed in section V. Section VI concludes this article with conclusions and suggestions for future work.

2. LITERATURE REVIEW

2.1. CUTTING AND PACKING PROBLEM

The Bin-Packing Problem (BPP) appears in various real-world applications, particularly in vehicle loading optimization (Arenales et al. 2007). For a problem associated with aircraft, the BPP involves accommodating the maximum amount of cargo in the minimum number of aircraft possible. The BPP can also be classified according to its dimensional constraints, such as weight, height, width, and length. In the one-dimensional problem, the items to be allocated have only one variable, which in this study will be considered as weight, and the value of this variable cannot exceed the capacity of the container, which will be referred to as a bin (Wessa and Atia 2021).

An important characteristic of Operational Research (OR) that facilitates the process of analysis and decision-making is the use of models, which allow for experimentation with the proposed solution. Thus, the standard model of a one-dimensional BPP can be defined as follows: given i = {1,..., m} objects with their respective weights wi and j = {1,..., n} identical bins with finite capacity C, determine the allocation of the n items (where $wi \leq$ Cj, ∀ j), such that the number of bins required is minimized, respecting the capacity constraints in each bin (Arenales et al., 2007). The mathematical formulation can be described as follows:

Minimizar:	$\sum_{j=1}^{n} y_j$	(1)
Sujeito à:	$\sum_{i=1}^{m} x_{ij} w_i \leq C y_j$, ∀ j	(2)
	$\sum_{j=1}^{n} x_{ij} = 1$, ∀ i	(3)
	y_i and x_{ij} , are binary	(4)

The Objective Function (FO) expressed in (1) seeks to minimize the total number of bins used. In (2), it is ensured that the capacity of each bin used is not violated, while (3) imposes that each object i is allocated to exactly one bin j. The constraint expressed in (4) ensures the integrality of the decision variables.

However, BPPs are highly complex computational optimization problems with resolutions in nondeterministic polynomial time (Fan et al. 2020), making them intractable or unfeasible for exact solutions. For this reason, most references in the literature on BPP refer to heuristics or metaheuristics that offer algorithms based on very simple planning strategies and often provide satisfactory results.

2.2. Alternative to the Exact Model – Hybrid Algorithm

Greedy algorithms are commonly used in solving BPP due to their efficiency and simplicity. They provide a pragmatic approach where obtaining exact solutions can be computationally prohibitive. Although they do not guarantee an optimal solution, these algorithms often generate sufficiently good solutions in practice, making them an excellent choice when efficiency is a priority. Additionally, due to their intuitive nature, these algorithms are easy to implement and understand, facilitating rapid prototyping and iterative experimentation.

Some classic heuristics for solving the one-dimensional BPP continue to be studied due to their simple implementation and quick resolution. Examples include the Next-Fit, analyzed by Saraiva and Schouery (2019), the Best-Fit-Decreasing by Jangiti (2020), and the Better-Fit, developed by Bhatia and Hazra (2009). In these heuristics, objects are ordered by the limiting factor, and rules are applied for the allocation of objects to bins. These heuristics aim to simplify the decision-making process.

However, these algorithms can face limitations, such as a tendency to converge to suboptimal local solutions. To mitigate these limitations, researchers have integrated heuristics with metaheuristics, seeking solutions closer to the global optimum (Munien et al. 2020).

The Next-Fit (NF) is an algorithm that, without altering the arrangement of items, packs the first item into the first bin and then checks whether each subsequent item fits into the bin where the last item was placed. If so, the item is included in that bin; otherwise, the bin is closed, and a new one is opened where the item is added (Saraiva and Schouery 2019). The Best-Fit-Decreasing (BFD) (Jangiti 2020) also orders items in decreasing order; however, when packing them, it tries to place each one in the bin that will leave the smallest possible empty space. If no existing bin can accommodate the item, a new bin is started. The Better-Fit (BF), developed by Bhatia and Hazra (2009), follows the same logic as the BFD, incorporating an evaluation phase with item permutation to try to optimize the allocation, potentially reducing the number of bins used even further.

