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A stochastic approach for planning airport ground support resources

Daniel Guimarans[a] and Silvia Padrón[b,*]

[a]*Data Science and AI, Faculty of IT, Monash University, 900 Dandenong Road, Caulfield East VIC 3145, Australia*
[b]*TBS Education, 20 Boulevard Lascrosses, 31068, Toulouse, France*
E-mail: daniel.guimarans@monash.edu; s.padron@tbs-education.fr

Abstract

Airport ground operations are one of the main causes of late departures. Hence, reliable work plans for ground support resources can help mitigate these delays while limiting the under-/over-utilization of equipment. In this paper, we propose a stochastic approach for modeling the routing problems encountered during scheduling of each activity. We embed Monte Carlo simulation within an optimization approach to assess solutions during the search and guide the algorithm toward more robust schedules that account for resource cost. Actual flight arrival data, random service, and travel times are used in the simulation process. Results prove that our method clearly increases the robustness of the obtained schedules and the number of aircraft being handled within the planned time. To further identify potential causes of delay, we propose a reliability analysis based on the study of survival functions for each turnaround activity, combined with the dispersion of the resources' arrival to the parking stand.

Keywords: ground support resources; ground handling planning; stochastic optimization; simulation-optimization; vehicle routing problem with time windows

1. Introduction

The future of the aviation sector relies on the development of a more solid foundation to better balance customer demand with the limitations of airport capacity. As airport infrastructure cannot be sustainably expanded at the same pace as demand growth (Gelhausen et al., 2013), it is only natural to resort to the optimization of ground airport services and available resources.

Aircraft turnaround is a major cause of delayed takeoffs (Schmidt, 2017). Specialized support vehicles and teams have to perform several interconnected services between the arrival and departure of an aircraft. Numerous stakeholders are involved in the different operations, and each of them aims to optimize their own resources while maximizing their benefits. In many cases, goals and decisions of each individual may contradict. Thus, an optimal schedule for a specific type of resource can lead to delays for

*Author to whom all correspondence should be addressed (e-mail: s.padron@tbs-education.fr).

dependent operations and affect the performance of the entire turnaround. Cooperation between these partners, operational and from an optimization point of view, is key to enhance the utilization of the ground equipment (Weiszer et al., 2015).

In a prior study (Padrón et al., 2016), we considered the simultaneous allocation of different handling resources to regard the interactions between operations. We proposed a deterministic optimization methodology that produced global schedules while modeling and independently solving the operation of each type of resource as a vehicle routing problem with time windows (VRPTW). However, ground handling services are inherently a stochastic process. Planned flight arrivals suffer from frequent deviations, and operation durations can be affected by, for example, workers' skills and mechanical failures. Additionally, vehicle travel times are highly sensitive to congestion on the apron, which is shared by multiple services, aircraft, and personnel.

This uncertainty is another important challenge to be overcome (Schmidt et al., 2016), but it is barely considered in the handling optimization literature, nor in airport ground operations in general (Brownlee et al., 2018; Ng et al., 2018). Most research studies use deterministic values to model the operations' processing time (Al Bazi et al., 2016; Antonio et al., 2017), and only a small number of ground handling optimization studies address the unpredictable environment encountered in airports. Deterministic times are typically an optimistic estimate, so vehicle schedules are highly optimized but more likely to fail due to disturbances. Furthermore, airlines have significantly reduced the time that their aircraft spend on the ground between consecutive flights in an attempt to increase productivity. This implies that arrival delays and perturbations can hardly be compensated with a buffer time, particularly in the case of short-haul flights. The high cost of non-availability either imposes the use of redundant plans, generally with a high level of lowly utilized resources, or leads to an excessive usage without the required maintenance time. This situation results in costly and inefficient resource management for handling companies. Therefore, explicitly considering the risk of perturbation while planning support services is crucial for improving the reliability of operations and to increase on-time performance in airports.

In the present study, we define the stochastic ground support planning problem (SGSPP) to capture the inherent variability of turnaround processes, and then we propose an efficient method to solve it. Each type of support resource is scheduled using a stochastic VRPTW approach. Expected servicing and travel times, which are assumed to follow known distributions, are used to design the routes. To solve the SGSPP for the entire process, we extend the methodology introduced previously by Padrón et al. (2016) to cover stochastic scenarios, defining a simulation-based optimization approach that accounts for random service, traveling, and real aircraft arrival times. The proposed simulation-optimization approach allows us: *(i)* to evaluate the reliability of the solutions found under real operational conditions; and, *(ii)* to use this evaluation to provide feedback to the optimization algorithm and drive the search toward more reliable global solutions with a better balance between resource performance and turnaround time. Finally, we compare the results of our new approach with the results presented by Padrón et al. (2016) to quantify the influence of using simulation to guide the optimization algorithm.

The remainder of this paper is structured as follows. Section 2 reviews the literature related to turnaround scheduling under uncertainty and stochastic VRPTWs. The SGSPP is described and formulated in Section 3, and then the detailed implementation of the simulation-based optimization approach is presented in Section 4. The computational experiments used to validate the proposed methodology are reported in Section 5. Finally, conclusions are summarized in Section 6.

2. Literature review

In this section, we present a review of the scientific literature related to planning support services under variable conditions. First, we summarize studies that focused on modeling turnaround operations. Second, we discuss existing works focusing on scheduling support resources addressing uncertainty. Finally, we provide an overview of stochastic VRPTW approaches.

Different modeling and simulation techniques have been used to examine the turnaround process. Wu and Caves (2004) present an aggregated approach based on Markov Chains and Monte Carlo simulation (MCS) to investigate the importance of the available turnaround time to manage uncertainty. A more detailed model is developed by Schultz et al. (2013), where statistical analysis of historical data is used to better predict the turnaround time. Contrary to these studies wherein only one turnaround is examined, works based on discrete event simulation (DES) consider several aircraft being handled simultaneously (Norin et al., 2012). DES is also used by Bevilacqua et al. (2015) and Mota et al. (2017) to investigate the turnaround performance under different operating conditions and airport layout configurations. Ip et al. (2010) exploit agent technology to dynamically allocate handling resources. Activities are modeled as a set of autonomous specialized agents that can collaborate to achieve global goals. For the interested reader, Schmidt (2017) provides a comprehensive survey of the existing literature related to aircraft turnaround modeling approaches.

Regarding the optimization of support resources, only few studies address uncertainty. Clausen (2011) dynamically plans the transportation of connecting baggage by dividing the planning horizon into a set of decision periods and solving a static problem for each of them. A greedy approach is introduced to address the problem in two steps. First, the route is obtained using expected (mean) traveling times that follow a normal distribution. Second, the route is tested with random travel times and bag arrival. Diepen et al. (2013) generate robust schedules for passenger buses by maximizing the slack between two consecutive visits in a route. The authors include a simulation study to evaluate the resulting planning over perturbations. To assess the deterministic routing solutions for planning de-icing vehicles, Norin et al. (2012) develop a DES model that represents various operations during the turnaround time to examine their interaction. Findings prove that the performance of the global process is improved when vehicles are planned using an optimization process accounting for these interactions.

The flow of vehicles and teams between different turnarounds is typically modeled as a deterministic VRPTW, which has been extensively investigated in the literature. To improve the robustness of deterministic solutions, different stochastic variants of this problem have been proposed, including the VRPTW with stochastic travel and service times (SVRPTW). However, addressing the SVRPTW is computationally complex, particularly in the case of hard time windows, and has not been as extensively studied as other classical stochastic routing problems. Kenyon and Morton (2003) solve the problem exactly for a small number of scenarios, proposing a branch-and-cut algorithm to minimize the finish time of the longest route and the probability of not meeting a given deadline. Taş et al. (2013) consider a gamma distribution to model travel times in a VRPTW with soft time windows and deterministic service times. A Tabu Search metaheuristic is applied to minimize the expected transportation and service cost. Miranda et al. (2018) introduce a multi-objective approach considering transportation costs and customer service levels. Service and traveling times follow a normal distribution that has been left-truncated to avoid negative values. In a different approach, Li et al. (2010) apply Monte Carlo sampling to compute the expected service and travel times as an average of the realizations of random variables.

Similarly , Kenyon and Morton (2003) use MCS embedded in a branch-and-cut scheme to solve the VRPTW with stochastic travel times.

Simulation approaches have great flexibility, not only for modeling stochastic elements but also for describing the ground handling system. However, when they are used as a standalone decision support tool, the quality of the achieved solution cannot be ensured. When simulation is combined with optimization approaches, it is typically used to assess the optimal deterministic solution in stochastic scenarios. To overcome these limitations, there is an increasing research interest in using simulation, not only to evaluate solutions but also to guide the search process (Juan et al., 2015; Calvet et al., 2019; Raba et al., 2020). As far as we know, this is the first study that plans different turnaround support services simultaneously through an optimization approach that accounts for stochasticity. Thus, each activity is scheduled by solving a SVRPTW. Then, simulation is enclosed in the stochastic optimization model to obtain overall solutions that can increase the reliability of the designed plan.

3. Stochastic ground support planning problem (SGSPP)

Airline activities are generally based on a flight network structure wherein an aircraft performs a set of successive flight legs over a period of time. Between two consecutive flight legs, different support activities are performed at the aircraft, as shown in Figure 1.

