An improved method for scheduling aircraft ground handling operations from a global perspective

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The turnaround is a critical airport process where a set of interrelated operations need to be performed to get an aircraft ready for its next flight. These activities are carried out by different vehicles, which need to be coordinated to guarantee an efficient utilization of resources. Due to the relations between operations, the order in which these resources are scheduled has a critical influence on the planning and performance of the turnaround. In this work, we present a novel methodology for solving the proposed bi-objective ground handling scheduling problem from a global perspective. This means solving a set of interconnected routing problems with restrictive time windows for each operation. We first explore the solution space using a fast heuristic, focusing then on the most promising solutions to intensify the search in the vicinity of the Pareto frontier. This two-step schema permits significantly reducing the required computational time, which, in turn, allows a more thorough exploration of solutions. Different experiments over real data from two Spanish airports have been conducted to assess the proposed methodology. Our results show that the new method not only outperforms previous approaches in terms of computational requirements, but can also improve the quality of scheduling solutions.

Keywords: air transportation, multi-objective optimization problem, Pareto solutions, Vehicle Routing Problem with Time Windows

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1. Introduction

Air transportation is an essential factor in the economic and social progress of the modern world. Nowadays, the notable increase of traffic is one of the major challenges this important industry has to face. According to the International Air Transport Association (IATA), the global number of passengers raised by 8% in 2017 and is expected to be more than 7 billions by 2035, nearly doubling 2016's passenger traffic (IATA, 2018). This considerable rise in the level of traffic leads to increasingly congested airports, negative impacts on the environment, and significant flight delays. Extending airport capacities or building new infrastructure is an expensive and difficult solution. Hence, better planning and an efficient use of the resources is crucial for a sustainable growth of the aviation industry.

One of the most critical processes at airports is the turnaround, i.e. the time between an aircraft arrives at the parking position from an inbound flight until its departure for a following outbound flight. During a turnaround, a set of interconnected ground operations are required for handling the aircraft, such as fueling, catering, cleaning services, etc. These activities are performed using specific Ground Support Equipment (GSE). GSEs have to be coordinated to be available at the stand where the aircraft is parked, carry out the service within a time window, and travel to the next aircraft to continue their operations. Due to dependencies between tasks, any perturbation during one operation can affect the beginning of the other activities within the same turnaround and have a knock-on effect on subsequent turnarounds. Hence, ground handling coordination is key to ensure turnaround punctuality and mitigate undesired delays.

Ground handling coordination can be addressed in two different ways. The first approach deals with real-time operations monitoring and data sharing between the different turnaround stakeholders. This strategy has been supported by the Airport-Collaborative Decision Making (A-CDM) initiative (EUROCONTROL, 2012), which has shown the need for cooperation between the involved actors.

The adoption of novel technology solutions such as Radio-Frequency Identification (RFID) or wireless networks has also contributed to more accurate and timely information transmission (Ansola *et al.*, 2011; Pestana *et al.*, 2011; Makhloof *et al.*, 2014). The second approach relies on more suitable resource planning. Employing optimization processes for routing GSE reduces the unproductive driving time and improves the on-time availability of equipment to serve the aircraft. However, most of the scheduling approaches found in the literature look at ameliorating one individual service without studying the impact this optimization has on the whole ground process (Diepen *et al.*, 2013; Du *et al.*, 2014; Guo *et al.*, 2018). Applying the concept of A-CDM not only at an operational level, but for performing an integrated optimization of different ground equipment, is essential to further increase the utilization of airport resources (Weiszer *et al.*, 2015).

This work focuses on the second approach, particularly, on the holistic scheduling of ground handling vehicles. In a previous work (Padrón *et al.*, 2016), we introduced a new approach called Sequence Iterative Method (SIM), where different operations and types of vehicles, each of them with their own available fleet, are modeled to explicitly consider the dependencies between operations. Contrary to approaches considering only one operation, we aimed at obtaining global solutions scheduling all required ground handling activities in an effective way. We did so by proposing a bi-objective optimization approach with two objectives: (i) minimizing the waiting time before an operation starts and the total reduction of the available time windows to perform each operation; and, (ii) minimizing the completion time of the aircraft turnaround. A set of solutions representing a trade-off between these objectives is obtained, which facilitates the selection of the most suitable solution under diverse circumstances.

Scheduling all the involved operations means solving a set of Vehicle Routing Problem with Time Windows (VRPTW). Each VRPTW is solved in two steps: (i) a quick initial solution is obtained using the I3 *Insertion Heuristic* method (Solomon, 1987); and, (ii) a local search process based on Large Neighborhood Search (LNS)

(Shaw, 1998) combined with Constraint Programming (CP) (Guimarans, 2012) is launched to improve the initial solution. The proposed SIM method iteratively modifies the sequence for solving the VRPTW sub-problems in such a way that yields a good approximation of the non-dominated solutions in the Pareto frontier (Collette and Siarry, 2003). Solving this set of VRPTWs is computationally expensive, and the process should be repeated several times to obtain a range of Pareto solutions. For that reason, SIM was defined to find the minimum set of solutions that can provide a proper representation of the Pareto frontier.

The order in which different types of vehicles are scheduled –i.e. the order in which the VRPTWs are solved– has an important influence on the quality of solutions. For this reason, it might happen that the number of sequences explored with SIM is not sufficient to obtain a representative set of solutions in the Pareto frontier. Depending on the problem and the decision maker requirements, a more exhaustive method might be necessary to provide a wider Pareto set. Moreover, the time required to produce this set of solutions can be a disadvantage if the planning is not performed with enough time before the moment operations will take place. Although the goal of SIM was to tackle the problem at a tactical level, carrying out the scheduling process closer to the time operations occur ensures the schedule is generated on the basis of more accurate information.

In this work, we propose an enhanced method called *improved* Sequence Iterative Method (iSIM), aimed at reducing the computational effort required to find the Pareto solutions. Contrary to SIM, the scheduling process is carried out in two stages in the new approach: solutions are obtained using only the I3 method, and just the most promising ones are improved with the CP-based LNS local search process. Two strategies are suggested to determine which solutions are the best from the initial set. These rules can be also employed to guide the decision maker towards the selection of the right schedule to implement. With the first rule, we select solutions with the best global results according to the objective values. Solutions having the best resource planning for critical activities are preferred in the second rule. Finally, the reduction in computational time also permits implementing in iSIM mechanisms for a more exhaustive exploration of sequences, improving the coverage of the Pareto frontier.

The remainder of this article is organized as follows. We provide an overview on related work in Section 2. The problem is formally introduced in Section 3. The proposed iSIM method is explained in detail in Section 4, followed by the corresponding experiments to assess its performance in Section 5. Finally, conclusions are presented in Section 6, as well as possible future research lines.

2. Related work

Proposals to effectively coordinate ground handling resources at an airport have focused in two different alternatives: (i) improving monitoring systems and information sharing for real-time decision making, and (ii) better scheduling of resources.

