Strategically Influencing Seat Selection in Low-cost Carriers: A GRASP Approach for Revenue Maximization

Andrés Merizalde[1], Gustavo Rubiano[1], Germán Roberto Pardo[1,2], Alejandra Tabares Pozos[1], and David Álvarez-Martínez[1*]

[1] Department of Industrial Engineering, Universidad de Los Andes, Bogotá, Colombia

[2] Department of Mathematics, London School of Economics and Political Science, London, UK

* d.alvarezm@uniandes.edu.co

Abstract. In the competitive passenger air transport market, low-cost airlines continue strengthening their position, contrasting sharply with traditional carriers. This article delves into the unique operational strategies of these airlines, focusing on their reliance on ancillary services. Among these services, seat selection stands out as a crucial revenue enhancer. The study emphasizes the importance of low-cost carriers ensuring the availability of specific seats for direct purchase, thereby avoiding their allocation through automatic seat assignment algorithms, commonly activated for passengers who do not opt for specific seating. A notable consumer behavior observed is the preference for passengers on the same booking to be seated together. Low-cost airlines can capitalize on this trend by encouraging seat purchases and using automated seat assignments to strategically separate passengers traveling together unless they opt for paid seat selection. This work presents a novel approach to the seat assignment problem based on a GRASP algorithm; this approach is beneficial due to its low requirement for extensive parameter calibration, intuitive nature, and adaptability to different airline scenarios. Using an actual flight database of a low-cost Colombian airline, we have compared the airline's rule-based heuristics, a network flow model, and our metaheuristic approach; the results obtained are satisfactory in terms of solution quality and computational cost. The proposed solution offers a viable, cost-effective alternative to specialized software solutions, aligning with the financial constraints typical of low-cost carriers while effectively enhancing their seat assignment process to optimize revenue generation.

Keywords: low-cost carrier · ancillary services · seat assignment · GRASP

1 Introduction

The air transport industry has undergone a significant transformation with the emergence and consolidation of low-cost carriers (LCCs). These airlines have challenged the traditional model of established carriers, offering a reduced cost structure and lower fares for passengers [19]. Unlike traditional airlines, which focus on service differentiation, including multiple seating classes and additional amenities, LCCs have adopted a more homogeneous approach, prioritizing efficiency and simplicity in their business model [9,11].

A case in point is Allegiant Air, an LCC that reported a significant 115% increase in net revenue in 2009, primarily attributed to the income generated from unbundled flight products. As a global leader in converting ancillary services into revenue, Allegiant Air saw these products constituting 30% of its total income in 2009, demonstrating the potential for airlines to augment revenue streams and profitability through ancillary services [8]. These services, notably seat assignment, typically cost passengers between \$5 and \$25 [11].

Intriguing developments in 2021 revealed airlines implementing novel strategies to boost ancillary incomes. For instance, Eurowings allowed passengers to pre-book middle seats, and Spirit Airlines averaged \$7.00 per passenger for early seat selection [8]. As noted, the vital auxiliary seat assignment service enables airlines to generate additional revenue. However, optimizing seat assignment sales is challenging, involving passenger preferences, capacity constraints, and pricing considerations.

A study by [12] indicated that LCC passengers are more likely to purchase auxiliary products and services than those flying with traditional airlines, with these fees being the third most accepted auxiliary service. Offering unbundled services, like seat reservations, can be an effective way for airlines to increase revenue flows and meet the growing demand for auxiliary services among passengers.

The applications of operations research in the airline industry are diverse, ranging from addressing overbooking issues [14] to online seat assignment [5], floating allocation [15], simultaneous routing of aircraft and crew scheduling [6], air traffic management through deterministic and stochastic optimization [1], boarding strategies [4], and even addressing social distancing in aircraft seating.

Although various studies have explored revenue optimization strategies in airlines [3,2,18], there is a lack of specific research on how Low-Cost Carriers (LCCs) can optimize their automatic seat allocation algorithms to maximize revenue without incurring significant costs. LCCs could significantly boost their revenue by adjusting their seat assignment system. This adjustment would involve strategically not assigning seats that historically have a high likelihood of being purchased, thereby stimulating the sale of these seats. Additionally, by not automatically allocating individuals from the same reservation together, the airlines could encourage passengers to opt for paid seat selection to ensure they are seated with their travel companions. In this work, we present a GRASP algorithm for the seat assignment problem of a Colombian low-cost airline.

The paper is structured as follows: Section 2 presents the definition and formulation of the problem. Section 3 provides a detailed description of the proposed metaheuristic. Section 4 conducts the metaheuristic's performance analysis. Finally, Section 5 presents the conclusions and discusses potential future research.