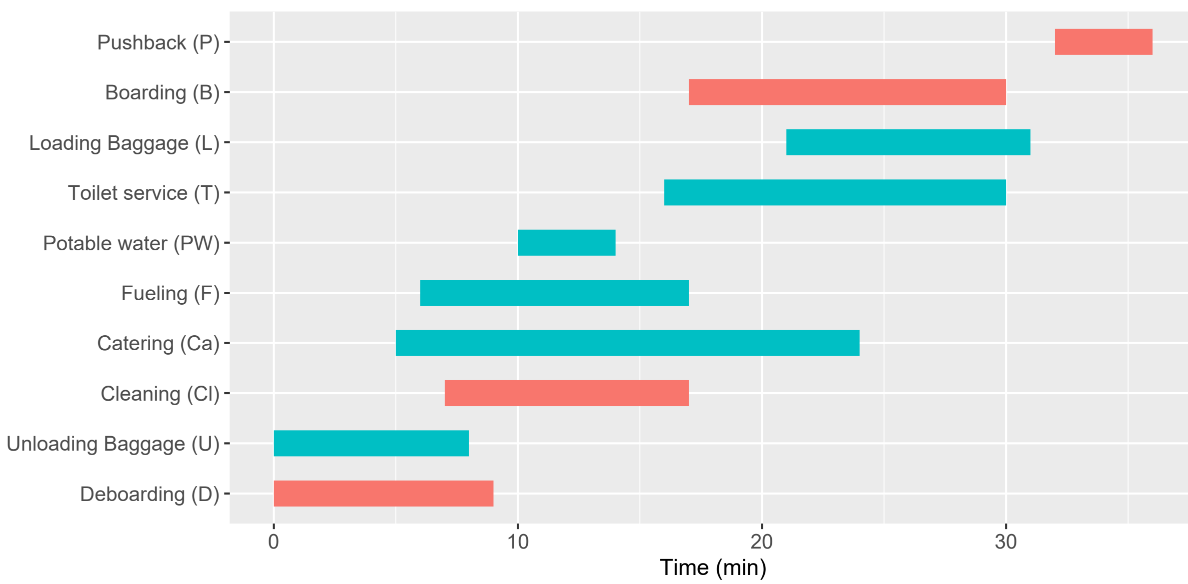


Fig. 1: Schedule of a standard turnaround at a gate. Critical operations are highlighted in red.

The main ground services are as follows: disembarking or *deboarding* (D), boarding (B), fueling (F), catering (CA), cleaning (CL) services, potable water refilling (PW), toilet service (T), and unloading (U) and loading baggage (L). The beginning of pushback (P) indicates that the turnaround has been completed. Depending on the type of service requested by the airline, some activities are not performed, or their duration might be shorter than the standard case. The planned time to complete a turnaround is delimited by the *scheduled time of arrival* (STA) and the *scheduled time of departure* (STD). Specially adapted ground resources are required to process each operation, and they move physically from one aircraft to another to fulfil the tasks assigned. An available slot is allocated to complete each activity in a manner that the existing precedence connections between the services are respected. The slot is not fixed and can vary depending on the schedule of the dependent operations.

Under real conditions, the typical deterministic approach for planning ground operations cannot reflect the inherent uncertainty of actual operations. To draw a more accurate representation of the problem, we define the Stochastic ground support planning problem (SGSPP). In particular, uncertainty is considered through modeling activity durations and travel times as random variables with a known probabilistic distribution. This is an extremely challenging stochastic optimization problem owing to different resources involved and interdependencies between ground tasks. Applying classical stochastic-programming methods to model this problem will result in excessive computational time. Hence, we propose a simpler but efficient approach to produce schedules robust enough in reasonable execution times.

In the proposed approach, the stochastic parameters of each SVRPTW are replaced by their expected values, which is a common strategy applied in heuristic approaches (i.e., law of large numbers). The distributions of the random variables are independent, but they are not identically distributed given that its variability is proportional to the deterministic value. Therefore, the classical central limit theorem cannot be applied in our problem. Moreover, a reliability criterion is introduced to assess the robustness of the global ground schedule under stochastic scenarios.

3.1. Formulation

The following parameters and variables are used to model the problem:

Parameters and instance variables

- T set of turnarounds
- l_i type of service requested by turnaround $i \in T$ —i.e., full or minimum service
- m_i aircraft model of $i \in T$
- STA_i scheduled start of $i \in T$
- STD_i scheduled end of $i \in T$
- A set of standard activities for handling an aircraft
- A_i subset of activities to be completed in i, which depends on the service type l_i, $A_i \subseteq A$
- $\tilde{\xi}_{a_i}$ duration of activity a in turnaround i, which is a random variable following a known distribution. The mean depends on the aircraft model m_i
- q_{a_i} amount of supplies requested by activity a in turnaround i, which only applies to a subset of activities (e.g., catering, fueling, toilet service, and potable water)
- P_{a_i} set of direct predecessors of activity a in i, which depends on the aircraft model m_i
- e_{a_i}, l_{ai} earliest and latest starting time at which the activity a can begin while still fulfilling the scheduled turnaround time of i
- Δ_a set of positive parameters used to further restrict the time windows of activity a to reflect operational rules applied by airlines during a turnaround

F set of types of resources (fleets) required to process the activities
a_f activity to be carried out by each fleet $f \in F$, $a_f \in A$
T_f subset of turnarounds where resources of type f are required to complete the activity a_f
K_f set of units of f available
Q_f capacity of each unit of fleet f, which only applies to a subset of fleets
$\tilde{\delta}_{ij}$ travel time between turnaround i and j ($i, j \in T$), which is a continuous random variable $\tilde{\delta}_{ij} = \delta_{ij} + \tilde{d}_{ij}$, where $\tilde{d}_{ij}$ is a random delay following a non-negative distribution. The deterministic travel time δ_{ij} is considered as the minimum time required to travel between i and j

Decision variables
s_{a_i} starting time of activity a in a turnaround i
x_{ijk} routing decision variable, where $x_{ijk} = 1$ if an activity in turnaround j is performed immediately after turnaround i by resource k, and $x_{ijk} = 0$ otherwise
w_i waiting time of a resource at turnaround i

Depending on the type of turnaround, some operations have narrower or restricted time windows for specific tasks. For instance, wide-body aircraft typically require turnarounds of several hours, but boarding of passengers can only start shortly before the STD. For these cases, we introduce the set of parameters Δ_a.

To ensure easier notation, we substitute a by the corresponding operation abbreviation; for example, s_{P_i} refers to the starting time of pushback for turnaround i. The time to start handling an operation is delimited by e_{ai} and l_{ai}, which are computed using a constraint programming model using the following constraints:

$$s_{a_i} \geq s_{b_i} + \mathbb{E}(\tilde{\xi}_{b_i}) \quad \forall a, b \in A_i : b \in P_{a_i}, \forall i \in T \tag{1}$$

$$s_{P_i} \geq \text{STD}_i - \Delta_P \quad \forall i \in T \tag{2}$$

$$s_{B_i} \geq \text{STD}_i - \Delta_B \quad \forall i \in T \tag{3}$$

$$s_{U_i} \leq \text{STA}_i + \Delta_U \quad \forall i \in T \tag{4}$$

$$s_{L_i} + \mathbb{E}(\tilde{\xi}_{L_i}) \geq \text{STD}_i - \Delta_{L_e} \quad \forall i \in T \tag{5}$$

$$s_{L_i} \geq \text{STD}_i - \Delta_{L_s} \quad \forall i \in T \tag{6}$$

Expression (1) ensures that standard precedence restrictions between operations are satisfied. Constraint (2) prevents aircraft from being pushed back too early (e.g., earlier than 5 minutes before STD, $\Delta_P = 5$), regardless whether all other turnaround tasks have been completed. Constraint (3) ensures that boarding does not start earlier than a defined time before departure, typically 30 minutes ($\Delta_B = 30$). With constraint (4) and (5), we guarantee that unloading and loading baggage activities are performed at the start and end of a turnaround. That is, baggage unloading has to start at a maximum of Δ_U minutes after the arrival of the aircraft to the stand, according to its STA. Meanwhile, baggage loading must end no earlier than Δ_{L_e} minutes before STD. This operation can generally start 30–40 minutes before STD, depending on the check-in closing time. Constraint (6) ensures that baggage loading does not start earlier than Δ_{L_s} minutes before STD.

Airline and airport revenues are intrinsically linked and have a common interest in decreasing the time aircraft remain on the ground to maximize aircraft utilization and the highest possible rotation of stands. An important goal of handling companies is to service the aircraft at the earliest opportunity to comply with their service-level agreements (SLAs). However, they also pursue the efficient use of their resources, which can conflict with the minimum stopover time objective. We have modeled the SGSPP regarding two optimization objectives: *(i)* minimizing the utilization cost of the involved support resources, and *(ii)* minimizing the overall turnaround time. Supplying solutions with a tradeoff between both criteria allows the user to choose the most satisfactory plan to be implemented.

The allocation of the required resources to process each activity is modeled through a SVRPTW problem. To simplify the formulation of each SVRPTW, we establish T as the set of turnarounds to be serviced by the type of resource $f \in F$. The special visit 0 represents the depot, and we denote the entire set of nodes including it as $T_0 = 0 \cup T$. If the vehicle arrives at the aircraft stand before its corresponding time window opens, it will wait until e_i to start the operation.

Traveling and waiting time of the used vehicles are considered to compute the utilization cost of the resources. Moreover, the addition of a third argument (h_i) is necessary to account for the incurred STD violations in a stochastic case. Precedence restrictions between activities are hard constraints, at least at a planning level. Given that expected durations, in general, are longer than in the deterministic case, turnarounds might not finish within the scheduled time. This is particularly prevalent in stopovers with a short buffer, typically observed in airlines with tight schedules (e.g., low-cost carriers).

The formulation of the SVRPTW related to each type of resource is based on the classical VRPTW formulation (Cordeau et al., 2002). The objective function (7) aims to schedule resources in a manner that the expected travel time, vehicle waiting time, and tardiness regarding the scheduled finish time of the turnaround are minimized, where $w_j = \max\{e_j - (s_i + \mathbb{E}(\tilde{\xi}_i) + \mathbb{E}(\tilde{\delta}_{ij})), 0\}$, and $h_i = \max\{s_{P_i} - \text{STD}_i, 0\}$.

$$ut = \min \sum_{\substack{i,j \in T_0 \\ i \neq j}} \sum_{k \in K} \mathbb{E}(\tilde{\delta}_{ij}) x_{ijk} + \sum_{i \in T} w_i + \sum_{i \in T} h_i \tag{7}$$

To maximize the resource utilization of the entire set of fleets (i.e., minimize their unproductive time), we define the following:

$$UT = \min \sum_{f \in F} ut_f \tag{8}$$

where each ut corresponds to the objective function (7) for each individual SVRPTW.