Regarding the first approach, Makhloof *et al.* (2014) presented a real-time system to supervise handling activities through advanced mobile technologies. The Program Evaluation and Review Technique (PERT) model was used to manage different operations within the turnaround and to determine the critical path. The utilization of RFID allows locating and tracking handling vehicles. Ansola *et al.* (2011) used this information to propose a multi-agent system to dynamically manage turnaround operations. Pestana *et al.* (2011) developed an implementation of the Advanced Surface Movement, Guidance and Control System (A-SMGCS) concept to improve the communication between airport stakeholders and handling workers. The approach is based on Geographical Information Systems (GIS) to represent the airport layout and requires vehicles to be equipped with a GPS receiver. The TITAN project (TITAN, 2010) has expanded the scope of the A-CDM to control the progress of the different activities during a turnaround and enhance the situational awareness of the concerned actors. Moreover, it confirmed the importance of collecting operation time stamps to increase the predictability of the turnaround. In a similar line, Wu (2008) proposed a framework to collect the start and finish times of individual turnaround activities. The information is then shared between the different ground handler partners on real-time using wireless technologies.

Compared to aircraft or gate resources, there are few examples in the literature addressing GSE scheduling problems. Du *et al.* (2014) tackle the problem of general towing processes at airports, i.e. the scheduling of vehicles performing the push-back during a turnaround or required for moving empty planes in case of maintenance or repositioning. A column generation heuristic is applied to solve a complex VRPTW with heterogeneous fleet and multiple depots and trips. An aggregated objective function minimizes the cost caused by delays, travel, and service time. Diepen *et al.* (2013) considered the problem of planning passenger buses in a robust way. They presented a column generation approach to solve a gate assignment-based model maximizing the idle time between two pairs of trips assigned to the same bus. Guo *et al.* (2018) proposed optimizing the schedule of baggage transport vehicles by means of an improved genetic algorithm. Flights are divided into several groups regarding the service time window, and all flights in one group are performed by the same vehicle. The authors defined two optimization objectives, which are correlated in a unique function with similar weights: maximizing the number of flights in each group –i.e. minimizing the total number of required vehicles–, and minimizing the travel distance.

Alternatively, other works have focused on scheduling handling vehicles or crews in a generic fashion, without considering the specific characteristics of operations. Marintseva *et al.* (2015) look at solving the resource allocation problem to optimality using dual theory. The authors aim at maximizing profit by the optimal allocation of resources between the two divisions involved: aircraft and terminal handling. Kuhn and Loth (2009) repeatedly solve a static scheduling problem over a short period of time, with the goal of using more reliable information as it becomes available. Assuming they are able to detect the vehicles on the apron, a genetic algorithm-based heuristic is applied to significantly reduce the computational time. Similarly, Andreatta *et al.* (2014) also adopt a fast heuristic for assigning GSE and their staff with the aim to be used in a real-time context. An integer programming model allows the feasible allocation of resources to tasks following a dispatch approach, i.e. one activity at a time. Ip *et al.* (2013) developed a genetic algorithm to schedule handling crews performing one type of job to a set of aircraft. The authors modeled the problem as a VRPTW whose objective consists of minimizing the total lateness of the service at each flight.

Closer to the objective of the present work is the approach presented by Norin *et al.* (2012), where the interaction between the optimized de-icing schedule and other operations during a turnaround is considered through a simulation model. A VRPTW-based model and a Greedy Randomized Adaptive Search Procedure (GRASP) are used for planning the de-icing vehicles. Although only one operation is optimized, the authors obtain better results for the overall set of turnarounds in terms of delays. To the best of our knowledge, so far only the work by Padrón *et al.* (2016) has addressed the GSE scheduling from a global perspective, considering resource allocation and the interaction between operations. The proposed problem aims at maximizing resource utilization while minimizing the makespan of the turnarounds. Given the complexity of solving each individual VRPTW subproblem and the existing interactions, the authors developed an approach designed to reduce the number of explored solutions, while still yielding a good representation of the Pareto set. However, this strategy might limit the coverage of the Pareto frontier provided by the obtained solutions. Building on this approach, the methodology proposed in the present work intends to overcome this limitation by reducing the required computational time during the exploration of solutions, also increasing its applicability in operational scenarios. Furthermore, this reduction in computational time allows a more thorough exploration of the search space, which can eventually lead to a better approximation of the Pareto frontier.

3. Problem description

Turnaround operations take place at the aircraft parking position between the time it arrives at the stand (*In-Blocks*) and its departure (*Off-Blocks*). Figure 1 shows an example of the main activities during a typical turnaround when the aircraft is parked at a contact stand, i.e. the aircraft is connected to the terminal using an air bridge.

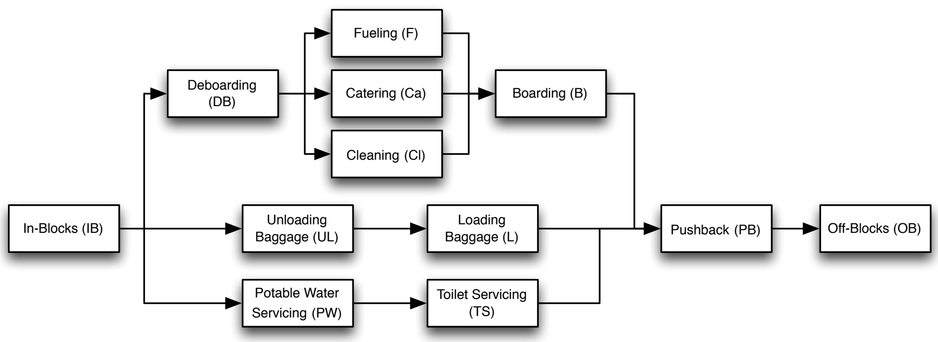


Fig. 1: Example of main operations during a typical turnaround at a contact point.

The duration and complexity of a turnaround depends on many different factors. These include operational variables related to the aircraft type (family, size, number of seats, etc.), parking position (contact or remote stand), and the design of the turnaround (full servicing or minimum servicing) based on the airline business model. Some activities are affected by precedence constraints imposed due to security issues, space requirements, or airline policies. The end of the turnaround process is determined by the off-block time, when all doors are closed, the air bridge is removed, the push-back vehicle is present, and the aircraft is ready for startup and push back.

For each aircraft, operations must be performed within the defined turnaround time to prevent departure delays. Hence, a time window to begin the service is assigned to each activity, which considers the duration of each task and the precedence constraints. Due to these relations, the time when an operation starts could have an impact on subsequent activities within the same turnaround, potentially reducing their available time windows.

Let $N = \{1, ..., n\}$ be the set of scheduled turnarounds, $A = \{1, ..., a\}$ the set of aircraft types, and $O = \{1, ..., o\}$ the set of operations. According to the aircraft type $a \in A$ and the specific turnaround design $i \in N$, each operation $o \in O$ has a duration δ_{oa_i}, and precedence restriction rules Ψ_{oa_i}, which represent the set of tasks that must be finished before operation o starts.