The logic behind ordering items in decreasing order is that by dealing with larger items first, there is a higher probability of efficiently filling the bins, avoiding leaving "wasted" space that cannot accommodate the smaller items considered later. Tlili and Krichen (2023) also demonstrate through

extensive simulations with real-world data that BFD consistently shows superiority in terms of resource utilization and packing efficiency. An advantage of this algorithm is that, in addition to approaching the optimal solution, the last bin in its distribution receives the smallest number of items out of the total distributed, a characteristic that differentiates it from other heuristics used to solve BPP.

A metaheuristic is a high-level optimization approach that combines heuristics with a flexible framework that can be adapted to different types of problems (Almufti et al. 2023). These methods balance the exploration of new solutions and the exploitation of the best-known solutions, aiming to find optimal or near-optimal solutions efficiently and effectively, even for large-scale and highly complex problems.

The genetic algorithm (GA) is a metaheuristic inspired by the process of natural evolution, using operations that emulate selection, crossover, and mutation processes to evolve solutions to complex problems. Initially, a population of candidate solutions is randomly generated. The solutions are evaluated based on a fitness function, and the best are selected for reproduction. During crossover, parts of the selected solutions are combined to create new solutions, while mutation introduces small random changes to maintain genetic diversity. This iterative process continues until a satisfactory solution is found or a stopping criterion is reached, always seeking optimization of the target problem (Almufti et al. 2023), (Fan et al. 2020), (Munien et al. 2020).

Fan et al. (2020) and Munien et al. (2020) present the formation of hybrid algorithms by combining GA with BF and BFD. Their work demonstrates its high performance, capable of presenting the optimal result more often than other competing metaheuristics, and standing out for the low computational time to achieve it. The alternative model for the development of BPP in this work will therefore be GA combined with BFD and BF, a high-performance hybrid algorithm (HPHA).

3. MATERIALS

To represent the model, a specific case study was conducted using the Special Border Platoons (PEFs) of Roraima, which are under the command of the 7th Jungle Infantry Battalion (7th BIS). Located in the city of Boa Vista, the 7th BIS acts as a distribution center for the logistical supply network of its subordinate PEFs.

The PEFs in the localities of Surucucu and Auaris present the greatest logistical access challenges, as they are only accessible by air. The other PEFs under the 7th BIS can receive supplies by land, using trucks on highways. Thus, the PEFs selected to be part of the model were the 4th PEF - Surucucu and the 5th PEF - Auaris.

Data collection was carried out with the operators of the C-98A aircraft from the Boa Vista Air Base (BABV) and the Seventh Air Transport Squadron (7th ETA), which, although based in Manaus, serves the entire Northern Region. The Brazilian Army was consulted through the 7th BIS.

Records indicate an average demand of 13,873 kg of supplies for a PEF with an effective force of 60 soldiers, transported in approximately 200 boxes, over 25 trips, during 15 days.

To evaluate the proposed model, data provided by the 7th BIS was used, including a list of 200 items totaling 13,873 kg. Based on this data, additional lists were generated with different quantities of items to analyze the effect of granularity on the performance of the exact algorithm and the proposed algorithm. The additional lists were created with 50, 100, 150, 350, 500, and 750 items, all with random weights, but maintaining the initial total weight of 13,873 kg. This allowed for observation of how distribution into a larger number of items impacts the efficiency and effectiveness of the algorithm.

In the first phase, to determine the constraints in the context of this work, which aims to distribute the items across the trips to be made, the bin size will be the aircraft's carrying capacity. For a trip to a location, the aircraft will always have the same carrying capacity, meaning the capacity of each bin C_j will be considered a fixed value.

For safety reasons, the operation of the C-98A aircraft in the Amazon region is restricted to daytime flights, limiting the trips to times between sunrise and sunset. Analyzing the sunrise and sunset times in Boa Vista during the years 2019, 2020, 2021, 2022, and 2023 (Brasil 2023), it was found that the available times for operation are consistent, with twelve hours per day.

In this scenario, each flight is a round trip to the destination, noting that the aircraft is required to return to Boa Vista on the same day. Before each takeoff, the crew performs ground procedures that take 1 hour. Thus, the travel time for each location is calculated by adding the round-trip flight time to the destination, plus the time spent on the prior ground operation.