2 Problem Description

The core challenge in this paper is the assignment of airplane seats, a critical component in the operational strategy of low-cost carriers (LCCs). At the heart of this problem lies the airline's objective to optimize seat allocation during check-in. The seat assignment process incorporates various factors, such as seat preferences, pricing strategies, and passenger group dynamics [16].

The seat allocation process in low-cost airlines follows a continuous and sequential flow, dynamically adjusting as new bookings are received, with a significant surge in check-ins occurring just hours before flight closure. Upon receiving a new reservation, it distinguishes between individual and group bookings. For both, seats with special attributes should be avoided. In group bookings, efforts are made to allocate seats apart from each other, typically at a distance stipulated by the airline, encouraging the purchase of seat selection service by offering more favorable locations for an additional fee. After each assignment, seat availability on the plane's seating map is updated to reflect the allocations made.

Special seat attributes in low-cost airlines typically include seats with extra legroom, window or aisle locations, proximity to the bathroom and/or aircraft exit, and seats historically in high demand despite lacking the features above. These attributes translate into additional fees when purchasing the seat selection service. Consequently, the assignments may restrict options for future bookings seeking to acquire this service.

Each seat assignment within a reservation can be mathematically formulated as an optimization problem aiming to allocate seats with the lowest additional cost while maximizing the distance between passengers belonging to the same reservation [17]. Logically, separation distance only applies when the bookings have more than one person (let q the number of seats in the reservation, $q > 1$).

Without loss of generalization, let the current seating map be I, representing only the available seats at that moment. We will use the networks-flow based model from [13] to represent the seats and the distance between them. For this purpose, let $G = (N, E)$ be the graph, where N is the set of nodes in the network, which in this case is equivalent to the bookable seats on the plane ($N = \{i\}, \forall i \in I$). On the other hand, the edges of the network correspond to relationships between seats within the same reservation ($E = \{(i, j)\}, \forall i \in I, j \in I | i \neq j$).

It is important to note that before the flight check-in begins, only part of the problem information is available, and reservations are gradually revealed until the flight closure. The additional fee of each seat is mapped to the parameter c_i. The distances d_{ij} between each pair of seats i and j are known (measured as

Manhattan distance). Additionally, a minimum separation distance δ between seats of the same reservation is established to encourage seat purchases. The binary parameter a_i takes value 1 if the seat $i \in I$ has not been previously assigned and 0 otherwise. Also, we will use the binary parameter β_{ij} to pre-calculate whether a pair of seats i and j meet the minimum separation distance. The number of required seats (q) is revealed with each reservation. Given the multi-criteria nature of the proposed problem, we will use parameters w_1 and w_2 to weigh the costs and distances, respectively.

Let x_i be the binary variables representing whether seat i is assigned to the current reservation. We will use y_{ij} as the set of binary variables to represent whether a pair of seats i and j are assigned in the reservation. This way, we can formulate the problem as a binary linear program.

Objective Function:

$$\min w_1 \sum_{i \in N} c_i x_i - w_2 \sum_{(i,j) \in E} d_{ij} y_{ij} \tag{1}$$

Subject to:

$$\sum_{i \in N} x_i = q \tag{2}$$

$$(q-1)x_i - \sum_{j|(i,j) \in E} y_{ij} = 0, \quad \forall i \in N \tag{3}$$

$$(q-1)x_i - \sum_{i|(i,j) \in E} y_{ij} = 0, \quad \forall j \in N \tag{4}$$

$$x_i \leq a_i, \quad \forall i \in I \tag{5}$$

$$y_{ij} \leq \beta_{ij}, \quad \forall (i,j) \in E \tag{6}$$

$$x_i \in \{0,1\}, \quad \forall i \in N \tag{7}$$

$$y_{ij} \in \{0,1\}, \quad \forall (i,j) \in E \tag{8}$$

The objective function, Equation (1), minimizes the cost of the seat assignment at check-in, selecting the cheapest seat available in the aircraft, and at the same time, it maximizes the distance between each pair of seats selected (when $q > 1$). Constraint (2) guarantees that the number of seats selected equals the number of people in the booking. Constraints (3) and (4) connect each node selected and guarantee flow through the connecting arcs. Constraints (5) ensure that an occupied seat is not selected by the model. Constraint (6) guarantees that the pair of seats $(i, j) \in E$ are at the minimum distance δ.

Ultimately, Equations (7) and (8) represent the domain of the variables; in this case, every variable is binary. This model is executed reservation by reservation, and its parameters must be recalculated each time. It must be clarified that the model becomes infeasible when the aircraft is mainly occupied. Therefore, the parameter δ must be iteratively relaxed until a feasible solution is reached.