Let t_{oi} be the start time of each operation o in a turnaround i with initial domain $t_{oi} \in [STA_i..STD_i]$, where STA_i and STD_i stand for the aircraft arrival and departure times, respectively. We calculate the time windows to start each operation using the following expression:

$$t_{oi} \geq t_{o'i} + \delta_{o'a_i} \quad \forall o, o' \in O : o' \in \Psi_{oa_i}, \forall i \in N, a \in A \tag{1}$$

When restriction (1) is propagated, the domain of t_{oi} is reduced such that $t_{oi} \in [est_{oi}..lst_{oi}]$, where est_{oi} and lst_{oi} represent the earliest and latest start time.

Each operation is performed by a specific type of GSE. These vehicles need to travel between parking stands to perform all the allocated turnaround operations, effectively defining a VRPTW related to each activity. Let $V = \{1, ..., v\}$ be the set of types of vehicle and $O_v = \{1, ..., n\}$ the set of operations to be performed by each $v \in V$, such as $O_v \subset O$. The objective function of the VRPTW associated to each $v \in V$ is defined as follows:

$$\min \sum_{i \in N} w_i \tag{2}$$

where w_i is the waiting time at turnaround i, defined as the difference between the lower bound of the time window est_i and the moment the operation begins ($w_i = t_i - est_i$).

Finally, we aim at solving a bi-objective optimization problem with two objectives: performing operations within a turnaround as soon as possible to maximize resources utilization, and minimizing the total completion time of ground services at each aircraft. The first objective is achieved by minimizing the operation waiting time and the total reduction of the available time windows. This reduction is represented by $\Delta_i = (est_i - oest_i) + (olst_i - lst_i)$, where $oest_i$ and $olst_i$ are the original values obtained after applying constraint (1) and before solving any VRPTW. An aggregate function f_v is defined for each type of vehicle $v \in V$:

$$f_v = \sum_{i \in N} (w_i + \Delta_i) \quad v \in V \tag{3}$$

The first objective function F_1 is then defined as:

$$F_1 = \min \sum_{v \in V} f_v \tag{4}$$

Minimizing the completion time of turnarounds is the goal of F_2, formulated as follows:

$$F_2 = \min \sum_{i \in N} t_{li} \tag{5}$$

where t_{li} represents the start time of the last operation in the turnaround (i.e. the push-back).

4. *improved* Sequence Iterative Method (iSIM)

We have developed the iSIM methodology to solve the bi-objective ground handling scheduling problem. This approach permits overcoming some of the limitations found in the SIM algorithm (Padrón *et al.*, 2016), allowing for a reduction of computational times and a more thorough exploration of the search space.

The SIM method was proposed as an *a posteriori* heuristic, aiming to find a good approximation of the non-dominated solutions of the ground handling problem. A set of trade-off solutions with respect to the objectives is generated to allow the decision maker choosing the preferred one to implement and avoiding *a priori* specifications of preferences. Because the computational effort of this process is high, the goal is to obtain the minimum number of solutions required to produce a good coverage of the Pareto frontier. With SIM, the problem is solved by scalarization, a common method for solving multi-objective optimization problems (Jozefowiez *et al.*, 2008). That is, the problem is solved with respect to F_1, and the value of F_2 is calculated from the obtained solution.

As mentioned, one VRPTW is solved individually for each type of vehicle involved in ground handling operations. This leads to solving multiple interconnected VRPTWs following a sequence to obtain a complete solution for the problem, exploiting a workcenter-based decomposition strategy (Sourirajan and Uzsoy, 2007). For solving each routing problem, SIM applies a two-step approach: I3 is used to get an initial solution, which is later improved using a CP-based LNS methodology. At each iteration of SIM, the sequence is modified in such a way that an improvement of F_1 is reached, but affecting as little as possible the value of F_2. To do that, the algorithm starts with an initial sequence where the *push-back* is the first operation to be scheduled, therefore providing a lower bound for F_2. To improve F_1, one operation is scheduled in the first place –i.e. its corresponding VRPTW is solved first– at each round. To reduce the execution time, SIM only explores one sequence in each round, corresponding to scheduling first the sub-problem with the highest value of f_v.

However, the local search process is clearly the most time-consuming part of the algorithm. Thus, the aim of iSIM is to reduce the number of times the VRPTWs are solved using both steps, while still providing a good representation of the Pareto set. In iSIM, only I3 is used to generate a more extensive set of solutions. Next, we select the solutions improving F_1 to a greater extent while affecting F_2 the least –i.e. solutions less likely to become dominated after the local search–, and only this group is explored by the hybrid LNS methodology. The two proposed criteria for selecting a promising subset of solutions are explained in Section 4.1. Figure 2 presents an outline of the main components of iSIM.

The proposed approach can be implemented due to the I3 heuristic and the local search process having similar minimization criteria. Although the I3 method does not explicitly minimize the operation waiting time, this criterion is considered

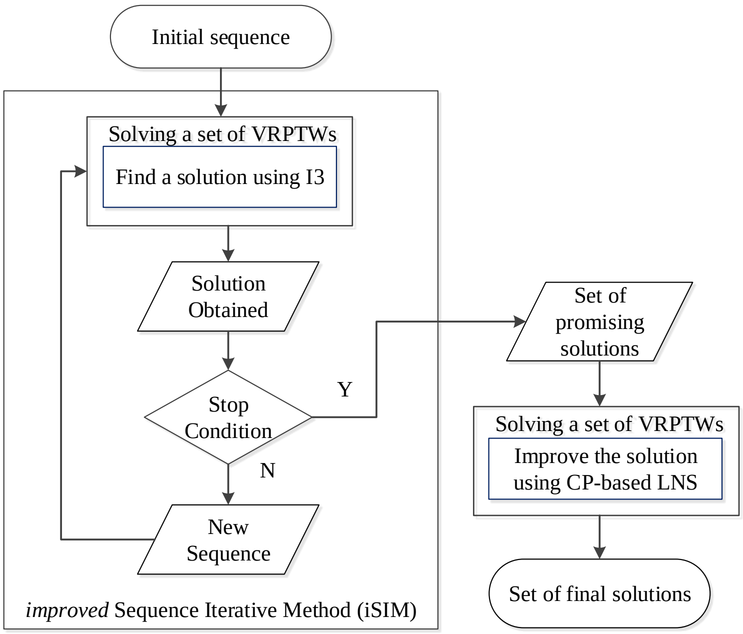


Fig. 2: Outline of the *improved* Sequence iterative Method (iSIM).

when turnarounds are selected to be inserted in the routes of specific vehicles. Moreover, the earliest start time is also considered when initializing all routes, which contributes to reducing the waiting time.

Using I3 in the exploratory phase, and LNS to improve only a subset of promising solutions, permits reducing the overall computational effort required to solve the ground handling problem. Hence, iSIM allows implementing a more exhaustive exploration of sequences, potentially leading to better Pareto solutions. Algorithm 1 provides a detailed view of the methodology.