For example, a trip from Boa Vista to Surucucu takes 1 hour of preparation before takeoff from Boa Vista, 1 hour and 10 minutes of outbound flight, 1 hour of preparation before takeoff from Surucucu, and 1 hour and 10 minutes of return flight, totaling 4 hours and 20 minutes.

For the optimization of the flight schedule, the second phase of this work, the bin will be the day of air operation, which will have a "size" value of 13 hours, starting 1 hour before sunrise and ending at sunset.

4. METHODS

4.1. METHOD - FIRST PHASE

The proposed model to increase the efficiency of cargo delivery to the PEFs using the FAB's C-98A aircraft is divided into two phases. In the first phase, the goal is to determine the minimum number of trips required for each of the two locations to meet the entire demand for items. The initial objective function (FO) is thus the minimization of the total number of trips needed to transport all items. The notation for this mathematical model is the same as presented in Section 2.1.

The next step is to analyze the possibility of a trip that passes through both locations, with the intention of further minimizing the number of trips required. In this phase, the minimum number of trips becomes a system constraint, and the objective now is to minimize the number of items in one of the trips to be made. This second optimization follows the following model:

Minimize:	$\sum_{i=1}^{m} x_{i1} w_i$	(5)
Subject to:	$\sum_{i=1}^{m} x_{ij} w_i \leq C y_j \, , \forall \, j$	(6)
	$\sum_{j=1}^{n} x_{ij} = 1 \, , \forall \, i$	(7)
	$\sum_{i=1}^{n} y_j =$ Minimum number of required trips → 1ª FO	(8)
	y_i e x_{ij} , are binary $\forall \, i$ e j	(9)

The difference in this notation is that FO (5) seeks to minimize the weight of the items transported on the first trip. In (6), the aircraft's carrying capacity is always constant due to the aircraft's weight loading limit. Equation (8) ensures that the number of trips will be exactly that which was previously found by the first FO, the minimization of the number of trips.

However, since the execution time of the algorithm may extend excessively, a maximum execution time limit of 30 minutes (1800 seconds) is established. For exceeded cases, the HPHA will be used, also paying attention to the bin that offers the lowest weight.

For each location, the minimum number of trips and the minimum load to be transported on each trip will be determined. Next, the feasibility of conducting a "Efficiency Trip" (ET) will be analyzed, which consists of a single trip that passes through both locations, transporting the minimum necessary load for each.

For the ET to be viable, the sum of the minimum load quantities to be transported to Surucucu and Auaris must not exceed the capacity of an aircraft. This aircraft must depart from Boa Vista, passing through both locations in a single route.

The aircraft's available carrying capacity needs to be reassessed for this specific route, as the journey is longer and, consequently, the capacity constraint will be different from the previous trips

made directly to each location. Therefore, the analysis should include the new load capacity of the aircraft considering the extended route, ensuring that the combined transport of the loads for Surucucu and Auaris is possible within this adjusted capacity.

With the possibility of conducting the ET, the calculation of trips will be adjusted to account for one less trip for each location and one trip that serves both locations. Let Z be the minimum number of trips made, the total number of necessary trips will be represented by the formula: $Z_{\text{Auaris}} + Z_{\text{Surucucu}} - y * Z_{\text{efficiency trip}}$, where y is a binary value that can be 0 or 1, indicating whether the ET was conducted or not. This solution will determine the minimum number of trips necessary to meet the entire demand of both PEFs.

4.2. METHOD - SECOND PHASE

After the first phase, which determines the total number of trips required to serve the locations, the goal is to achieve maximum efficiency in delivering the demand. A new BPP is now presented, with the Objective Function aimed at minimizing the delivery time, i.e., the minimum number of days required to complete all the trips.

In this problem, the trips are considered as "items," possessing two or three different values, depending on the occurrence of the ET. The optimization problem is to find the best distribution of the trips according to the available flight time on each day, in order to minimize the total number of days required to complete all flights.