The minimization of the total time required to finish the ground support operations at each aircraft is formulated according to the equation (9). It is calculated using the planned time to start the final service (pushback) in the turnaround.

$$CT = \min \sum_{i \in T} s_{P_i} \tag{9}$$

As part of the assessment process performed in the experimental section (see Section 5), we compare the results obtained by both the stochastic and the deterministic approach. In the case of the deterministic formulation, we replace the expected parameters with the corresponding deterministic value. That is, $\mathbb{E}(\tilde{\xi_i}) = \xi_i$ and $\mathbb{E}(\tilde{\delta}_{ij}) = \delta_{ij}$, where ξ_i and δ_{ij} are the deterministic service and traveling times, respectively. Furthermore, the turnaround tardiness accounted by h in Equation (7) is equal to zero.

Finally, we define a reliability metric to help in the decision making in stochastic scenarios. We generate scenarios based on a sampling procedure of random variables; this is a common approach in the context of stochastic programming. Schedules are updated considering these random times and the actual time of arrival (ATA), instead of the STA. The actual ending time of each turnaround is computed, and the schedule incurs a penalty if at least one of the turnarounds is not completed on time within a certain level of tolerance. The SGSPP aims to minimize the probability of the overall actual termination time exceeding the STD by more than a specific threshold β:

$$\min \sum_{i \in N} P(\mathbb{A}(s_{P_i}) > STD_i + \beta) \tag{10}$$

To define the objective function under a discrete set of scenarios, we have followed the linear formulation proposed by Adulyasak and Jaillet (2014). As we are interested in increasing the reliability of ground plans, we have redefined the objective function as a maximization function. Let Ω be the set of scenarios, each representing a joint realization of travel and service times. The variable θ_ω is equal to 1 if all turnarounds $i \in N$ in scenario $\omega \in \Omega$ are completed on time, and it takes value 0 if at least one turnaround in the scenario exceeds its STD_i by more than a given threshold β. Thus, the objective function can be redefined as follows:

$$r = \max \frac{1}{|\Omega|} \sum_{\omega \in \Omega} \theta_\omega \tag{11}$$

subject to:

$$s_{P_i\omega} \leq \mathrm{STD}_i + \beta + M(1 - \theta_\omega) \quad \forall i \in N, \forall \omega \in \Omega \tag{12}$$

$$\theta_\omega \in \{0, 1\} \tag{13}$$

where the reliability of the ground support solution denoted by r is maximized. Expression (12) guarantees that θ_ω takes value 1 if the punctuality of all turnarounds is respected in scenario ω; that is, the pushback time of turnaround i in scenario ω ($s_{P_i\omega}$) does not exceed the defined punctuality threshold β.

4. Simulation-based optimization approach

Planning handling resources using expected traveling and service values introduces slack in the routes, and this helps reduce the probability of having a knock-on effect when the same resources are used in successive turnarounds. However, owing to the interconnections between SVRPTWs, the variability of the entire solution is not exclusively dependent on individual problems; that is, it is not the sum of the individual variability of each SVRPTW. Moreover, the time buffer to process an operation at each aircraft is a key to not only prevent the delay of the turnaround but also manage the utilization of resources. This buffer can be significantly reduced depending on how the other services are scheduled, since the routing problems for the different tasks are mutually dependent. That is, scheduling an operation with maximum slack to account for unforeseen events can result in tight plans for other operations.

To address the SGSPP by considering the impact of operation dependencies on the schedule deviations, we propose a simulation-based optimization approach, which we call the Stochastic sequence iterative method (SSIM). The SSIM extends the SIM approach (Padrón et al., 2016) to deal with stochastic scenarios, iteratively combining optimization with simulation techniques to find a set of robust solutions with a trade-off between the defined objectives (see Section 4.1). Initially, the SVRPTWs related to different operations in the turnaround are sequentially solved following an ordered list. Each SVRPTW is solved by applying a Variable neighborhood search (VNS) approach (see Section 4.2) and considering the impact on the time windows of the dependent tasks. Subsequently, several simulation runs are used to estimate the behavior of the schedules under realistic conditions (see Section 4.3). We define a set of robustness metrics to evaluate the reliability of solutions. Through these metrics, the simulation step automatically provides feedback to the search process and guides the SSIM toward more reliable solutions.

4.1. Stochastic sequence iterative method (SSIM)

The SIM heuristic was developed for deterministically scheduling the entire set of ground fleets. In particular, scheduling different resources require solving multiple VRPTWs, one for each specific service required. A bi-objective problem is regarded as a single-objective optimization problem; that is, only the primary objective is optimized, and the secondary objective is measured through an optimal solution. Approximations to the best trade-off between both objectives—UT and CT in this case, as per expressions (8) and (9)—are found by altering the solving sequence of the different routing problems. A pure optimization criterion is applied for accepting solutions: a solution is accepted if it improves the primary or the secondary deterministic objective of the incumbent.

In contrast, simulation results are used in the SSIM to determine the solving sequence to be inspected. Further, solutions are only accepted if their simulated average is better than the actual best value and if they lead to more reliable solutions while improving them. That is, the acceptance criterion checks the simulated average of the unproductive time UT ($\overline{UT}$) and the reliability r. Additionally, operations are ordered in the solving sequence by the number of time window violations to reduce the impact of the improvement of UT on reliability. Hence, the goal of the SSIM is not only to identify solutions that reasonably cover the Pareto front but also show a better behavior under uncertainty. The CT objective is implicitly considered when updating the ordered list of SVRPTWs. Thus, the simulated ending time of the turnarounds $\overline{CT}$ is not directly optimized, but computed when a solution is stored. Algorithm 1 outlines the SSIM approach. To ensure consistency and facilitate the comparison between SSIM and the previous SIM approach, we have used a similar notation to Padrón et al. (2016).

The ordered list to solve each SVRPTW is represented by the sequence S, which is defined as $S = B \cup \mathrm{P} \cup R$. P is the sub-problem related to the pushback activity, B is the set of SVRPTW sub-problems to be solved prior to P, and R is the set of remaining sub-problems. The algorithm starts by first solving the

Algorithm 1: Stochastic sequence iterative method (SSIM)

Data: S: Ordered list to schedule the SVRPTWs related to the different fleets in F. $setSolution$: set of accepted solutions

```
S ← B ∪ {P} ∪ R
B ← ∅
R ← S \ {P}
bestsolution ← obtCompleteSchedule(S)
bestsolution < r, ν̂_f, UT̄ > ← simulate(bestsolution)
findBest ← false
repeat
    R′ ← rank (R) by decreasing ν̂_f
    S′ ← {P} ∪ R′
    currentSolution ← obtCompleteSchedule(S′)
    currentSolution < r, ν̂_f, UT̄ > ← simulate(currentSolution)
    if currentSolution.r > bestsolution.r then
        if currentSolution.UT̄ < bestsolution.UT̄ then
            findBest ← true
        end
        S ← S′;
        bestsolution ← currentSolution
    end
until findBest or currentSolution.r < bestsolution.r
add(bestsolution, setSolution)
repeat
    l ← max(R, ν̂_f})                 // determine the most critical activity with respect to ν̂_f
    B ← add(l, B)                  // insert the most critical activity in the first position of S
    R ← remove(l, R)
    S ← B ∪ {P} ∪ R
    currentSolution ← obtCompleteSchedule(S)
    currentSolution < r, ν̂_f, UT̄ > ← simulate(currentSolution)
    findBest ← false
    if curentSolution.UT̄ < bestsolution.UT̄ or currentSolution.r > bestsolution.r then
        if currentSolution.UT̄ < bestsolution.UT̄ and currentSolution.r > bestsolution.r then
            findBest ← true
        end
        bestsolution ← currentSolution
        add(bestsolution, solutionSet)
    end
    if not findBest then
        repeat
            B′ ← rank (B) by decreasing ν̂_f
            R′ ← rank (R) by decreasing ν̂_f
            S′ ← B′ ∪ {P} ∪ R′
            currentSolution ← obtCompleteSchedule(FL′)
            currentSolution < r, ν̂_f, UT̄ > ← simulate(currentSolution)
            if currentSolution.UT̄ < bestsolution.UT̄ or currentSolution.r > bestsolution.r then
                if currentSolution.UT̄ < bestsolution.UT̄ and currentSolution.r > bestsolution.r then
                    findBest ← true
                end
                S ← S′
                bestsolution ← currentSolution
                add(bestsolution, solutionSet)
            end
        until findBest or currentSolution.r < bestsolution.r
    end
until B = S \ {P}
return solutionSet
```

routing problem associated to P, aiming at scheduling turnarounds to be finished at the earliest possible time (i.e., the lowest CT value). This reduces the available slot to perform other services, which can lead to having lower rates of resource utilization (i.e., higher values of UT). In general, the waiting time of the vehicles tends to increase when the tolerance to perform activities is low, which consequently contributes to the robustness of the solution. Therefore, the simulation process is executed to evaluate the solution found, and the sub-problems in R are ranked by decreasing order in terms of time window violations ν_f. The new sequence is accepted if it is able to produce a more reliable solution that also improves $\overline{UT}$. Otherwise, the process is run again to explore different scheduling lists if at least the reliability is increased. Hence, the computational effort of the heuristic is reduced without affecting the robustness of the objective.

As not all operations are required to be performed at all aircraft, the number of turnarounds depends on the specific sub-problem. To account for this characteristic, we normalize ν_f according to the number of turnarounds present in the SVRPTW sub-problem:

$$\hat{\nu}_f = \frac{\nu_f}{|N_f|} \tag{14}$$

In the following step, the sub-problem in R with the worst value of $\hat{\nu}_f$ is selected at each iteration to be solved before P. When performing this, the availability for processing the activity is expanded, and better solutions in terms of fleet utilization are achieved as more visits are generally assigned to each route. Although decreases in unproductive time might also lead to less reliable plans, reliability can still be preferred when the operation that is more likely to produce delays is planned before solving P. Scheduling P first has the effect of packing tasks in a smaller time window, aiming to minimize the termination time of the turnaround. This reduces the margin to complete services later than scheduled without affecting successive activities. That is, if the duration of a task is longer than expected, this activity is more likely to delay the beginning of subsequent operations. Thus, solving first the least robust operation can reduce $\overline{UT}$ while affecting reliability the least.