The first step of the algorithm aims at finding a lower bound on F_2, and a minimum value of F_1. Let S be the sequence of routing problems –i.e. the order in which the different VRPTW are solved–, such that $S = B \cup s_l \cup R$, where s_l is the sub-problem corresponding to the last operation in the turnaround (*push-back*), B the set of sub-problems to solve before s_l, and R the rest of sub-problems. The sub-problem s_l is solved first in this step, which implies that the turnaround is

Algorithm 1: *improved* Sequence Iterative Method (iSIM)

Definition S: sequence of VRPTW sub-problems ($|S| = |V|$); s_l: last operation; $S = B \cup s_l \cup R$; Sol: set of solutions found

$B \leftarrow \phi$; $S \leftarrow \{s_l\} \cup R$ `/* obtain a lower bound solution on` F_2 `*/`

$< F_1, F_2 > \leftarrow NewSolution(S)$

repeat `/* improve` F_1 `keeping the position of` s_l `*/`

- $R' \leftarrow$ sort R by f_v in a decreasing order; $S' \leftarrow \{s_l\} \cup R'$
- $< F_1', F_2 > \leftarrow NewSolution(S')$
- **if** $F_1' < F_1$ **then**
  - $S \leftarrow S'$; $F_1 \leftarrow F_1'$; $f_v \leftarrow f_v'$ $\forall v \in V$
- **end**

until F_1 *is not improved*

$Sol \leftarrow < F_1, F_2 >$

repeat `/* improve` F_1 `planning the sub-problems before` s_l `*/`

- $i \leftarrow 0$; $F_1^* \leftarrow F_1$
- **repeat** `/* all operations in` R `are added in` B `one by one */`
  - $b \leftarrow R_i$; $B' \leftarrow \{b\} \cup B$
  - $R' \leftarrow R \setminus b$
  - $S' \leftarrow B' \cup \{s_l\} \cup R'$
  - $< F_1', F_2' > \leftarrow NewSolution(S')$
  - **if** $F_1' < F_1^*$ **then**
    - $Sol \leftarrow < F1', F2' > \cup Sol$
    - $S^* \leftarrow S'$; $B^* \leftarrow B'$; $R^* \leftarrow R'$; $F_1^* \leftarrow F_1'$; $F_2^* \leftarrow F_2'$
  - **end**
  - **else if** $F_1' < F_1$ *or* $F_2' < F_2$ **then**
    - $Sol \leftarrow < F_1', F_2' > \cup Sol$
  - **end**
  - **repeat**
    - $R'' \leftarrow$ sort R' by f_v in a decreasing order
    - $B'' \leftarrow$ sort B' by f_v in a decreasing order
    - $S'' \leftarrow B'' \cup \{s_l\} \cup R''$
    - $< F1'', F2'' > \leftarrow NewSolution(S'')$
    - **if** $F_1'' < F_1^*$ **then**
      - $Sol \leftarrow < F_1'', F_2'' > \cup Sol$
      - $S^* \leftarrow S''$; $B^* \leftarrow B''$; $R^* \leftarrow R''$; $F_1^* \leftarrow F_1''$; $F_2^* \leftarrow F_2''$
    - **end**
    - **else if** $F_1'' < F_1'$ *or* $F_2'' < F_2'$ **then**
      - $Sol \leftarrow < F_1'', F_2'' > \cup Sol$
      - $S' \leftarrow S''$; $F_1' \leftarrow F_1''$; $F_2' \leftarrow F_2''$; $f_v' \leftarrow f_v''$ $\forall v \in V$
    - **end**
  - **until** *F1 is not improved*
  - $i \leftarrow i + 1$
- **until** $i = |R|$
- $S \leftarrow S^*$, $B \leftarrow B^*$, $R \leftarrow R^*$, $F_1 \leftarrow F_1^*$, $F_2 \leftarrow F_2^*$

until $|B| = |S \setminus \{s_l\}|$

$Sol^* \leftarrow Non-Dominated(Sol)$

$Sol^* \leftarrow LNSLocalSearch(Sol^*)$

return Sol^*

planned to be completed in the minimum possible time. This comes at the expense of reducing the time window of other operations on the same aircraft, leading to high values of F_1. Then, different permutations are explored in an iterative process, ordering sub-problems in R by f_v, with the goal to improve F_1 while keeping the best value of F_2.

In the second step, the remaining sub-problems are solved before s_l. Solving a sub-problem in the first position means its resources are scheduled within its original time windows, which conducts to a lower bound of its f_v. To intensify the search in the solution space, all operations in R are added, one by one, to the set B. At each iteration, the sequence providing the best F_1 value is kept. In other words, given a position of s_l, the operation leading to the best value of F_1 when solved before s_l will be finally included in B. Next, sub-problems in R and B are ordered by f_v again, and a new solution is obtained with this new sequence. This step permits improving F_1 ensuring the lowest impact on F_2, as well as finding a range of solutions representing a trade-off between the two objectives.

Once all activities have been scheduled before s_l, the non-dominated solutions are selected from the set of obtained solutions, and improved using the CP-based LNS methodology. This process refines the routing aspects related to each operation, and does not modify the scheduling sequences. Finally, the set of improved non-dominated solutions is returned by the algorithm as an approximate representation of the Pareto frontier.

4.1. *Selecting promising sequences*

Two criteria are suggested to select a subset of the Pareto solutions obtained during the exploratory phase using the I3 heuristic. These selection criteria are used to identify promising solutions, but can also be used by decision makers to choose what specific solutions are more suitable for implementation. In the first rule, we identify points that represent different ranges from the complete set of Pareto solutions. We split the Pareto frontier into three areas according to the objective values. In the first area, we have solutions where the completion time of the turnaround is prioritized. Both objectives are balanced in the second area, and minimizing the tightness of the available time windows is favored in the third area. An example is presented in Figure 3. Notice that the number of areas the Pareto frontier is divided into can be different and can be specified according to different needs.

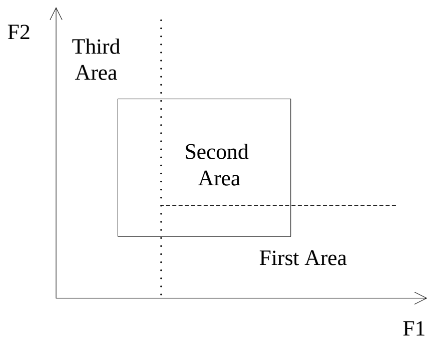


Fig. 3: Pareto frontier division into three areas according to the first selection criterion.