Minimize:	$\sum_{j=1}^{n} D_j$	(10)
Subject to:	$\sum_{i=1}^{m} v_{ij} t_i \leq HD_j$, ∀ j	(11)
	$\sum_{j=1}^{n} v_{ij} = 1$, ∀ i	(12)
	D_i e v_{ij} , are binary	(13)

The Objective Function (FO) expressed in (10) seeks to minimize the total number of days used. In (11), it is ensured that all flights v_i with time t_i are less than or equal to the hours H (available for air operation) on days D_j, while in (12) it is imposed that each flight i is allocated to exactly one day D_j. The constraint expressed in (13) ensures the integrity of the decision variables. If it is not possible to reach the exact answer in a reasonable time, the HPHA will be used.

5. RESULTS

Currently, the 7th BIS carries out the bimonthly distribution of cargo for trips to the PEFs using a sequential item loading method until the load limit is reached, a method analogous to the Next-Fit (NF) algorithm. For this reason, NF is used as a comparison to the proposed model during the simulation phase. Similarly, the trips are scheduled to meet demands in chronological order, also following the NF logic, and the ET is not included in the planning.

Thus, Table 1 was generated, presenting the results of the implemented process. The computational effort was measured using a computer with an AMD® Ryzen™ 5 1500X Quad-Core processor at 3.50 GHz and 16 GB of RAM. The NF heuristic and the hybrid model were implemented in Python, while the exact model was implemented in AMPL software using the CBC (Coin-or Branch and Cut) solver.

Table 1 Comparison of Heuristic and Exact Model Performance for Load Optimization

	Responses	Auaris Trips	Surucucu Trips	Load Auaris	Load Surucucu	ET	Travel Days
50 items list	Next-Fit	35	39	*	*	N	25
	Exact Model	*	*	*	*	*	*
	Exact Mod. Time	>1800s	>1800s	*	*	*	*
	Proposed Heuristic	26	25	348	181	N	22
	Heuristic Time	4s	4s	*	*	*	5s

100 items list	Next-Fit	34	27	*	*	N	25
	Exact Model	*	*	*	*	*	*
	Exact Mod. Time	>1800s	>1800s	*	*	*	*
	Proposed Heuristic	25	24	505	285	N	21
	Heuristic Time	9s	8s	*	*	*	4s
150 items list	Next-Fit	36	30	*	*	N	24
	Exact Model	25	24	*	*	N	22
	Exact Mod. Time	138s	146s	>1800s	>1800s	*	23s
	Proposed Heuristic	25	24	376	192	N	22
	Heuristic Time	12s	12s	*	*	*	4s
200 items list	Next-Fit	29	26	*	*	N	24
	Exact Model	25	24	322	107	S	21
	Exact Mod. Time	692s	574s	595s	627s	*	23s
	Proposed Heuristic	25	24	327	73	S	21
	Heuristic Time	9s	9s	*	*	*	2s
350 items list	Next-Fit	34	27	*	*	N	25
	Exact Model	25	24	289	78	N	21
	Exact Mod. Time	1322s	1317s	1534s	1637s	*	22s
	Proposed Heuristic	25	24	329	78	S	21
	Heuristic Time	32s	29s	*	*	*	3s
500 items list	Next-Fit	25	24	*	*	N	21
	Exact Model	*	*	*	*	*	*
	Exact Mod. Time	>1800s	>1800s	*	*	*	*
	Proposed Heuristic	25	24	314	73	S	21
	Heuristic Time	71s	62s	*	*	*	3s
750 items list	Next-Fit	25	24	*	*	N	21
	Exact Model	*	*	*	*	*	*
	Exact Mod. Time	>1800s	>1800s	*	*	*	*
	Proposed Heuristic	25	24	314	73	S	21
	Heuristic Time	71s	62s	*	*	*	3s

* The exact model could not produce results within the set time limit of 1800 seconds.

5.1. DISTRIBUTION OF ITEMS PER TRIP

For all the analyzed lists, the proposed model improved the number of trips required, whether using the exact model or the HPHA, demonstrating a significant enhancement compared to traditional approaches like the NF algorithm. The data used were derived from interviews with members of the Brazilian Army (EB) and the Brazilian Air Force (FAB) and included variations in items according to five different configurations: 50, 100, 150, 200, 350, 500, and 750 items, simulating different levels of cargo granularity.