An example of the graph that represents the solution to one iteration when $q = 3$ can be seen in Figure 1. One can see that an undirected arc connects every node in the solution and that there are $qP2 = 6$ arcs (counting twice each arc since they are undirected). Each node in the solution represents a cost c_i, and each arc stands for a distance between each node d_{ij}, thus representing the flow which, in this case, we want to maximize. This solution would represent that the seats B01, D03, and C06 have been selected for a booking whose number of people q was 3.

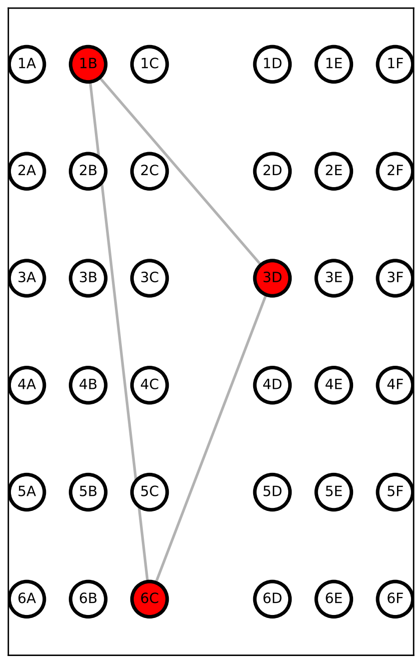

Fig. 1. Example of a solution graph with three seats in a 6-row airplane [13]

As usual, the solution gets significantly more complicated when the number of nodes increases. All the nodes in the solution must be connected to fulfill Equations (4) and (5) and represent the flow through the nodes chosen in the same iteration. Moreover, the nodes that are not part of the solution are disconnected, and there is no flow through them. Thanks to the practitioner from the company interested in this study, the parameters of the objective function and minimum separation distance were set as follows: $w_1 = 1.8$, $w_2 = 1.5$, and $\delta = 7$ (or $w_1 = 0.55$, $w_2 = 0.45$ if the decision-maker prefers them normalized).

The previously outlined model addresses the problem's static component, where seat allocation is resolved at each check-in instance for a specific booking. However, this solution approach may be myopic as it focuses solely on the aircraft's current conditions, overlooking future demand and seat availability projections. This short-term perspective could lead to lost seat sales opportunities for LCCs. Consequently, it is also crucial to tackle the problem's dynamic dimension, which significantly heightens the challenge and adds complexity to the model.

3 Proposed Methodology

Seat assignment is not static but highly dynamic and complex. Each booking introduces new variables—passenger preferences, group sizes, and current seat occupancy—that can significantly alter the optimal seating arrangement. This fluidity requires a methodology capable of responding to the immediate situation but also adaptable enough to predict and prepare for future booking patterns.

This paper presents a novel approach based on the GRASP (Greedy Randomized Adaptive Search Procedure) metaheuristic to optimize seat allocation in low-cost airlines, incorporating airline check-ins' dynamic and real-time nature. The core innovation of this methodology lies in its consideration of "ghost groups," (or more formal blocked seats introduced in [10])which represent potential future bookings based on historical demand data. These blocked seats are crucial for simulating promising future purchases, aligning with industry studies indicating passengers are more inclined to buy seats as check-in deadlines approach. By integrating this dynamic element, our methodology aims to optimize seat allocation for current and anticipated future passenger configurations.

The GRASP algorithm, initially proposed by Feo and Resende [7], is adapted herein to address the seat allocation challenges within the booking process of a Colombian low-cost airline, as delineated in Algorithm 1. The GRASP operates through a two-phase iterative cycle (line 1), comprising a constructive phase (lines 3-14) and an improvement phase (lines 15-20). Notably, our work introduces an initialization phase (line 2), wherein passenger reservation attributes are mixed with the most promising seats. Specifically, this phase involves the creation of "ghost seats" based on historical demand data, the seating map of the aircraft, and flight origin and destination information, thereby enhancing predictive capabilities.

During the construction phase, a passenger in the reservation or a blocked seat is selected randomly (line 4). If the selected passenger is a ghost seat (we will use the terms ghost and blocked seats interchangeably), the algorithm assigns the seat directly (lines 5-7). Otherwise (line 7), a candidate list of available seats is created based on minimum distance constraints (line 8). Then, it forms a restricted candidate list (RCL, line 9) using a degree of randomness (α). The algorithm selects a seat from the RCL using weighted random selection based on seat costs (line 10). This process is repeated until all passengers and ghost seats are chosen and assigned (line 3).

Algorithm 1 Proposed GRASP

Parameters: $Seats$: map of seats of aircraft, $(Head, Tail)$: flight origin and destination, $History$: historic purchased seats, δ : minimum distance between seats, w_1 : weight cost, w_2 : weight distance, c: costs of each seat, $Iterations$: total GRASP iterations, α : degree of randomness/greediness**;**

Input: List a : list of seats already assigned, **List** q : passengers in the reservation.