Then, we select a specific number of points from each area such that the relation between objectives is the best. Let L be the set of solutions in the Pareto frontier and $K = \{1, 2, 3\}$ the established areas. The best relation between two points i, j in the area l_k is defined as:

$$r(i,j) = (F_{1_i} - F_{1_j})/(F_{2_j} - F_{2_i})|F_{2_i} < F_{2_j} \quad \forall i, j \in l_k, \forall k \in K \tag{6}$$

Equation (6) aims at measuring how the improvement of F_1 affects the F_2 function. If the value of $r(i,j)$ is greater than 1, the first objective is improved to a greater extent than the second one is worsened. In this case, the solution j is considered better than the solution i. In contrast, if improving F_1 comes at the expense of a higher increase of F_2, solution i is the preferred, with $0 \leq r(i,j) < 1$. Solution i dominates solution j if $r(i,j)$ is negative, and two solutions are equivalent with respect to the relation between objectives when $r(i,j) \approx 1$.

The second proposed criterion is applied sequentially after we have selected a set of ‘best points’ using the $r(i, j)$ values. To do this, we consider the operations individually and how they are scheduled in the different solutions. For instance, the number of vehicles required to perform a certain operation might be a measure to determine the preferred solution, e.g. due to high operation costs or limited number of resources. With this idea in mind, we have defined two rules to guide the selection process and choose solutions where the minimum number of vehicles is required for two kinds of operation:

(1) Complex activities with expensive vehicles

    The availability of resources for performing the operations is a key aspect to guarantee aircraft on-time departure, particularly when these resources are expensive or complex to use. For example, fueling is one of the most complex tasks during the turnaround and strict precautionary measures have to be fulfilled in order to guarantee safety. A correct configuration and a proper maintenance of all the necessary equipment, including fueling vehicles, are crucial in this operation. So, saving on vehicles utilization, particularly in this task, permits reducing costs and favors the efficiency of the process.

(2) Operations with longer duration

    These operations have little margin to deal with unexpected events or incidents with vehicles. Employing fewer resources in longer activities might contribute to the resilience of the solution, since they leave spare vehicles that could be used in case of perturbations.

These rules can also applied sequentially, e.g. if two solutions require the same number of vehicles for performing fueling, the solution using the fewer vehicles in the longest operation is selected.

With the two proposed criteria, we can select a small subset of promising solutions and reduce the overall computational effort required to provide a good approximation of the Pareto frontier. Using iSIM, only a limited subset of solutions are improved with the more computationally expensive CP-based LNS methodology, while quality is preserved by carefully selecting promising solutions from the original set.

5. Computer experiments

To assess the iSIM performance, we have used real-data instances from an important handling company in Barcelona-El Prat (BCN) and Palma the Mallorca (PMI) airports (Padrón *et al.*, 2016). We have considered a typical turnaround at a contact stand to be composed of seven operations with their corresponding type of vehicle. For simplicity of notation, we have identified each operation by a number: (1) unloading and loading baggage, (2) catering, (3) cleaning, (4) fueling, (5) potable water, (6) toilet services, and (7) push-back. Deboarding and boarding have also been considered, despite them not having any associated vehicles. In the case of a turnaround at a contact stand, these operations are performed by means of an air bridge connected to the gate. However, their influence in the turnaround is critical and, therefore, we take them into account when determining the time windows of the other operations.

Our approach has been implemented in Java and connected to the ECLiPSe CP platform. All tests have been performed on a personal computer with an Intel Core i5 processor at 2.3GHz and 4GB RAM. We compare our results with the ones published by Padrón *et al.* (2016). The latter were obtained using a non-dedicated server with an Intel Xeon processor at 2.66GHz and 16GB RAM.

We present results for three different tests, performed to validate different aspects of iSIM. We first include a comparison of solutions with and without applying the LNS-based local search (see Section 5.1). We then compare iSIM and SIM both in terms of solution quality and computational time (see Section 5.2). Finally, we assess the suitability of the defined selection criteria in Section 5.3.

5.1. *Comparison I3 vs. I3 + LNS*

First, we verify if solutions obtained with iSIM using only I3 are comparable with those found once the hybrid methodology (iSIM using I3 and LNS) is applied, i.e. if the relation between objectives is similar. For illustrative purposes, we will use results for one of the instances from BCN airport: C4J4. Table 1 presents the values corresponding to the obtained non-dominated solutions for this instance, both using only I3 and I3 with the addition of the local search process (I3 + LNS). For each solution, we include the objective values (F_1 and F_2), the reduction of the original time window (Δ), the total operation waiting time (w), and the computational time (T) in seconds. Additionally, we also present the corresponding gaps for all solution parameters.

We observe that, for both methods, better values of F_1 imply worse values of F_2, and that the improvement of one objective affects in a similar extent the second objective. In the first iterations, where the push-back (7) is scheduled early in the sequence, the best values of completion time are obtained in both cases. We also observe that parameters Δ and w are inversely proportional. As expected, a larger decrease of the available time windows implies there is less margin to schedule operations, therefore reducing the overall waiting time. Notice, though, that this situation might lead to an increase of the number of resources required to perform all the scheduled turnarounds.

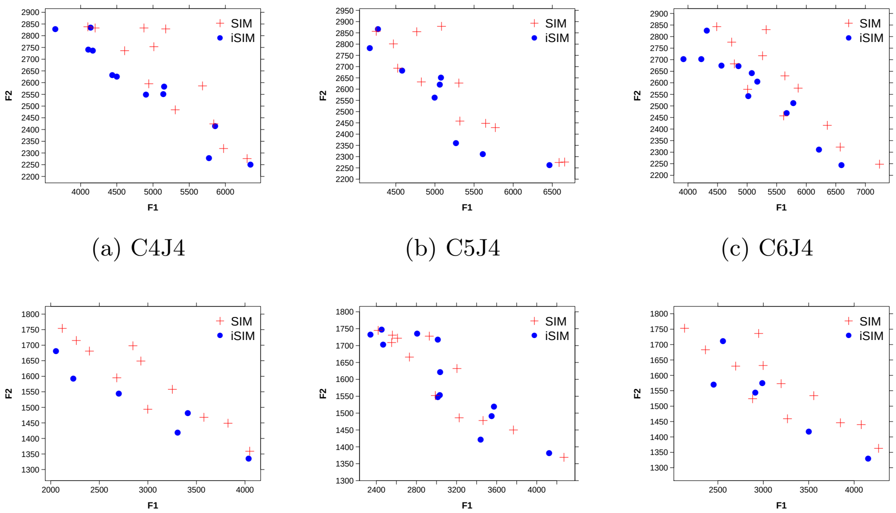
Gap values show that the LNS methodology is able to significantly reduce the values of F_1. This is especially relevant for those solutions where F_2 is clearly above its lower bound, i.e. those solutions where the push-back (7) is not scheduled early in the sequence. Again, planning to finish the turnaround at the earliest possible time might cause a significant reduction of the available time windows for all operations, as well as the inability to schedule vehicles efficiently. When there exists more slack for the scheduling of operations, results prove that applying the LNS methodology is an effective way to improve the quality of solutions, although at an evident computational expense.