Keeping the same position of P in S, the process is executed until $\overline{UT}$ is reduced by a more reliable solution, or until reliability cannot be further improved. Otherwise, sub-problems in B and R are ranked again by $\hat{\nu}_f$ to increase resource utilization with the lowest impact on reliability. The algorithm stops when all sub-problems have been planned before P (i.e., $B = S \setminus \{P\}$ and $R = \emptyset$), and no further improvement can be obtained in terms of reliability or $\overline{UT}$. The SSIM returns the accepted non-dominated solutions as an approximation of the Pareto set.

4.2. Solution method for the VRPTW

Each SVRPTW is solved using a VNS approach (Mladenovic and Hansen, 1997), combined with the *I1* heuristic (Solomon, 1987) to obtain an initial solution. Although the performance of the constraint programming-based method used by Padrón et al. (2016) was later improved (Padrón and Guimarans, 2019), VNS turned out to be more efficient in solving the stochastic version of this problem.

VNS is a metaheuristic that has proved to be very effective both for classical VRP problems and VRP variants, including real-world constraints. One of the main advantages of VNS with respect to other metaheuristics is the fact that the basic versions of VNS and their extensions have few parameters and only require simple adjustments. VNS is based on the principle of systematically changing the used neighborhoods both in the exploration phase (i.e., local search) to find a local optimum and perturbation phase (*shaking*) used to escape from the local minimum. In our study, we have implemented a general VNS algorithm (Hansen et al., 2010), which uses variable neighborhood descent (VND) as a local search process.

After obtaining the initial solution using *I1*, the process starts by perturbing this solution in the shaking step. The first neighborhood operator is used to move to a random solution in the vicinity. Then, the VND local search process is applied. Considering the first search neighborhood, the algorithm explores the neighboring search space of the current solution to obtain a local optimum. If the solution cannot be improved, the algorithm moves to the next neighborhood. Otherwise, whenever a better solution is found, the search process is restarted from the first neighborhood. At the end of the exploration phase, when all neighborhoods have been explored, and the solution cannot be further improved (i.e., the current solution is a local minimum with respect to all defined neighborhoods), this result is compared with the best solution found thus far. If the obtained solution improves the incumbent, the search restarts from the first shaking neighborhood. Otherwise, the algorithm proceeds with the next neighborhood. The process is repeated until the algorithm reaches the defined stopping criterion.

Five types of neighborhoods (operators) are used in the shaking phase, which exploits inter- and intra-route movements: Relocate, Swap, Or-opt, 2-Exchange, and the general CROSS exchange (Taillard et al., 1991). First, a simple Relocate operator is applied, where only one turnaround is removed and inserted in another route. In Swap, the position of two turnarounds from two different routes are interchanged, Or-opt consists of moving a chain of visits to another route, and CROSS interchanges two sequences of visits with different lengths from two different routes. In addition, 2-Exchange is a special case of the CROSS method where the length of the sequences is limited to two. For all the operators, the route(s), as well as the visit (segment) to be relocated (swapped), are chosen randomly, and the process is executed many times. The same sequences of operators are considered for the exploration step, where only one of the routes and its visits—in the case of Swap—are selected randomly. Moreover, the Relocate and Or-opt operators are generalized to consider single- and multi-route movements during the local search process. That is, the turnaround(s) can be transferred to another location in the same route or to another route, depending on the quality of the obtained solution.

In addition, we have implemented the route minimization heuristic proposed by Ferreira et al. (2018). This procedure aims to decrease the number of routes required in the initial solution before the fleet utilization is further improved by the VNS algorithm. Although the number of resources mobilized is not explicitly minimized, savings in handling equipment is a key issue in terms of acquisition and maintenance costs. Two procedures are executed in this heuristic. First, a route-elimination process is performed to move customers out of one route and into another, starting with the route which has the fewest customers. Inter-route Relocation and Swap movements are continuously applied until the current route is empty or until a maximum number of iterations is reached. In the latter case, a perturbation phase is launched over the remaining routes considering the five neighborhoods defined in the VNS method. The route elimination process is performed again by finding successful moves in the modified solution. If the route cannot be emptied, the entire process is repeated with the next route. The process stops whenever no route is removed after a preset number of rounds.

4.3. Simulation procedure

We use an MCS sampling-based approach to generate the stochastic scenarios. Using the simulated travel and service durations, as well as the ATA, we update the starting time of all the required operations in each turnaround. Two conditions must be satisfied to start an operation: *(i)* the vehicle scheduled to carry out the operation must be available at the associated parking position, and *(ii)* the precedent activities in the turnaround should have been completed.

The variability of ground services can delay operations in a single aircraft or have a knock-on consequence because vehicles are shared between turnarounds. Suppose that there are two successive activities to be performed within the same turnaround. If the duration of the first activity is longer than expected, the second task can be delayed. This situation can affect not only the punctuality of this turnaround, but the delay can also be propagated through subsequent turnarounds. If the team performing the second operation has to wait until the first task is finished, this could delay the next assignment in another aircraft, as well as the completion of the next turnaround. A similar situation is encountered if the resource does not arrive on time because the trip between turnarounds took longer than expected. Therefore, we consider this delay propagation when updating the schedules in each scenario. Algorithm 2 provides the main steps of the procedure.

For each scenario, we calculate the actual time windows of the activities and the minimum time to process the turnaround under actual conditions (i.e., $\mathbb{A}(s_{Pi})$). To guarantee that precedence restrictions are fulfilled, we verify if the scheduled starting time of each activity is within their actual time windows. If it is earlier than the actual earliest time, the operation is delayed to fall within the window. On the other hand, a later actual start regarding the latest scheduled start time implies a delayed turnaround. In this case, the stop time is relaxed and $\mathbb{A}(s_{Pi})$ is updated. The routes associated with each fleet are also changed considering the actual servicing, travel times, and the associated time windows. If the updated starting time of one operation exceeds the latest start time —i.e., there is a time window violation—, the procedure is launched again to ensure feasibility if a knock-on effect occurs.

Finally, we use $\mathbb{A}(s_{Pi})$ to compute the reliability of the solution as the percentage of scenarios in which all turnarounds finish on time within different tolerance thresholds. Additionally, the simulation procedure returns the normalized number of time window violations per operation $\hat{\nu}_f$, that is, the number of times that the actual start time exceeds the scheduled latest starting time of each task over the number of turnarounds where this operation is required. As discussed previously, the latter is used by the SSIM to rank the operations to be scheduled before P in the solving sequence, actively feeding back simulation results to the optimization process and helping guide the search.

5. Computer experiments

The SGSPP approach has been tested using real flight data from a ground service provider in Barcelona-El Prat (BCN) and Palma de Mallorca (PMI) airports (Padrón et al., 2016). Additionally, the precedence constraints between activities and deterministic durations are established according to each aircraft model. We also modeled two types of services, namely, full or minimum service, where the minimum service is typically provided to low-cost carriers. To test this approach, we used a set of 5 eight-hour schedules with different numbers of turnaround and operations to be handled. Each instance is tested

Algorithm 2: Simulation procedure

Data: $\mathbb{E}(\tilde{s}_{ai}), a \in A, i \in T$: set of planned start times. R_f: set of routes (vehicles) required for operation (type of fleet) $f \in F$. R_{kf}: set of turnarounds to be served by vehicle k of type f. x_{ijk}: routing decision variable.

foreach $\omega \in \Omega$ **do**
  $s_{ai\omega} \leftarrow s_{ai}$
  $< \xi_{ai\omega}, \delta_{ij\omega} > \leftarrow$ Generate $< \tilde{\xi}_{ai}, \tilde{\delta}_{ij} >$
  Calculate $< e_{ai\omega}, l_{ai\omega} >$
  Calculate $\mathbb{A}(s_{Pi\omega})$
  repeat
    violation $\leftarrow$ **false**
    foreach $a' \in A$ **do** `// Update operation schedules per plane`
      foreach $j \in T$ **do**
        if $s_{a'j\omega} < e_{a'j\omega}$ **then**
          $s_{a'j\omega} \leftarrow e_{a'j\omega}$
          violation $\leftarrow$ **true**
        else if $s_{a'j\omega} > l_{a'j\omega}$ **then**
          violation $\leftarrow$ **true**
        end
        if violation **then**
          Update $< e_{ai\omega}, l_{ai\omega} >$ `// update the actual time windows of all the tasks`
          Update $\mathbb{A}(s_{Pi\omega})$
        end
      end
    end
    foreach $k \in R_f$ **do** `// Update operation schedules per route`
      foreach $i, j \in R_{kf}$ **do**
        if $x_{ijk} == 1$ **then**
          $s_{aj\omega} \leftarrow \max\{e_{aj\omega}, s_{ai\omega} + \xi_{ai\omega} + \delta_{ij\omega}\}$
          if $s_{aj\omega} > l_{aj\omega}$ **then**
            violation $\leftarrow$ **true**
          end
        end
      end
    end
  until ***not*** violation
  `computeStatistics`$(< \mathsf{r}_\omega, \hat{\nu}_{f\omega} >)$
end
$\mathsf{r} \leftarrow \sum_{\omega\in\Omega} \mathsf{r}_\omega / |\Omega|$
$\hat{\nu}_f \leftarrow \sum_{\omega\in\Omega} \hat{\nu}_{f\omega} / |\Omega|$
return $< r, \hat{\nu}_f >$

under two degrees of uncertainty: high variability (HV) and low variability (LV). Thus, we define a total of 10 instances, which are identified according to the following convention: *AirportxLVyyy-zzz*, where *x* is the number of the instance, *yyy* is the number of scheduled turnarounds, and *zzz* is the total number of operations to be processed.