Output: Map $incumbent$: seat assignment map.

```
for i = 1 to Iterations do
    List GhostSeats ←CreateGroup(Seats, (Head, Tail), History, q, a)
    for j = 1 to |q| + |GhostSeats| do
        Passenger ←SelectRandomlyWithoutReplacement(q ∪ GhostSeats)
        if Passenger is in GhostSeats then
            Seat ← Passenger
        else
            List CandidateSeats ←CreateCandidateList(δ; a, q)
            List RCL ←RestrictedCandidateList(CandidateSeats, α)
            Seat ←WeigthedRandomSelection(RCL, c)
        end if
        Map S ←Assign(Passenger, Seat)
        List a ←AddSeatAssigned(Seat)
    end for
    for each k in q and each l not in a do
        Map S′ ←SwapAssignment(S, k, l)
        if OF(S, w1, w2) > OF(S′, w1, w2) then
            S ← S′
        end if
    end for
    S, a ←Unassign(GhostSeats)
    if OF(incumbent, w1, w2) > OF(S, w1, w2) then
        Map incumbent ← S
    end if
end for
return incumbent
```

Furthermore, the proposed local search process assesses and potentially optimizes assigned seats through swaps with unassigned seats (lines 15-16), factoring in differential costs (lines 17-20). Once the constructed solution is improved, the assigned ghost seats are released as they may be needed for the subsequent reservation (line 21). Iterations continue until all reservations are allocated, with the best objective function value and corresponding seat assignments retained (lines 22-25).

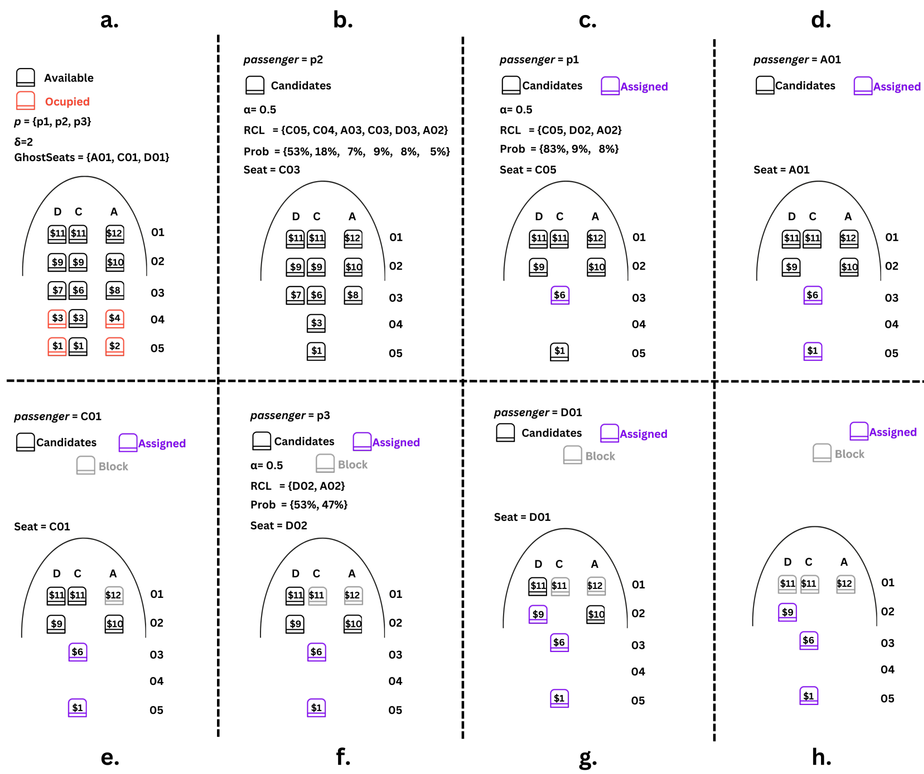

Fig. 2. Example of the constructive phase

It is worth noting that each reservation and its passengers enter the GRASP algorithm sequentially. The final assignment, not explicitly depicted in Algorithm 1, is determined deterministically, ensuring optimal passenger-seat assignments with the lowest overall objective function, at least for the last reservation.

Figure 2 illustrates an example of the constructive process. For this example, a minimum separation distance of two units ($\delta = 2$) has been stipulated, and the generated group of blocked seats coincides with the first row of the aircraft (D01, C01, and A01). Figure 2.a illustrates an aircraft with five rows and three columns of seats, showing that seats D04, A04, D05, and A05 have already been assigned in previous reservations. Currently, a reservation for three passengers must be assigned.