Table 1: Non-dominated solutions obtained for instance C4J4 using I3, and later explored with LNS. Δ and w are the reduction of the available time windows and the overall waiting time, respectively.

#	**Sequence**	**I3**					**I3 + LNS**					**Gap (%)**			
		F_1	F_2	Δ	w	$T(s)$	F_1	F_2	Δ	w	$T(s)$	F_1	F_2	Δ	w
1	{7,1,2,3,4,5,6}	6540	2290	5475	1065	0.16	6347	2250	5483	864	1196.96	-2.95	-1.75	0.15	-23.26
2	{6,7,5,4,3,1,2}	6002	2483	4154	1848	0.13	5859	2414	4441	1418	1328.39	-2.38	-2.78	6.46	-30.32
3	{5,7,6,4,3,2,1}	6140	2435	4429	1711	0.19	5774	2278	4899	875	1213.52	-5.96	-6.45	9.59	-95.54
4	{4,7,1,2,3,5,6}	5683	2635	3418	2265	0.17	5154	2582	3336	1818	1399.39	-9.31	-2.01	-2.46	-24.59
5	{2,7,1,3,4,5,6}	5714	2593	3595	2119	0.18	5142	2552	3423	1719	1357.76	-10.01	-1.58	-5.02	-23.27
6	{5,4,7,6,3,2,1}	5368	2665	3030	2338	0.10	4903	2549	2997	1906	1339.68	-8.66	-4.35	-1.10	-22.67
7	{2,4,7,1,3,5,6}	5181	2704	2752	2429	0.12	4500	2626	2619	1881	1382.85	-13.14	-2.88	-5.08	-29.13
8	{5,4,2,7,6,3,1}	5057	2730	2458	2599	0.13	4438	2633	2343	2095	1452.72	-12.24	-3.55	-4.91	-24.06
9	{3,2,4,7,1,5,6}	5030	2797	2196	2834	0.10	4169	2736	1932	2237	1292.69	-17.12	-2.18	-13.66	-26.69
10	{5,4,3,2,7,6,1}	4873	2809	1983	2890	0.11	4107	2740	1713	2394	1377.63	-15.72	-2.46	-15.76	-20.72
11	{5,6,4,3,2,7,1}	4657	2841	1665	2992	0.09	3651	2829	1116	2535	1295.82	-21.60	-0.42	-49.19	-18.03
12	{1,5,6,4,3,2,7}	4543	2869	1414	3129	0.10	4140	2835	1273	2867	1415.34	-8.87	-1.19	-11.08	-9.14

5.2. *Comparison iSIM vs. SIM*

In this section, we compare the non-dominated solutions provided by iSIM with those obtained with the SIM approach (Padrón *et al.*, 2016). Figures 4 and 5 present an overview of results obtained for BCN and PMI instances, respectively.



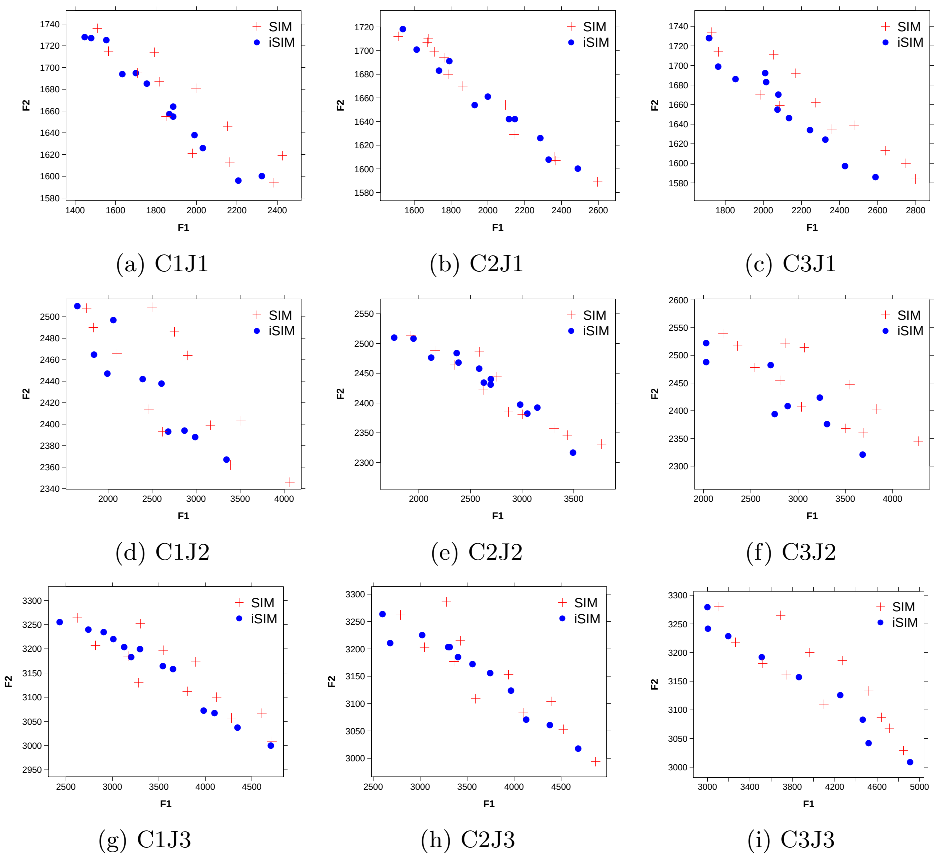
(a) C4J4 (b) C5J4 (c) C6J4

(d) C4J5 (e) C5J5 (f) C6J5

Fig. 4: Solutions obtained using SIM (crosses) vs. iSIM (bullets) for BCN instances.

As can be observed in all graphs, the quality of solutions found using iSIM is, in most cases, better than those obtained with SIM. Even though the coverage of the Pareto frontier reached by SIM appears higher in a few instances, e.g. C6J5 (Figure 4f), both methods are comparable in this sense.

For a numerical comparison of the quality of solutions, we use the criterion $r(i, j)$ defined in Equation (6), as well as two well-known metrics for multi-objective problems: HyperVolume (HV) (Zitzler and Thiele, 1998) and Inverted Generational Distance (IGD) (Zhang *et al.*, 2008). As mentioned $r(i, j)$ aims at comparing two solutions regarding the relation between objectives. The value of r giving the best result depends on F_2. If $F_{2_i} < F_{2_j}$, solution i is the best if $0 < r < 1$, and j is



(a) C1J1 (b) C2J1 (c) C3J1

(d) C1J2 (e) C2J2 (f) C3J2

(g) C1J3 (h) C2J3 (i) C3J3

Fig. 5: Solutions obtained using SIM (crosses) vs. iSIM (bullets) for PMI instances.

the preferred if $r > 1$. Moreover, r will be negative if the two solutions are non-dominated between them. For a comparison between methods, this criterion has to be adapted to be able to determine if a group of solutions is better than another one. Thus, r values have to be comparable to obtain a total sum. To achieve this, we stated that, if a solution found with iSIM is better than a solution found with SIM, r takes a negative value; otherwise, it takes a positive value.