We perform three different tests to validate our approach. First, we measure the behavior of the deterministic schedules in stochastic scenarios. Second, the SIM algorithm is applied using expected times to address each VRPTW problem. In this case, simulation is only used to assess the final solutions, and is not used during the search process. Finally, we solve the SGSPP by applying the SSIM to improve the reliability of the proposed solutions. We compare the results obtained with the SIM and the SSIM to analyze the impact of using simulation to guide the search.

A standard personal computer, Intel Core i5 processor at 2.3GHz and 4GB RAM, was used to run all the experiments. The optimization and simulation processes have been developed in Java and the ECLiPSe CP platform.

5.1. Parameter settings

To obtain the random service times, we apply an asymmetric triangular distribution (min, μ, max), whose peak value corresponds to the deterministic (or the expected) duration. We use this distribution owing to the difficulty in obtaining comprehensive data regarding ground operations (Al Bazi et al., 2016). The parameters have been set to $(min = \mu - 1, \mu, max = \mu + \mu * \zeta)$, where the ζ value is set to 0.25 or 0.5 under LV or HV, respectively. The stochastic delay in traveling times $\tilde{d}_{ij}$ is modeled using a log-normal distribution (μ, σ), as it is a suitable representation of positive random values (Juan et al., 2011; Guimarans et al., 2018; Raba et al., 2020). The deterministic time δ_{ij} has been calculated considering the maximum speed of vehicles moving on the apron (30 km/h). The log-normal function is defined as $\mu = 0$, and $\sigma = 0.25$ or $\sigma = 0.5$, depending on the variability.

We generate 1000 scenarios using MCS. We use the ATA, instead of the STA. However, we only consider the case in which the deviation from the STA is below 15 minutes. That is, the goal of the methodology is to improve the robustness of the schedules in the case of small perturbations and not disrupted scenarios.

The expected times used to solve the SGSPP were calculated using the first moment of the corresponding distribution. The expected traveling time delay is defined as $\mathbb{E}(\tilde{\delta}_{ij}) = \delta_{ij} + \mathbb{E}(\tilde{d}_{ij})$, where $\mathbb{E}(\tilde{d}_{ij}) = \exp(\mu + \sigma^2/2)$. The expected duration is set to $E(\tilde{\xi}_{ai})$ = $(min + \mu + max)/3$.

5.2. Evaluation of deterministic Pareto solutions

The Pareto deterministic solutions obtained by the SIM method, as well as the simulations results, are provided in Table 1. For each solution, we include: the total vehicle waiting time (w) and the traveling time (δ) that correspond to the objective value (UT) and the total turnaround time (CT). For the stochastic scenarios, we present the average values of the objectives ($\overline{w}$, $\overline{\delta}$, and $\overline{UT}$), and the reliability of the solutions (r_{15}) imposing a threshold $\beta = 15$, given that in practice a turnaround is considered *late* if it is delayed by more than 15 minutes.

As shown in the figures, the reliability of almost all the obtained solutions is zero. As routes are highly optimized to reduce vehicles' idle time and turnaround duration, delays caused by longer-than-scheduled services and traveling times can barely be absorbed. Additional metrics have also been recorded for an in-depth investigation of the obtained results, such as the average delay per late turnaround (D) and the proportion of turnarounds that have been completed on time with 95% confidence (OT_{15}). To compute the former, we divide the total delay incurred per simulation by the number of delayed turnarounds. For example, 21% of turnarounds in the instance PMI1 departed on time—with 95% confidence—in a scenario with high variability where solution 2 is deployed, with an average of 23.34 minutes of delay per late turnaround. This type of information can be applied by ground handlers to select the appropriate schedule to implement, which can have an important effect on their operations. The cost impact associated with a late departure is set per minute, and it is generally included in the SLAs between ground handlers and airlines.

Table 1: Deterministic non-dominated solutions and simulation results for PMI and BCN instances.

		Deterministic solutions				Stochastic scenario (LV)						Stochastic scenario (HV)					
Inst	N	w	δ	CT	#V	$\overline{w}$	$\overline{\delta}$	$\overline{CT}$	r_{15}	D	OT_{15}	$\overline{w}$	$\overline{\delta}$	$\overline{CT}$	r_{15}	D	OT_{15}
PMI1 42_336	1	215	52	1735	41	304.82	399.25	2246.06	0	18.09	0.93	300.30	432.78	2452.61	0	20.37	0.62
	2	200	48	1743	41	322.33	394.92	2453.35	0	19.80	0.60	324.14	429.06	2700.02	0	23.34	0.21
	3	210	50	1742	42	279.09	396.93	2379.13	0	19.50	0.62	285.77	431.31	2560.93	0	23.20	0.50
	4	184	50	1747	43	346.39	396.92	2429.95	0	19.46	0.67	363.78	430.76	2651.22	0	23.43	0.38
	5	147	46	1764	45	307.71	392.92	2396.61	0	18.57	0.76	318.99	427.14	2558.84	0	19.75	0.40
	6	158	47	1760	42	317.68	393.43	2588.66	0	22.44	0.55	313.12	426.81	2785.00	0	25.39	0.26
PMI2 83_649	1	5780	95	3256	39	5414.08	764.53	4179.47	0	20.11	0.73	5256.57	830.87	4516.08	0	24.84	0.60
	2	5358	96	3261	39	5040.72	765.98	4253.09	0	21.10	0.67	4879.51	832.17	4598.17	0	25.81	0.58
	3	5110	101	3267	38	4837.93	770.72	4398.33	0	25.63	0.71	4699.15	837.18	4781.81	0	28.62	0.53
	4	5045	98	3313	38	4794.3	767.98	4233.99	0	20.10	0.67	4677.36	833.86	4633.66	0	24.81	0.51
	5	4862	97	3347	40	4579.06	766.43	4215.24	0	18.00	0.80	4472.86	832.44	4585.80	0	21.52	0.54
PMI3 64_508	1	2335	63	2545	39	1884.05	587.17	3266.56	0	17.89	0.80	1760.56	638.72	3627.07	0	20.61	0.50
	2	2236	63	2548	39	1837.83	587.55	3378.92	0	19.50	0.61	1716.74	638.76	3751.56	0	23.81	0.44
	3	2162	64	2554	40	1801.42	587.90	3289.72	0	17.86	0.83	1668.53	639.45	3622.73	0	20.75	0.44
	4	2091	64	2573	39	1733.72	588.33	3326.61	0	19.47	0.78	1618.62	639.15	3654.38	0	22.32	0.58
	5	2102	65	2569	39	1729.31	588.88	3235.27	0	17.05	0.86	1602.75	641.15	3574.52	0	20.26	0.53
	6	2042	65	2585	38	1709.77	589.47	3354.92	0	17.81	0.72	1594.77	640.57	3787.41	0	23.34	0.45
BCN1 56_446	1	3384	700	2942	35	3047.1	1160.6	3627.67	0	18.39	0.80	2931.66	1205.44	3861.20	0	20.93	0.63
	2	3058	732	2954	35	2730.32	1192.34	3664.81	0	19.26	0.82	2615.45	1237.46	3886.14	0	21.10	0.63
	3	2919	682	2965	35	2673.46	1141.93	3800.04	0	19.78	0.63	2582.16	1187.41	4087.80	0	23.97	0.46
	4	2900	679	2990	32	2577.35	1139.26	3644.25	0	18.78	0.84	2447.98	1185.16	3867.66	0	21.17	0.63
	5	2872	684	3006	32	2578.15	1144.02	3746.14	0	19.83	0.71	2455.58	1189.70	3950.78	0	22.07	0.54
BCN2 37_282	1	1369	382	1842	29	1223.56	672.74	2222.47	0	17.94	0.89	1161.21	701.5	2349.98	0	19.51	0.73
	2	1282	381	1850	29	1102.53	671.50	2137.60	0.33	10.47	0.97	1036.78	700.21	2229.16	0	17.10	0.89
	3	1234	381	1853	27	1039.33	672.43	2117.14	0.21	12.82	0.95	957.21	700.47	2203.85	0.004	17.80	0.95
	4	1252	388	1851	28	1093.23	679.21	2249.71	0	18.24	0.78	1026.74	707.69	2392.49	0	21.27	0.70
	5	1174	372	1859	31	1040.33	662.53	2151.73	0.10	14.84	0.97	993.93	691.27	2255.17	0.001	16.87	0.86
	6	1201	392	1854	29	1057.91	683.52	2211.46	0	18.30	0.89	994.24	712.29	2367.14	0	20.73	0.70

The OT_{15} metric is particularly useful for determining potential causes of delay when solutions' reliability is very low. According to the reliability criterion, if at least one turnaround does not finish on time in a scenario, the solution is considered not reliable for this scenario. Therefore, we cannot differentiate between a plan where most of the turnarounds were late and one where only one turnaround was delayed.

Additionally, we use the survival functions of turnaround activities and the dispersion on the arrival of vehicles to the respective parking stand to further analyze our scheduling. Figure 2 provides an example of survival analysis for the turnaround 24 in solution 5 of the PMI1 instance with high variability (see Table 1). The aircraft arrives to the parking position 7 minutes later than the STA (365), and is pushed back more than 15 minutes later than the STD (410). The overdue aircraft arrival delayed the beginning of operations and has a notable impact in the most constrained services, such as cleaning. Moreover, late arrivals of vehicles due to longer service and traveling times is an important cause of delays. In this case, the aircraft departure is particularly affected by a delayed pushback vehicle. Given that the pushback is a short activity, the deterministic schedule consists of a small number of vehicles handling several turnarounds. This makes the routes very sensitive to perturbations, increasing the probability of delay

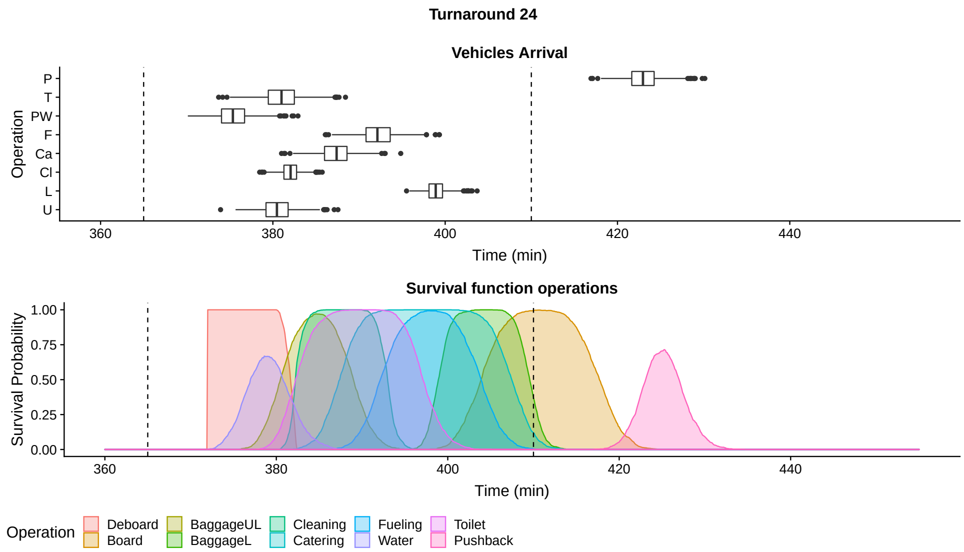


Fig. 2: Survival analysis of a delayed turnaround in the deterministic solution 4 of the PMI1 instance with high variability, including the dispersion of arrival of vehicles.

propagation between consecutive turnarounds.