The construction phase iteratively selects a random element among the passengers to be assigned and the generated ghost seats. Figure 2.b shows that the first chosen element is passenger p2. The list of candidate seats consists of all available seats since no passenger has been assigned yet, and there is no minimum distance to be met for now. A value of $\alpha = 0.5$ has been stipulated, so the restricted candidate list (RCL) halves the candidates; a seat from this list will be randomly assigned to the passenger, using a probability that is inversely proportional to the seat cost. In this case, seat C03 is chosen. Figure 2.c depicts the next random element among the passengers to be assigned and the generated blocked seats is passenger p1. It also shows that a passenger was already assigned in the previous iteration (blue seat). The list of candidate seats consists only of the available seats that meet a minimum distance from the assigned seats. The creation of the RCL will again halve the seats, and one seat will be randomly selected from this RCL based on the previously described probability. In this case, seat C05 is chosen.

In the third iteration of the construction, the example in Figure 2.d shows that the ghost seat A01 is randomly selected; in this case, the algorithm suggests blocking this seat directly. This same process occurs in the fourth iteration, where, according to the example in Figure 2.e, the ghost seat C01 is selected. For the fifth iteration, the example in Figure 2.f shows that passenger p3 is selected. Their list of candidates consists of three seats (D01, D02, and A02) because they are the only ones that meet the distancing requirements and are available (neither assigned nor blocked). The restricted candidate list will have only two seats ($\lceil 3 \times 0.5 \rceil$). One of the two seats is randomly selected; in this case, passenger p3 is assigned to seat D02. In the last iteration, the remaining ghost seat is chosen, as shown in Figure 2.g, and their seat is blocked directly. Finally, Figure 2.h shows the constructed seat assignment map. The constructed solution has a cost of 16 units and a distance of 8 units. Using the weights suggested by the company, an objective function value of 16.8 is obtained.

4 Computational Analysis and Results

Our GRASP-based methodology was meticulously evaluated through a series of computational experiments. These experiments were designed to rigorously compare the efficacy of our GRASP metaheuristic algorithm with a sophisticated network flow solution proposed in the literature [13]. For this purpose, a computational environment was established, featuring an Intel® Core™ i5-8365U CPU @ 1.60Hz 1.90 GHz and 8 GB RAM, operating on a 64-bit x64-based processor. This setup ensured a reliable and efficient testing ground for our algorithm.

4.1 Case of study

The empirical foundation of our study was grounded in a comprehensive analysis of historical data obtained from a collaborating airline. We meticulously identified the ten most sought-after seats across a spectrum of 345 flights, leveraging this information to construct a realistic and relevant test scenario. This data was instrumental in synthesizing blocked seats. Additionally, the airline provided essential data regarding original seat pricing, a critical input for our algorithm's cost calculation component; the cost of each seat $i \in I$ is determined by its base price (provided by the airline) plus a relative importance factor $rank_i$ multiplied by an additional cost b; Equation (9) describes the seat cost.

Using historical data from the airline, we identified the top 10 most frequently purchased seats. We found that each seat has been purchased at least once, ensuring that the $rank_i$ for every seat is above 0. Moreover, our rank model highlights seats 24B and 24A as the most commonly purchased seats. These chairs are often desired because a photo usually captures the plane's wings in this aircraft type. Also, we identified the probability distribution of passengers per reservation. An analysis of 345 flights revealed that single passengers are most common in a booking, followed by groups of two or three. This finding is significant for optimizing the algorithm's efficiency for these group sizes and influences the probability parameters for generating ghost seats.

$$c_i = \text{base}_i + \text{rank}_i \times b \quad \forall i \in I \tag{9}$$

Lastly, the airline provided the original costs for the $base_i$ variable in Equation (9), listed in Table 1. These costs, expressed in thousands of Colombian pesos (COP), are differentiated for window (A), middle (B), and aisle (C) seats across all rows in the aircraft.

4.2 Numerical Results

We replicated the 53 instances detailed in [13] to ensure a fair comparison. This process was instrumental in directly contrasting our metaheuristic solution with the exact methods previously employed. It is important to note that the exact method we are comparing is used within a loop to mimic the dynamic behavior of the check-in process.

Key to our analysis was the calibration of the *Alpha* parameter, which is vital for the algorithm's performance. We methodically tested values ranging from 0.1 to 1.0, increasing in 0.1 increments. This iterative process, repeated 20 times for each *Alpha* value, enabled us to identify the most effective setting, ultimately settling on 0.5 as the optimal standard for our specific case.