For each Pareto solution found with iSIM, we have calculated $r(i, j)$ with each non-dominated solution found with SIM. If $F2_{iSIM} < F2_{SIM}$ and $0 < r < 1$, it means that iSIM outperforms SIM, so we have made $r = -r$. A similar situation is presented if $F2_{SIM} < F2_{iSIM}$ and $r > 1$. In this case, if $r < 0$, SIM dominates iSIM, so we have converted r to a positive value. Average r for each problem, as well as the time required by both methods for solving each instance, are outlined in Table 2.

Table 2: Time required for solving BCN and PMI instances, average value of $r(iSIM, SIM)$, HV ratio HV_R, and IGD normalized measures for solutions found using iSIM and SIM.

Instance	**Set**	$T_{iSIM}(s)$	$T_{SIM}(s)$	$r(iSIM, SIM)$	HV_R	IGD_{iSIM}	IGD_{SIM}
C1J1	PMI	16722.53	16829.53	-3.34	0.98	0.0059	0.0112
C2J1	PMI	14399.21	18112.82	-1.00	0.95	0.0099	0.0105
C3J1	PMI	16288.96	16254.98	-8.19	1.22	0.0074	0.0160
C1J2	PMI	13977.46	18023.17	-2.49	0.99	0.0200	0.0155
C2J2	PMI	17595.04	18792.33	-1.26	0.94	0.0120	0.0093
C3J2	PMI	10873.04	18798.34	-10.36	1.25	0.0197	0.0251
C1J3	PMI	16643.54	16375.34	0.71	0.88	0.0075	0.0096
C2J3	PMI	16046.41	17971.83	-1.06	1.01	0.0121	0.0133
C3J3	PMI	11897.47	17604.81	-3.05	0.98	0.0068	0.0128
C4J4	BCN	16052.80	16829.53	-11.11	1.27	0.0079	0.0292
C5J4	BCN	11678.25	18982.47	-1.73	1.29	0.0057	0.0225
C6J4	BCN	15289.94	17345.39	-8.57	1.27	0.0025	0.0352
C4J5	BCN	6622.19	17201.87	-6.12	1.27	0.0132	0.0386
C5J5	BCN	16062.02	18564.34	-1.97	1.06	0.0187	0.0128
C6J5	BCN	6776.64	16902.98	-0.88	1.09	0.0390	0.0232

We observe that iSIM produces better solutions than SIM for most of the tested instances, according to the $r(i, j)$ criterion. For some instances, the computational times are comparable, but the quality of solutions is notably higher, e.g. C4J4 or C3J1. In other cases, such as C4J5 or C3J2, a great improvement is reached in about half the execution time. Results obtained with iSIM for instances C1J3 or C2J3 are similar in quality and time to SIM. In these cases, the algorithm finds a greater number of non-dominated solutions that need to be later explored using LNS, increasing the execution time without improving the Pareto frontier. For these instances, selecting a smaller subset of non-dominated solutions instead of the complete set can lead to a better performance, keeping the same level of quality.

HV and IGD are mixed metrics which capture the diversity and convergence of an approximation set towards the Pareto-optimal front. HV calculates the volume of the objective space enclosed by the non-dominated set and a reference point, i.e. a vector of maximal objective values when minimizing or the origin in the case of a maximization problem. In a two-dimensional situation, the area of the rectangles formed by the reference point and each non-dominated solution are summed to obtain the size of the space covered. Hence, a higher value of HV indicates better performance. To compute the HV indicator, we have defined the reference point z for each instance considering the maximum objective values from each front, such as z=($\max\{F_{1_{iSIM}}; F_{1_{SIM}}\}, \max\{F_{2_{iSIM}}; F_{2_{SIM}}\}$).

The IGD metric computes the sum of Euclidean distances between each solution in the reference front and the nearest point in the approximation set, averaged over the number of solutions in the reference front. The optimal or the best-known Pareto frontier is taken as the reference, and a low value of IGD implies that the approximation set is close to the reference front. In the case of the ground handling problem, the optimal Pareto frontier is unknown. Selecting the SIM or the iSIM solutions as the reference is not an accurate alternative either, because they might dominate each other depending on the instance. Thus, a modified version of IGD is applied to be able to compare the performance of the two methods.

Taking into account the frontiers generated by the two algorithms, we established the non-dominated solutions of the combination as the reference front. That is, we consider the non-dominated solutions (S^*) of the set $S^*_{iSIM} \cup S^*_{SIM}$, without distinction of the method that generated them. Afterwards, we calculate the IGD of SIM and iSIM solutions with respect to the combined frontier. The front with the lowest value means that the corresponding algorithm generates closer solutions with higher coverage of the best-known Pareto frontier.

Table 2 includes the ratio $HV_R = HV_{iSIM} : HV_{SIM}$, where HV_{iSIM} and HV_{SIM} are the normalized HV measures for each algorithm. The normalized IGD values for iSIM and SIM are also reported in Table 2. As can be observed, the HV ratio is around 1 for most instances, which shows that the two algorithms are almost equivalent, with iSIM having a computational advantage. Regarding IGD, lower distances to the best-known frontier are obtained with iSIM for most instances, although the difference is small. Contrary to the r criterion, that can be seen as a convergence metric, the spread of solutions is also considered in HV and IGD.

Therefore, the range of values covered by the solutions has an important influence on these measures. In any case, the performance of iSIM is still higher than SIM even in some instances (e.g. C4J5 and C3J2) showing a notable reduction of the computational time as a result of providing fewer Pareto solutions.

5.3. *Selection of promising solutions*

In the previous results, we improved all non-dominated solutions with the LNS methodology, aiming at providing a fair comparison with SIM. In this section, we select a subset of Pareto solutions to be explored using the selection criteria described in Section 4.1. This way, we can compare solutions from iSIM with those obtained with the proposed criteria, assessing their suitability to provide a good representation of the Pareto set. An example of how the selection rules are applied is described as follows.

For illustrative purposes, we consider again the BCN instance C4J4, whose results were presented in Table 1. Using the first selection criterion, the Pareto frontier is divided into three areas according to the objective values. For each area, we select the solution where the greater improvement of F_1 is reached with the lower growth of F_2, that is, $r(i^*, j^*) = \max\{r(i,j)\}$. The relation $r(i,j)$ established in Equation (6) is calculated for each pair of solutions in each area. Results are presented in Table 3. Values are sorted in descending order, so the first pair represents the best relation. Depending on the available time for scheduling the vehicles or the decision maker preferences, the number of solutions to be kept can vary. For example, if we have to select two solutions from each area, solutions 2, 3, 6, 7, 10, and 11 are the most promising because all r values are greater than 1. We have finished the selection process in this case, and these six solutions will be improved using the LNS methodology. This criterion can be seen as a first step to sort the obtained Pareto solutions, permitting the selection of promising sequences in a fast and simple way.