5.3. Evaluation of SIM and SSIM expected solutions

Tables 2 and 3 outline all the solutions found with SIM when the expected travel and duration times are used, rather than the corresponding deterministic values. Tables 2 and 3 also present the equivalent results for the application of the SSIM. Since different trade-off solutions are obtained by each method, we have selected one solution per each under high variability for further comparison (see Section 5.3.1).

The solutions' robustness has clearly improved (c.f. Table 1), and delays caused by variability in the system are significantly reduced. As the reliability and the number of timely turnarounds are similar across solutions, considering a 15-minute tolerance, we include on-time statistics using other thresholds, such as OT_5 and OT_0 for 5 and 0 minutes, respectively. Thus, the two schedules with similar performance can be compared.

Unlike the deterministic solutions, the schedules obtained when using expected values present higher vehicle waiting times. Although resource utilization is an important objective for ground handlers, the additional margin in the routing plan improves reliability and makes the schedules more suitable for realistic conditions. However, SIM searches for global solutions that minimize the overall deterministic objectives, which does not necessarily imply a better performance for the stochastic problem. In contrast, simulated unproductive times and different levels of reliability (15, 5, and 0 minutes) are examined in the acceptance criterion of the SSIM. That is, if two schedules have the same value of r_{15}, the algorithm will check whether r_5 or r_0 has been improved to make a decision.

The SSIM is able to obtain better results in terms of reliability for most instances with equivalent or, in some cases, with a significant decrease of actual vehicle waiting times. In problems such as PMI1 (LV and HV), PMI2LV, and BCN1LV, most solutions found with the SSIM are 100% reliable. In the case of PMI2HV and BCN2HV, incurred delays are significantly reduced. In other instances, r_{15} is similar. However, a higher number of aircraft left the parking position at the STD or within 5 minutes with lower values of waiting times (e.g., BCN2LV).

The simulated finishing time of the turnarounds is lower in most of the SSIM solutions, particularly in the case of LV scenarios. Under low variability, the slack created as a result of using expected values is logically smaller compared with HV scenarios. Moreover, the expected idle time of the obtained schedules is minimized with SIM, which generally leads to a worse performance. In contrast, more robust solutions are preferred in the SSIM, keeping a certain level of waiting time to absorb some variability, which consequently enhances the punctuality of the turnarounds. Meanwhile, the simulated unproductive time is lower in a few SIM solutions, but at the expense of lower reliability.

Regarding the performance of the different trade-off SSIM solutions, longer expected idle times generally produce solutions with shorter turnaround times when deployed in scenarios with uncertainty. The shortest expected turnaround duration does not necessarily correspond to the shortest simulated one. To reduce the turnaround time, the available time slots to perform each activity are highly constrained, affecting the system's capability to absorb perturbations. Thus, the shortest actual completion times typically result in the highest number of earlier departures, despite the fact that the schedules are not always the most reliable. For example, solution 1 for the PMI2HV instance has the shortest turnaround makespan and the best values of OT_5 and OT_0, but is less robust than solution 4. Regarding the waiting time, although reduced slack can still yield good results in terms of r_{15}, these solutions tend to present a less robust behavior. In instances such as PMI1LV, all turnarounds in solution 5 are on time within 15 minutes of STD, but only 76% and 36% of them are completed within 5 minutes and at STD, respectively. This implies that these solutions might be more sensitive to small additional perturbations, leading to an increasing number of delays and late departures.

Table 4 provides information about routing results according to the service type for each SSIM solution. Cl, U, L, and P activities employ uncapacitated trucks wherein the number of turnarounds that can be performed is unlimited. The capacity of the resources required to process activities T and PW is set to 1000 L, whereas Ca and F vehicles can contain up to 2000 and 100,000 L of supplies. When the capacity of a truck is exceeded, it must return to the depot to refill or empty the tanks before proceeding with the next assignment. The average number of activities processed per route ($\#A$) and the average number of refilling/empty ($\#R/E$) steps per route are included. To ensure time is balanced among routes, the total service duration of a route cannot be lower than 80% of the total average duration.

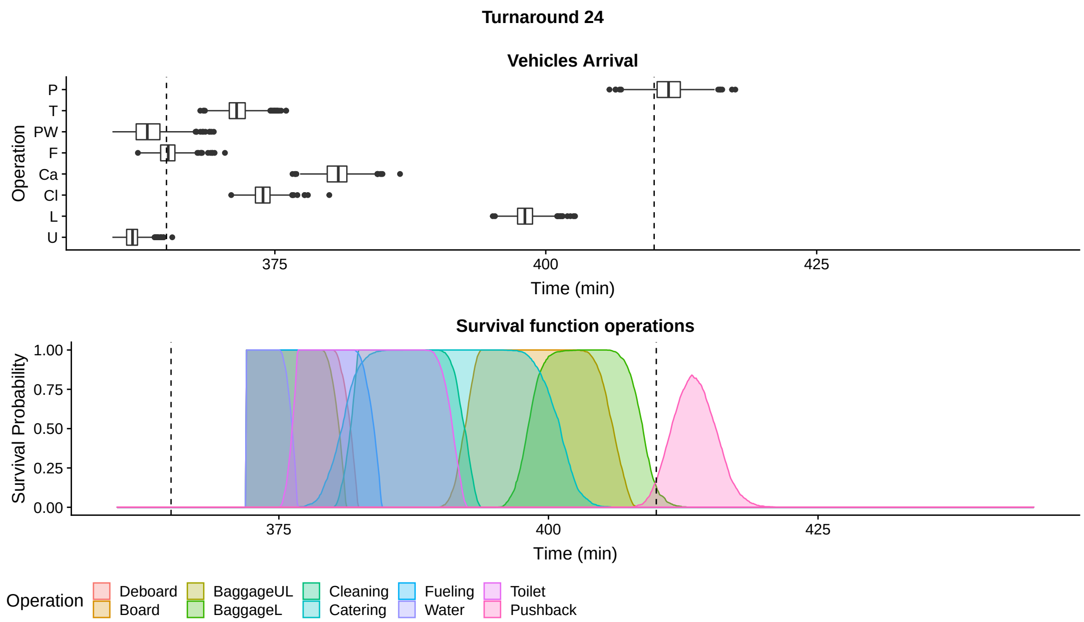
Finally, we revisit turnaround 24 from instance PMI1HV to visually analyze how solutions from the SIM and the SSIM alter the execution of the turnaround, as depicted in Figure 3. As observed, the margin created when using expected times to build the routes results in earlier arrivals of the vehicles, narrower operation survival functions, and a quicker turnaround. In the case of the SIM solution (Figure 3a), the robustness of the schedule has been improved. This turnaround is not considered late, but it exceeds the STD by more than 5 minutes. Late pushback vehicles remain the primary cause of this delayed departure, which is practically eliminated by the SSIM solution (Figure 3b) using more resources or scheduling vehicles to arrive earlier, as in this case. Both SIM and SSIM solutions have similar waiting times and comparable solving sequences, given that the pushback is planned in the same position. However, the difference regarding the order of certain activities shows how the sequence in which operations are planned can have a major effect on reliability.

5.3.1. Comparison of the SIM and SSIM solutions according to turnaround tardiness

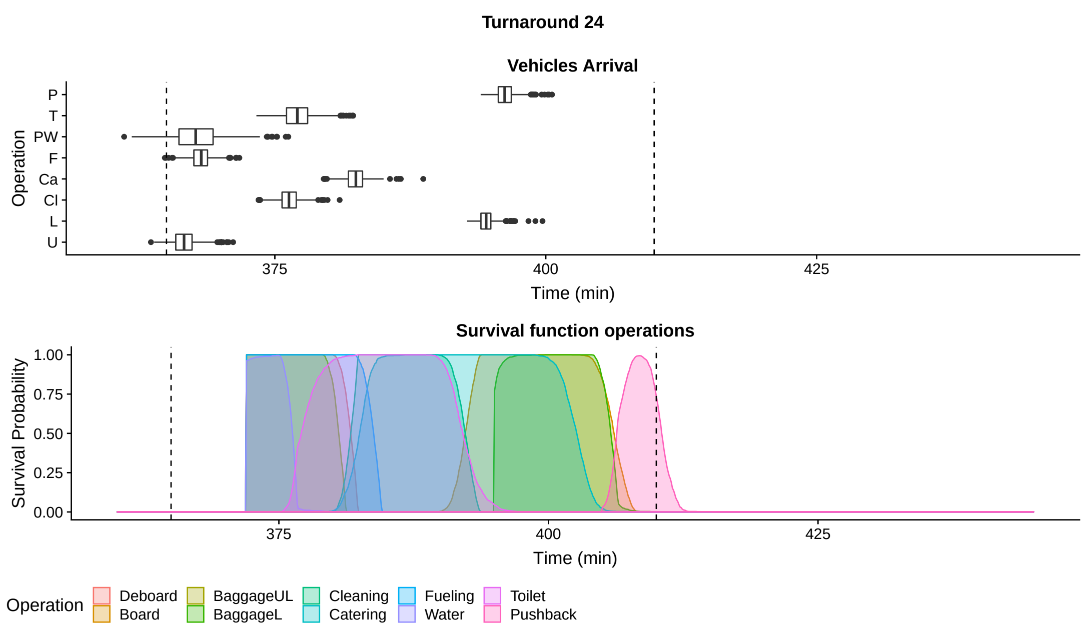
Our approach actively employs MCS in a closed loop. The randomness of the stochastic variables is exploited to guide the exploration of the sequences and lead the algorithm to produce solutions with the expected characteristics. The operations which are delayed the most are inserted in the first places of the sequence to schedule them with a larger margin, thus reducing the risk of affecting successive tasks. Moreover, the reliability of the solutions is considered to select the sequences to be explored. This prevents the algorithm from going toward better solutions with respect to the expected values, rather than more robust solutions in random scenarios.