We analyze the computational time required for seat allocation across the sequence of 66 reservations for the flight under study. Fig. 3 presents the results for each reservation using the proposed metaheuristic. This graph indicates that as the aircraft becomes more occupied, the feasibility space for solutions diminishes, resulting in the algorithm taking less time to find a solution. This trend can

Row	A Window	B Middle	C Aisle	Row	A Window	B Middle	C Aisle
1	39	34	39	17	18	12	18
2	34	29	34	18	18	12	18
3	34	29	34	19	18	12	18
4	34	29	34	20	18	12	18
5	34	29	34	21	18	12	18
6	27	22	27	22	18	12	18
7	27	22	27	23	18	12	18
8	27	22	27	24	14	9	14
9	27	22	27	25	14	9	14
10	27	22	27	26	14	9	14
11	27	22	27	27	14	9	14
12	29	24	29	28	14	9	14
13	29	24	29	29	14	9	14
14	18	12	18	30	14	9	14
15	18	12	18	31	14	9	14
16	18	12	18	32	14	9	-

Table 1. Base Costs of Aircraft Seats

be attributed to reduced available seat options as the flight fills up, streamlining the algorithm's decision-making process.

An additional layer of analysis was introduced by contrasting the impact of local search utilization. The results confirmed that local search contributes positively to refining the solution for each check-in. This refinement led to considerable minimizations in the objective function for some reservations without a significant increase in execution time—remaining below a 1% increase for all reservations executed.

Table 2 displays the results obtained by the current heuristic of the company (Heuristic Rule), the flow model presented by [13] (NFF), and the proposed algorithm (GRASP). The primary comparison indicator is the total value of the cost of seats sold for each booking (Sol). At a secondary comparison level, the objective function (O.F.) (used here to guide the search), along with the average computation time per booking (Time). The model of [13] was constrained to a maximum computation time of two minutes. For the proposed GRASP, the total number of iterations (Iterations) parameter was set to 100 iterations. Both cases comply with the system's maximum waiting time. The bookings for each flight were sequentially recreated to calculate the total value of the cost of seats sold for each booking. Bookings where customers are willing to purchase seats are predetermined, using a 23.9% probability of purchase (stipulated by the practitioner). Assignments are executed individually (for each of the three methods). For group bookings, the separation between seats is checked; if this criterion is met, contiguous seats are purchased and reassigned, maximizing customer comfort (more expensive ones). The same procedure is followed for individual bookings without checking the separation between seats. As illustrated in Table 2, the proposed algorithm achieves or exceeds the sales obtained by the company's heuristic in

Flight ID	# Bookings	Heuristic Rule	NFF [13]				GRASP		
		Sol(COP)	Sol(COP)	O.F.	Time(s)	# Opt	Sol(COP)	O.F.	Time(s)
59241	86	770	**962**	190	<1	86	**962**	235	11
59301	78	888	888	223	9	77	888	253	12
57461	77	851	**903**	242	<1	77	**903**	274	11
59601	75	902	**951**	160	<1	75	902	225	10
59421	70	887	887	593	1	70	887	613	9
57281	65	834	**885**	178	10	64	**885**	185	30
55221	63	807	**862**	623	1	63	857	228	23
55241	63	818	**864**	262	15	62	**864**	265	22
55421	62	752	**816**	204	2	62	**816**	208	21
55101	61	771	**960**	365	20	60	**960**	375	15
56221	60	778	**866**	324	30	59	**866**	326	17
59321	59	874	874	251	3	59	874	268	30
57301	59	876	**903**	146	40	57	**903**	195	33
59561	57	816	**833**	37	45	56	**833**	40	33
59281	57	753	**875**	160	48	54	**875**	208	37
56201	56	712	**781**	172	10	56	773	203	40
55461	56	680	**770**	175	10	56	770	221	45
56121	55	675	**747**	268	50	54	680	348	48
59221	54	709	**743**	306	12	54	**743**	310	49
59541	54	620	**735**	70	51	53	**735**	79	51
59481	52	752	**756**	132	53	51	**756**	144	50
59521	48	694	694	317	54	47	694	286	60
57481	46	660	**713**	117	30	46	696	121	64
55301	46	621	**658**	477	70	43	**658**	505	67
55201	45	623	627	376	68	43	623	402	69
59341	44	544	**642**	241	45	44	575	338	66
56261	43	597	597	127	80	41	597	114	65
55281	43	506	**654**	794	90	40	614	952	70
59401	42	560	560	196	95	40	560	198	72
56281	39	462	**477**	200	98	38	467	213	75
57261	37	432	**454**	332	60	37	**454**	336	77
55361	36	410	**464**	317	101	35	**464**	365	77
57341	34	449	459	123	103	33	449	139	80
56241	33	414	**446**	343	105	31	**446**	401	87
57441	32	416	**440**	146	104	29	**440**	151	76
58941	32	395	**479**	130	87	32	**479**	164	79
55321	31	428	428	366	80	31	428	385	89
55161	30	360	404	461	110	28	**455**	438	90
57321	30	345	**366**	417	109	29	**366**	403	99
56101	30	332	**389**	93	108	29	**389**	97	98
55181	27	363	363	495	111	25	363	444	95
55261	26	339	**385**	187	89	26	**385**	212	98
55381	26	368	**385**	473	89	26	**385**	478	102
58921	24	284	**323**	160	97	24	**323**	176	103
57401	22	244	**251**	105	90	22	**251**	113	104
59501	20	231	262	121	96	20	**277**	122	106
59581	15	304	304	23	100	15	304	30	107
83241	9	245	247	27	120	0	**253**	31	108
83361	9	150	180	16	120	0	**232**	19	109
83261	8	174	210	12	120	0	**265**	17	106
83381	8	190	**227**	15	120	0	**227**	17	102
TOTAL		28665	**30949**				30851		
AVERAGE				241	**62**			252	63
GAP			**8.0%**				7.6%		