Nevertheless, there are other situations where we need to consider the second rule and analyze the operations individually in order to select the best solutions. A first example occurs when the value of $r(i, j)$ is close to 1 and both solutions i and j can be considered equivalents. Another situation where we need to focus on how operations are scheduled happens when two pairs of solutions have similar values of r. In these cases, the second rule will be used to decide which solution should be chosen. Schedules where the most complex operations require less resources are preferred, followed by those solutions with less vehicles assigned to the activity with longer duration.

Table 3: Relation between each pair of solutions in each defined selection area obtained with iSIM using only I3, and with iSIM using I3 and LNS to improve all non-dominated solutions. Values are sorted in descending order.

I3						**I3+LNS**					
Area 1		**Area 2**		**Area 3**		**Area 1**		**Area 2**		**Area 3**	
i-j	**r(i,j)**	**i-j**	**r(i,j)**	**i-j**	**r(i,j)**	**i-j**	**r(i,j)**	**i-j**	**r(i,j)**	**i-j**	**r(i,j)**
3-2	2.88	4-6	10.50	9-10	13.08	3-2	-0.63	6-5	-79.67	11-12	-81.50
1-2	2.79	4-7	7.28	9-11	8.48	1-3	20.46	6-4	-7.61	10-12	-0.35
1-3	2.76	5-6	4.81	9-12	6.76	1-2	2.98	5-4	-0.40	9-10	15.50
		5-7	4.80	10-11	6.75			4-7	14.86	9-11	5.57
		6-7	4.79	10-12	5.50			5-7	8.68	10-11	5.12
		5-4	0.74	11-12	4.07			6-7	5.23	8-11	4.02
				8-12	3.70					8-10	3.09
				8-11	3.60					8-9	2.61
				8-10	2.33					8-12	1.48
				8-9	0.40					9-12	0.29

To evaluate these decision criteria, we have compared the selected solutions once the CP-based LNS methodology is applied with the case where all the non-dominated solutions were improved. As can be seen in the second half of Table 3, most of the rejected sequences have turned into dominated solutions, which correspond to negative values of r, e.g. solutions 4 and 5 are dominated by 6, and solutions 10 and 11 dominate 12. Promising sequences are, in most cases, also the best sequences after applying local search, as shown in Figure 6.

Using the proposed selection rules, only a small subset of non-dominated solutions will be chosen to be improved with the local search process. Proceeding this way might help significantly reducing the computation time required by the algorithm without compromising the quality of the Pareto solutions, as demonstrated

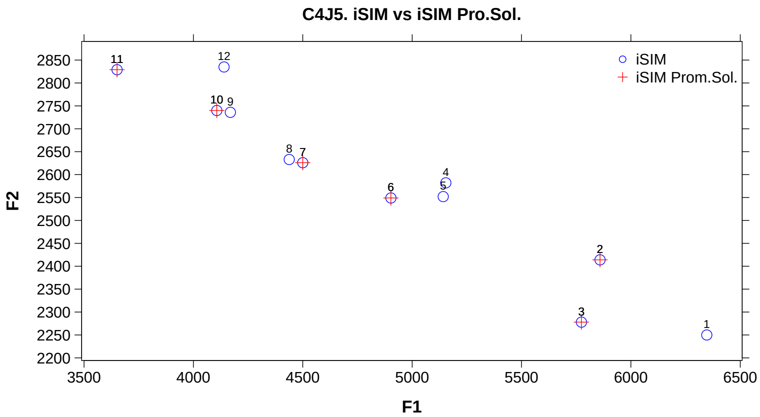


Fig. 6: Solutions obtained using iSIM improving all non-dominated solutions (bullets) and only the most promising solutions (crosses) for instance C4J4.

by the obtained results.

6. Conclusions and perspectives

In the present work, we have proposed an enhanced method called *improved* Sequence Iterative Method (iSIM) for scheduling ground handling operations from a global perspective. The goal of this method is to overcome computational time limitations from previous approaches (Padrón *et al.*, 2016), and to intensify the exploration of sequences in which operations are scheduled. With this purpose, the scheduling process is performed in two steps. First, solutions are calculated solving the routing problem associated to each ground activity using only the constructive I3 heuristic. Next, a set of promising solutions is selected to be improved with the CP-based local search process, being the most time expensive procedure of the approach. Due to interdependencies between operations, the sequence in which routing problems are solved has a major influence in the results. The proposed iSIM permits exploring a greater number of sequences, leading to better Pareto solutions or a wider Pareto set.

We proposed two selection criteria to decide which solutions are to be improved by the CP-based LNS methodology. With the first criterion, the Pareto frontier is divided into three areas according to the values of the objective functions. Solutions with the best relation between objectives are selected within each area, i.e. solutions where the greater improvement of one goal can be reached with the least impact on the other goal. A second criterion is suggested to decide which solutions are the best among the set of points obtained after applying the first rule. In this case, the focus is on choosing solutions where the minimum number of vehicles is required to perform complex operations, such as fueling, or activities with longer duration.

We have tested iSIM over a set of instances originating from Barcelona and Palma the Mallorca airports. First, we assessed the influence of the local search process on the quality of final solutions. Next, the obtained results for all instances were compared to those achieved with SIM. As our experiments show, the quality of the Pareto solutions has been increased with iSIM for most instances according to the relation between objectives. In other cases, the coverage and accuracy of the Pareto frontiers are similar, but iSIM clearly outperforms SIM in execution time. In general, the efficiency of iSIM is higher because only promising solutions are further explored with the LNS methodology, i.e. similar or more Pareto solutions are found with less sequences intensively explored. We have finally validated the proposed selection criteria. With this purpose, we applied the first selection rule to the set of solutions obtained in the first step of iSIM, using only I3. The LNS approach was used to improve the selected solutions, and results were compared to the case where all non-dominated solutions are improved by means of this methodology. We observed that, in most cases, the sequences selected with the proposed rule also yielded the best solutions after applying the local search process. Hence, we can state that, with the proposed schema and selection rules, the computational performance of iSIM is clearly enhanced without affecting the quality of solutions.

A potential concern about iSIM is that good sequences may be rejected because they appeared as dominated in the first step, and therefore they are not considered as promising to be further explored. That is, the coverage of the Pareto front is lower in some instances, which might be a drawback depending on the problem or the decision maker. To overcome this inconvenient, new decision criteria could be used to select a subset of best solutions from the dominated set when the number of non-dominated solutions found in the first step is not enough. Furthermore, more specific criteria can be defined to select sequences more likely to produce Pareto solutions after the local search is applied. For example, sequences where the push-back is scheduled in the last positions will have higher values of F_2 by definition. They also tend to have higher values of F_1 before local search, due to generally higher waiting times. This might cause these solutions to appear as dominated. However, once these solutions are further explored with the LNS methodology, the reduction on F_1 makes them likely to become Pareto solutions. The definition of such more elaborated selection criteria constitute potential lines for future development of the proposed approach.

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