When the traveling time variability is quite high, a higher number of resources can be required. However, the type of distribution used to model variability offers some protection as it is asymmetric and "skewed to the right" (i.e., lognormal). If the duration of the tasks is highly variable, there is a risk of turnaround violation—when a turnaround does not finish within the scheduled time—even when using dedicated resources. Turnaround parameters are inputs generally set a few months (flight times) or weeks (assignment of aircraft to sets of flights) in advance. Given that flight schedules are, in general, very tight, there is no other option than relaxing the time windows of the operations even when using deterministic values. Thus, solutions are never infeasible during the day of operation but incur delays. During planning time, schedules produced by the algorithm can become infeasible if we impose hard constraints. Nevertheless, they can reduce the overdue turnarounds during the day of operation, which is the most critical objective.

We have included a comparison between solutions obtained through open-loop and closed-loop simulation (i.e., SIM vs SSIM) considering the turnaround tardiness. For each scenario, we have calculated the total amount of time that the actual finish time of each turnaround exceeds the STD. We have selected one solution per method under high variability to provide a clear and fair comparative analysis: *(i)* the SSIM solution with the highest reliability and the lowest waiting times in the case of solutions equally reliable, and *(ii)* the SIM solution with the closest values of waiting times to the chosen SSIM solution. Selected solutions are highlighted in bold in Tables 2 and 3. Simulated tardiness for the set of instances under high variability are depicted in Figure 4. As expected, we observe a significant reduction of delays reached by the SSIM solutions, and a lower dispersion of delays, especially noticeable for the BCN2HV and PMI1HV instances.



(a) SIM solution



(b) SSIM solution

Fig. 3: Survival analysis of turnaround 24 in (a) SIM solution and (b) SSIM solution for the PMI1HV instance, including the dispersion of arrival of vehicles.

Table 2: Non-dominated solutions found with SIM (using expected values) and SSIM, and their simulation results for the PMI instances. Solutions selected for further comparison are highlighted in bold.

		SIM. Expected values					Stochastic scenario							SSIM					Stochastic scenario						
Instance	N	w	δ	h	CT	#V	$\overline{w}$	$\overline{\delta}$	$\overline{CT}$	r_{15}	D	OT_5	OT_0	w	δ	h	CT	#V	$\overline{w}$	$\overline{\delta}$	$\overline{CT}$	r_{15}	D	OT_5	OT_0
PMI1LV 42_336	1	337	483	41	1731	51	606	399	1905	1	0	0.80	0.54	383	480	41	1740	51	611	396	1881	1	0	0.81	0.55
	2	289	478	58	1752	48	612	394	2071	0.27	11.35	0.57	0.09	259	479	60	1762	50	558	394	1910	1	0	0.86	0.50
	3	253	480	52	1769	49	551	395	2083	0.32	10.63	0.57	0.21	253	480	55	1779	53	526	395	1908	1	0	0.88	0.48
	4	224	481	55	1773	48	533	396	2071	0.32	10.59	0.52	0.11	255	480	47	1779	47	512	395	1957	1	0	0.83	0.33
	5	212	481	58	1779	49	515	396	2040	0.32	10.59	0.59	0.23	258	478	50	1797	51	503	393	1966	1	0	0.76	0.36
		T(s)	2760.56											6169.57											
PMI1HV 42_336	1	432	531	114	1786	58	780	433	1896	0.99	0.02	0.88	0.54	446	528	120	1786	57	795	430	1900	1	0	0.90	0.48
	2	378	529	89	1798	55	729	431	2000	0.81	3.03	0.64	0.26	406	530	116	1785	59	744	432	1909	1	0	0.9	0.5
	3	312	527	83	1814	58	679	428	1986	0.12	14.37	0.73	0.35	330	527	119	1816	54	681	429	1907	1	0	0.83	0.48
	4	**288**	**529**	**85**	**1838**	**54**	**635**	**431**	**1989**	**0.1**	**14.71**	**0.71**	**0.4**	302	530	129	1830	54	641	432	1921	1	0	0.79	0.55
	5	278	524	87	1849	56	661	426	2033	0.94	0.87	0.57	0.16	**286**	**527**	**135**	**1835**	**53**	**624**	**429**	**1945**	**1**	**0**	**0.79**	**0.40**
		T(s)	2532.18											6291.24											
PMI2LV 83_649	1	5815	931	83	3277	47	6317	767	3567	1	0	0.75	0.42	5806	929	77	3277	47	6312	765	3507	1	0	0.81	0.48
	2	5605	929	91	3310	46	6101	766	3644	0.99	0.06	0.66	0.37	5652	933	77	3273	49	6164	769	3536	1	0	0.80	0.43
	3	5319	936	81	3313	45	5856	772	3642	0.89	1.69	0.68	0.36	5560	932	79	3327	47	6052	768	3562	1	0	0.75	0.46
	4	5274	929	83	3318	45	5812	766	3648	0.83	2.55	0.72	0.33	5381	934	80	3330	48	5875	770	3552	1	0	0.71	0.42
	5	5037	929	79	3337	46	5584	765	3708	0.96	0.58	0.59	0.26	5070	932	79	3375	43	5573	768	3688	0.99	0.015	0.64	0.31
														5152	929	87	3365	48	5668	766	3605	1	0	0.69	0.45
		T(s)	5843.38										14934.68												
PMI2HV 83_649	1	6126	1024	191	3368	49	6895	836	3635	0.37	9.94	0.72	0.38	6389	1021	192	3372	48	7114	832	3516	0.88	1.40	0.80	0.55
	2	5704	1024	154	3389	45	6497	835	3597	0.54	7.26	0.73	0.38	5822	1022	180	3399	50	6554	834	3530	0.90	1.63	0.80	0.48
	3	5561	1024	201	3409	51	6332	835	3584	0.64	5.66	0.75	0.43	5466	1021	187	3423	48	6253	832	3586	0.93	1.14	0.73	0.46
	4	**5514**	**1022**	**129**	**3418**	**48**	**6280**	**833**	**3594**	**0.55**	**7.06**	**0.77**	**0.45**	**5418**	**1022**	**200**	**3462**	**47**	**6181**	**832**	**3621**	**0.96**	**0.85**	**0.70**	**0.40**
	5	5106	1028	192	3450	49	5915	839	3633	0.55	7.04	0.72	0.36	5296	1021	187	3462	49	6079	832	3646	0.94	0.93	0.67	0.36
														5240	1021	187	3462	48	6023	833	3652	0.83	2.60	0.65	0.41
		T(s)	6728.74										15172.79												
PMI3LV 64_508	1	2560	715	58	2551	51	2886	587	2750	0.99	0.02	0.81	0.5	2587	714	60	2546	51	2884	586	2686	1	0	0.81	0.61
	2	2382	714	73	2579	52	2748	586	2761	0.99	0.05	0.75	0.48	2523	716	60	2563	51	2846	588	2729	1	0	0.89	0.45
	3	2427	715	71	2576	51	2701	587	2779	1	0	0.82	0.37	2391	717	73	2620	47	2650	589	2732	1	0	0.81	0.47
	4	2180	713	67	2601	48	2488	585	2792	0.95	0.76	0.7	0.43	2329	716	69	2624	50	2569	587	2752	1	0	0.84	0.50
	5	2129	714	66	2607	50	2458	586	2808	1	0	0.71	0.42	2134	714	72	2630	49	2515	587	2770	1	0	0.80	0.47
	6	2068	715	67	2649	49	2368	587	2849	0.99	0.02	0.68	0.37	2200	715	65	2583	50	2411	586	2800	1	0	0.69	0.39
	7	2072	716	73	2641	51	2379	588	2854	0.99	0.11	0.67	0.35												
		T(s)	5969.59										9300.49												
PMI3HV 64_508	1	2369	786	182	2638	54	2880	638	2757	0.81	2.89	0.84	0.48	2380	788	179	2639	54	2912	641	2735	0.82	2.84	0.81	0.52
	2	2153	786	143	2657	57	2694	638	2769	0.82	2.75	0.82	0.5	2611	788	175	2639	53	3108	640	2727	0.81	2.88	0.83	0.53
	3	**2077**	**785**	**195**	**2665**	**52**	**2607**	**638**	**2836**	**0.8**	**3.08**	**0.78**	**0.34**	2191	786	193	2678	56	2700	638	2763	0.80	3.05	0.75	0.48
	4	2024	786	155	2679	54	2569	638	2895	0.79	3.15	0.59	0.34	**2117**	**787**	**188**	**2677**	**52**	**2620**	**638**	**2777**	**0.84**	**2.52**	**0.78**	**0.44**
	5	1927	786	149	2688	53	2450	638	2865	0.76	3.59	0.7	0.29	2366	787	193	2689	51	2835	639	2746	0.84	2.47	0.77	0.48
	6	1908	788	151	2702	51	2442	639	2860	0.67	5.08	0.7	0.29	2011	784	195	2722	51	2499	636	2835	0.82	2.86	0.73	0.34
		T(s)	6774.16										14737.24												

Table 3: Non-dominated solutions found with SIM (using expected values) and SSIM, and their simulation results for the BCN instances. Solutions selected for further comparison are highlighted in bold.