Table 2. Results for the 53 instances from [13]

all instances, with a 7.6% improvement in sales. The difference in sales compared to the model of [13] is less than 1%. In several bookings, the model of [13] fails to reach optimality (# Opt), and its average computation time is 62 seconds, similar to the times obtained by the GRASP. This comparison underscores the effectiveness of the metaheuristic approach in a real-world application scenario, where computational efficiency and practicality are critical. The metaheuristic's performance in Python, a widely-used programming language, demonstrates its accessibility and ease of integration into existing systems, making it a valuable tool for airlines, particularly those with limited resources for specialized commercial software solutions.

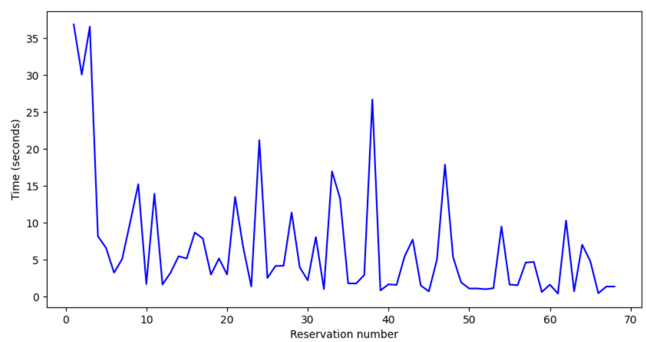

Fig. 3. Metaheuristic's Execution time per Booking

To complement the analysis of computation times, as demonstrated in Fig. 3, there is a direct correlation between the computational time required to determine a check-in solution and the number of passengers and blocked seats that the algorithm must assign in each iteration. This relationship arises because, with more actors involved in an iteration, there is a correspondingly larger set of potential solutions. This increase in volume leads to more combinations of available seats and actors, as well as a more significant number of distances and costs that need to be calculated.

This phenomenon can be attributed to the inherent complexity of the seat assignment process, which escalates as the number of variables –in this case, passengers and blocked seats– increases. Each additional actor introduces new constraints and possibilities, making the algorithm's task more computationally intensive. This complexity is a critical factor in the design and efficiency of seat assignment algorithms, especially in scenarios where time-sensitive decisions are paramount, such as during flight check-in. The results highlight the importance of optimizing these algorithms for accuracy in seat allocation and efficiency in computational time, ensuring a smooth and swift check-in experience for passengers. In comparing the objective function results per reservation, our metaheuristic approach delivered solutions closely mirroring those achieved by the exact method. This similarity in outcomes suggests that our approach is viable and competitive in terms of computational time and objective function performance.

5 Conclusion

Based on the comprehensive study and analysis presented, the developed metaheuristic with blocked/ghost seats provides a robust and innovative solution to the seating allocation challenge faced by low-cost carriers. This technique balances operational efficiency with strategic foresight, addressing immediate seat assignment during check-ins and anticipating future booking behaviors.

The metaheuristic's adaptability to dynamic booking patterns and its cost-effectiveness makes it a valuable tool for low-cost airlines looking to maximize revenue without extensive investment in sophisticated commercial solvers. For the first time, the concise and clear structure of GRASP has demonstrated that the strategic seat allocation aligns with the business objectives of low-cost airlines.

Future research should focus on the self-calibration of GRASP parameters, as there is a direct relationship between the *Alpha* value, the number of ghost seats, and the quantity of seat selection services sold.

Additionally, the proposed algorithm could be adapted to other less mature low-cost airlines, where seat selection can contribute to their revenue. However, due to low occupancy and the need to maintain a longitudinal balance of weight in the aircraft, seat selection becomes a more complex variant of the problem.