The results indicate that for the 200-item configuration, which most accurately reflects current operational demand, both the heuristic and exact models successfully reduced the number of trips required compared to the NF method. While the exact model was effective, it faced execution challenges when the volume of items increased to 500 or more, resulting in processing times exceeding the stipulated 30 minutes (1800 seconds). This reflects the reality of the algorithm needing to process a larger number of variables in the system. Additionally, the exact algorithm also encountered difficulties in scenarios where granularity was low—that is, where item dimensions were closer to the bin value—making it harder for the model to find the optimal distribution.

In comparison, the heuristic approach proved to be more agile, capable of providing solutions in significantly less time, usually in seconds. The developed model, HPHA, demonstrated high efficiency, producing results identical to the exact model whenever a comparison was possible.

In the 350-item list, the exact model required 1322 seconds to complete, while the heuristic model finished in just 32 seconds, highlighting the practical utility of heuristics in operational contexts where quick decision-making is a priority. The results of the heuristic model were also comparable to those of the exact model in terms of the number of trips saved, showing a reduction of 3 trips for Surucucu and 9 trips for Auaris compared to the NF method.

These results underscore the model's ability to adjust to different cargo sizes, with the proposed heuristic offering a viable alternative when time constraints are a factor. The model's effectiveness in reducing the number of necessary trips and optimizing loading is evident, with the 200-item list being the most representative of real-world operations.

5.2. DISTRIBUTION OF TRIPS PER DAY

Once the number of trips to be made is determined, the second model defines the minimum number of days required to complete all the necessary trips.

Given that trips from Boa Vista to the locality of Surucucu take an average of 1 hour and 10 minutes, the calculation for the model is composed of the round-trip time of 2 hours and 20 minutes, plus 1 hour of ground time before takeoff, and an additional 1 hour of ground time at Surucucu. Each trip from Boa Vista to Surucucu is entered into the proposed BPP model as an "item" of 4 hours and 20 minutes.

Trips from Boa Vista to the locality of Auaris, on the other hand, take an average of 1 hour and 40 minutes. The calculation for the model will then consist of the round-trip time of 3 hours and 20 minutes, plus 1 hour of ground time before takeoff, and an additional 1 hour of ground time at Auaris. Each trip from Boa Vista to Auaris is entered into the proposed BPP model as an "item" of 5 hours and 20 minutes.

The ET that departs from Boa Vista, passes through both localities, and returns is composed of the average time from Boa Vista to Surucucu, plus the average time from Surucucu to Auaris, which is 35 minutes, and then the time from Auaris to Boa Vista. The calculation for the model will therefore consist of the total flight time for the route, which is 3 hours and 25 minutes, plus 1 hour of ground time before takeoff and 1 hour of ground time at each intermediate stop. Each ET trip is entered into the proposed BPP model as an "item" of 6 hours and 25 minutes.

Based on the responses obtained from previous simulations, the data were input into the proposed trip distribution model. For example, in the analysis of List 4 (200 items), there were 24 trips from Boa Vista to Auaris representing "items" of 5 hours and 20 minutes, 23 trips from Boa Vista to Surucucu representing "items" of 4 hours and 20 minutes, and 1 ET representing an "item" of 6 hours and 25 minutes. The bin for the model's BPP was set to 13 hours, given the daily operational time available for completing the trips.

To determine the efficient distribution of trips, the proposed algorithm was applied, configuring the trips within the operational limits of each day. The results indicated that the proposed model required fewer days to complete all the trips compared to the empirical approach. Specifically, for the mentioned list, the result was a savings of 3 days compared to the traditional sequential method.

Thus, the mathematical model proved effective in reducing the total number of operational days, enhancing aircraft utilization, and optimizing the daily operational window. Once again, whenever a comparison was possible, the HPHA demonstrated results identical to the exact model.