References

1. Agustín, A., Alonso-Ayuso, A., Escudero, L.F., Pizarro, C.: On air traffic flow management with rerouting (2012)
2. Alavi Fard, F., Sy, M., Ivanov, D.: Optimal overbooking strategies in the airlines using dynamic programming approach in continuous time. Transportation Research Part E: Logistics and Transportation Review **128**, 384–399 (2019). https://doi.org/https://doi.org/10.1016/j.tre.2019.07.001, `https://www.sciencedirect.com/science/article/pii/S1366554519300250`
3. Birolini, S., Besana, E., Cattaneo, M., Redondi, R., Sallan, J.M.: An integrated connection planning and passenger allocation model for low-cost carriers. Journal of Air Transport Management **99**, 102160 (2022). https://doi.org/https://doi.org/10.1016/j.jairtraman.2021.102160, `https://www.sciencedirect.com/science/article/pii/S0969699721001411`
4. Fonseca i Casas, P., Angel, A., Mas, S.: Using simulation to compare aircraft boarding strategies. In: Simulation in Produktion und Logistik. pp. 237–246 (2013)
5. Castro, J., Fernando, S.: An online optimization-based procedure for the assignment of airplane seats. TOP (2020). https://doi.org/https://doi.org/10.1007/s11750-020-00579-6
6. Cordeau, J.F., Stojkovic, G., Soumis, F., Desrosiers, J.: Benders decomposition for simultaneous aircraft routing and crew scheduling. Transportation Science pp. 375–388 (2001). https://doi.org/https://doi.org/10.1287/trsc.35.4.375.10432

7. Feo, T.A., Resende, M.G.: Greedy randomized adaptive search procedures. Journal of global optimization **6**, 109–133 (1995). https://doi.org/https://doi.org/10.1007/BF01096763
8. IdeaWorksCompany.com LLC: The 2022 cartrawler yearbook of ancillary revenue. Airline Revenue and Transformation Series (2022)
9. Martín, J.C., Román, C.: Airlines and their focus on cost control and productivity. European Journal of Transport and Infrastructure Research **8**(2) (Apr 2008). https://doi.org/10.18757/ejtir.2008.8.2.3337, `https://journals.open.tudelft.nl/ejtir/article/view/3337`
10. Mumbower, S., Garrow, L.A., Newman, J.P.: Investigating airline customers' premium coach seat purchases and implications for optimal pricing strategies. Transportation Research Part A: Policy and Practice **73**, 53–69 (2015). https://doi.org/https://doi.org/10.1016/j.tra.2014.12.008, `https://www.sciencedirect.com/science/article/pii/S0965856414003000`
11. O'Connell, J.F.: Ancillary revenues: The new trend in strategic airline marketing. In: O'Connell, J.F., Williams, G. (eds.) Air Transport in the 21st Century, pp. 145–169. Ashgate Publishing Limited (2011)
12. O'Connell, J.F., Warnock-Smith, D.: An investigation into traveler preferences and acceptance levels of airline ancillary revenues. Journal of Air Transport Management **33**, 12–21 (2013). https://doi.org/https://doi.org/10.1016/j.jairtraman.2013.06.006, `https://www.sciencedirect.com/science/article/pii/S0969699713000677`, papers in Honor of Christina Barbot
13. Pardo González, G., Tabares Pozos, A., Quiroga, C., Álvarez Martínez, D.: Seat assignment recommendation in airlines purchase flow to increase ancillary revenue considering weight and balance constraints. Journal of Air Transport Management **117**, 102582 (2024). https://doi.org/https://doi.org/10.1016/j.jairtraman.2024.102582, `https://www.sciencedirect.com/science/article/pii/S0969699724000474`
14. ROTHSTEIN, M.: An airline overbooking model. Transportation Science **5**(2), 180–192 (1971), `http://www.jstor.org/stable/25767604`
15. Sherali, H.D., Bish, E.K., Zhu, X.: Airline fleet assignment concepts, models, and algorithms. European Journal of Operational Research **172**(1), 1–30 (2006). https://doi.org/https://doi.org/10.1016/j.ejor.2005.01.056, `https://www.sciencedirect.com/science/article/pii/S0377221705002109`
16. Shihab, S.A.M., Wei, P.: A deep reinforcement learning approach to seat inventory control for airline revenue management. Journal of Revenue and Pricing Management **21**(2), 183–199 (2022). https://doi.org/https://doi.org/10.1057/s41272-021-00281-7
17. Subramanian, R., Scheff, R.P., Quillinan, J.D., Wiper, D.S., Marsten, R.E.: Coldstart: Fleet assignment at delta air lines. Interfaces **24**(1), 104–120 (1994). https://doi.org/10.1287/inte.24.1.104, `https://doi.org/10.1287/inte.24.1.104`
18. Talluri, K.T., van Ryzin, G.J.: The Theory and Practice of Revenue Management. Springer Science Business Media (2004). https://doi.org/https://doi.org/10.1007/b139000
19. TTS.com: The rise of low-cost carriers: A new era for travel agents. `https://www.tts.com/blog/the-rise-of-low-cost-carriers-a-new-era-for-travel-agents/` (2023), accessed: 2024-01-28