6. DISCUSSION OF RESULTS

6.1. ANALYSIS OF THE CURRENT DISTRIBUTION CONDITION

In this section, the analysis focuses specifically on the 200-item list, which most accurately reflects the current and precise state of cargo operations for the PEFs, followed by a brief comparative analysis of the other item lists.

To compare the efficiency of the empirical method, represented by NF, with the proposed model, the air effort required to complete a trip, measured in flight hours, is used. The analysis centers on the efficiency of the proposed model for distributing 200 items, showing a 13% reduction in air effort compared to the traditional method, saving approximately 20 hours. The model primarily focuses on the weight of the items without considering volume, which was not a constraint in this specific study.

One limitation identified in the process is that the model concentrates predominantly on item weight as the restrictive variable, while volume, which is typically a significant constraint in packing problems, did not present itself as a limiting factor in this context. Despite the optimal results presented by the exact model, the resolution time still presents challenges when applied to problems involving a large volume of items.

Alternatively, the proposed heuristic method proved to be highly effective, generating results comparable to the exact model but within a substantially shorter time frame, usually in the order of seconds for all simulations.

The methodology currently employed for trip distribution is based on a sequence that does not optimize the use of daily operational time, similar to the application of the NF algorithm in each transport mission. In contrast, the proposed model achieved a savings of three days in the total number of journeys required due to optimization in load allocation.

6.2. Analysis of Other Lists

Through the diversity of the tested lists, it was possible to observe that increasing the granularity of items can improve packing efficiency. This occurs because more granular items allow for more precise adjustments within the aircraft's space limits, reducing the number of trips required.

However, this greater granularity also brings an increase in computational complexity, as demonstrated in simulations with 500 and 750 items, where the processing time required for the exact model frequently exceeded the established limits. The heuristic model, on the other hand, maintained a quick and effective response capability, even in the face of greater complexity, confirming its applicability and robustness in a dynamic and demanding operational context.

The analysis of the list configurations also highlights that the high granularity of items, specifically in lists exceeding 500 items with a constant combined weight of 13,873 kg, enhances the effectiveness of heuristic models in the search for optimal solutions. This translates into a more precise fit of the items within the aircraft's capacities, contributing to the reduction of trips and operational costs. Notably, even in denser list configurations, such as those with 750 items, simple strategies like NF managed to achieve results comparable to those of HPHA, highlighting the ability of these models to efficiently handle increased complexity, even under strict processing constraints.

7. CONCLUSION

This study focused on logistical optimization for the PEFs in Surucucu and Auaris, achieving significant reductions in the number of trips and the use of air resources. The implementation of the model resulted in a savings of 20 hours and 30 minutes of air effort and 3 operational days, demonstrating substantial improvements in logistical efficiency.

The study confirmed that the detailing and variation in item sizes and weights have a direct impact on the ability to accommodate them within the aircraft and, by extension, on the number of trips required. More sophisticated optimization techniques, such as the proposed heuristic model, proved not only feasible but superior in various test scenarios, providing efficient solutions within considerably reduced operational timeframes.

Moreover, the application of the trip optimization model offered a structure capable of maximizing the use of available space and flight time, contributing to a significant reduction in the total number of days needed to complete all logistical missions. This optimization was achieved by reformulating how loads and trips are planned and executed, replacing sequential and less efficient approaches with strategies that exploit the potential of packing algorithms.

Beyond applications to the PEFs, the approach developed in this study has significant potential to be adapted for humanitarian aid missions, where logistical efficiency is equally critical. For example, Operation Yanomami in 2023, which involved delivering food to indigenous communities, and the support missions to Rio Grande do Sul in 2024, which included delivering donations from across the country to those displaced by floods. In these contexts, resource optimization can play a

vital role in maximizing the desired impact, saving lives, alleviating human suffering, and minimizing costs.

A proposal for future studies is to develop models that consider the optimization of load size based on vehicle capacity. These models could be applied in different loading contexts, such as National Air Transport Lines and Humanitarian Aid Missions conducted by the FAB. Analyzing real data in these situations could provide a way to further improve the efficiency of air transport operations, ensuring optimized use of available resources and reducing operational costs.

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