		SIM. Expected values					Stochastic scenario							SSIM					Stochastic scenario						
Instance	N	w	δ	h	CT	#V	$\overline{w}$	$\overline{\delta}$	$\overline{CT}$	r_{15}	D	OT_5	OT_0	w	δ	h	CT	#V	$\overline{w}$	$\overline{\delta}$	$\overline{CT}$	r_{15}	D	OT_5	OT_0
BCN1LV 56_446	1	3974	1241	91	2984	37	4246	1128	3231	1	0	0.73	0.42	3970	1275	93	2987	35	4212	1162	3166	1	0	0.79	0.55
	2	3856	1216	79	3004	35	4173	1103	3342	0.67	5.07	0.57	0.3	3839	1255	88	3004	36	4098	1142	3193	1	0	0.82	0.50
	3	3397	1269	100	3045	35	3688	1157	3286	0.45	8.60	0.67	0.32	3672	1263	87	3016	36	3937	1150	3186	1	0	0.77	0.52
	4	3566	1263	81	3038	36	3848	1150	3272	0.85	2.20	0.69	0.44	3593	1263	97	3027	35	3883	1151	3192	1	0	0.73	0.57
	5	3302	1244	97	3048	37	3608	1131	3310	0.99	0.02	0.67	0.32	3572	1221	99	3033	35	3856	1108	3211	1	0	0.79	0.50
														3514	1254	78	3017	35	3763	1142	3227	1	0	0.73	0.48
		T(s)	2153.53											7750.77											
BCN1HV 56_446	1	3504	1304	233	3093	43	4074	1173	3224	0.75	3.91	0.78	0.46	3758	1343	230	3092	41	4299	1213	3169	0.93	1.07	0.82	0.63
	2	3262	1310	172	3107	42	3776	1181	3213	0.52	7.64	0.73	0.51	3635	1295	227	3107	40	4160	1166	3176	0.92	1.13	0.81	0.54
	3	3351	1321	232	3103	44	3860	1191	3211	0.91	1.29	0.76	0.53	3274	1303	217	3122	42	3832	1174	3199	0.93	1.02	0.82	0.5
	4	3220	1297	165	3113	44	3781	1167	3260	0.94	0.91	0.69	0.41	3150	1320	234	3129	41	3684	1190	3205	0.96	0.96	0.77	0.5
	5	**3144**	**1250**	**157**	**3126**	**41**	**3655**	**1120**	**3233**	**0.73**	**4.16**	**0.71**	**0.46**	3149	1284	229	3134	40	3655	1154	3241	0.94	0.90	0.75	0.38
	6	3080	1291	167	3142	42	3642	1162	3239	0.46	8.49	0.73	0.44	**3120**	**1299**	**221**	**3136**	**42**	**3575**	**1170**	**3255**	**0.94**	**0.85**	**0.67**	**0.46**
		T(s)	3735.25											9988.42											
	1	1317	774	74	1859	34	1476	703	1883	1	0	0.86	0.78	1348	771	74	1859	33	1474	700	1883	1	0	0.92	0.78
	2	1317	762	76	1861	34	1491	691	1921	0.4	9.42	0.86	0.72	1264	770	74	1878	34	1394	698	1879	1	0	0.95	0.84
BCN2LV 37_282	3	1290	773	78	1868	35	1462	701	1915	1	0	0.83	0.72	1221	764	87	1894	33	1358	692	1902	1	0	0.92	0.76
	4	1213	762	86	1892	34	1376	691	1968	0.34	10.49	0.81	0.54	1192	765	81	1889	34	1287	694	1930	1	0	0.84	0.62
	5	1171	724	83	1904	35	1305	653	2006	1	0	0.7	0.48	1128	754	90	1895	34	1239	683	1990	1	0	0.78	0.47
	6	1176	745	94	1903	34	1345	673	2019	0.35	10.39	0.7	0.45	1105	742	88	1897	35	1284	671	1949	1	0	0.81	0.65
		T(s)	974.57											3588.2											
	1	1571	827	162	1928	36	1837	745	1932	0.93	1.02	0.89	0.56	1413	816	111	1928	36	1687	734	1941	0.93	1.01	0.92	0.57
	2	**1438**	**802**	**170**	**1930**	**36**	**1732**	**719**	**2005**	**0.12**	**14.41**	**0.75**	**0.4**	1575	805	162	1926	36	1824	724	1933	0.94	0.86	0.89	0.59
BCN2HV 37_282	3	1352	818	173	1932	36	1612	736	1991	0.1	15.75	0.75	0.51	**1451**	**801**	**119**	**1933**	**37**	**1761**	**719**	**1925**	**0.94**	**0.96**	**0.89**	**0.59**
	4	1335	808	123	1942	36	1575	726	1989	0.13	14.33	0.81	0.45	1358	798	173	1940	37	1578	716	1946	0.93	1.06	0.89	0.51
	5	1280	805	120	1944	37	1534	723	1990	0.13	14.21	0.83	0.45	1301	818	124	1947	36	1546	736	1952	0.91	1.41	0.89	0.51
	6													1295	788	118	1953	35	1543	706	1999	0.92	1.22	0.86	0.32
		T(s)	1034.21											4926.35											

Table 4: Routing results per service type for each SSIM solution for PMI and BCN instances.

		Stochastic scenario (LV)											Stochastic scenario (HV)										
		U/L	Cl	Ca		F		PW		T		P	U/L	Cl	Ca		F		PW		T		P
Inst	N	$\#A$	$\#A$	$\#A$	$\#R/E$	$\#A$	$\#R/E$	$\#A$	$\#R/E$	$\#A$	$\#R/E$	$\#A$	$\#A$	$\#A$	$\#A$	$\#R/E$	$\#A$	$\#R/E$	$\#A$	$\#R/E$	$\#A$	$\#R/E$	$\#A$
PMI1 42_336	1	6	4	5	0	5	0.75	14	1.33	7	0.33	10	6	4	4	0	6	0.86	8	0.2	6	0.14	10
	2	6	5	4	0	7	1	8	0.2	8	0.4	10	6	5	4	0	5	0.63	14	1	7	0	10
	3	6	5	4	0	5	0.88	8	0.4	7	0	10	7	5	4	0	6	1.14	14	1.33	5	0.13	10
	4	6	5	5	0	5	0.75	14	1	6	0	10	7	5	4	0	5	0.38	11	1	5	0.13	8
	5	7	5	5	0	7	1.17	14	1	7	0	10	7	5	4	0	6	0.71	14	1.33	6	0	10
PMI2 83_649	1	17	10	10	0	14	2.5	26	2.33	11	0.71	17	15	10	10	0.13	14	2.5	19	1.5	13	1	17
	2	17	10	10	0	12	2.29	26	2.33	10	0.38	17	17	10	9	0	10	1.75	15	1.2	15	1.2	17
	3	17	10	10	0.13	16	3	13	1	15	1.2	17	17	10	10	0	14	2.33	15	1.2	13	1	17
	4	17	10	10	0	14	2.5	13	1	15	1.2	17	17	10	10	0	14	2.5	19	1.5	13	1	17
	5	24	10	10	0	14	2.33	19	1.25	15	1.2	17	17	10	10	0	14	2.5	13	1	13	1	17
	6	21	10	10	0	10	1.63	13	0.83	15	1.2	17	17	10	10	0	14	2.5	15	1.2	13	1	17
PMI3 64_508	1	11	6	7	0	9	1.43	20	1.67	10	0.67	16	12	6	5	0	9	2.5	16	0.71	9	0.27	16
	2	11	7	7	0	9	2.25	20	0.71	9	0.17	16	12	6	5	0	9	2.25	16	0.71	10	0.36	16
	3	12	8	6	0	11	1.83	20	2	12	0.8	16	12	7	5	0	8	2	16	0.63	8	0.09	13
	4	12	8	6	0	9	1.43	12	1	12	1	16	12	7	6	0	11	3	16	0.83	8	0.09	16
	5	12	8	6	0	9	2.5	13	0.71	12	0.27	16	12	7	6	0	11	1.83	16	1.25	10	0.67	13
	6	11	8	7	0	8	1.38	20	1.67	12	0.8	13	12	7	6	0	11	2	16	1.25	10	0.5	13
BCN1 56_446	1	12	9	11	0.8	9	2.17	18	2.33	18	2.33	18	12	8	8	0.14	9	1.83	13	1.5	11	1.2	18
	2	12	9	9	0.25	14	1.44	13	2.33	13	1	18	12	9	8	0.14	8	1.57	18	2.67	11	1.2	18
	3	12	11	9	0.17	9	1.33	13	1.33	18	2.67	18	12	9	8	0.14	7	1.13	13	1.75	11	1.2	18
	4	16	11	9	0.33	14	3.25	13	1.5	9	0.83	18	11	9	8	0.14	9	1.83	13	1.75	11	1.2	18
	5	16	11	9	0.4	14	2.17	11	1	11	1.2	18	11	9	8	0.29	9	2	18	2.33	11	1.2	18
	6	16	11	9	0.5	14	4.33	11	1	11	1.17	18	11	9	8	0.14	9	2	13	2	11	1.2	14
BCN2 37_282	1	11	5	5	0	9	1.75	15	1.5	10	1	12	11	5	5	0	7	1	10	1	10	0.67	12
	2	11	5	5	0	9	1.75	10	1	10	1	12	11	5	5	0	7	1	10	1	10	1	12
	3	11	5	6	0	7	1.2	15	1.5	10	1	12	11	5	4	0	7	1.2	10	1	10	1	12
	4	11	5	5	0	9	1.5	10	1	10	1	12	11	5	4	0	7	1.2	10	1	10	1	12
	5	11	5	5	0	7	1.2	15	1.5	10	1	12	11	5	5	0	7	1	10	1	10	1	12
	6	11	5	5	0	7	1.2	10	1	10	1	12	11	5	5	0	7	1.2	15	1.5	10	1	12

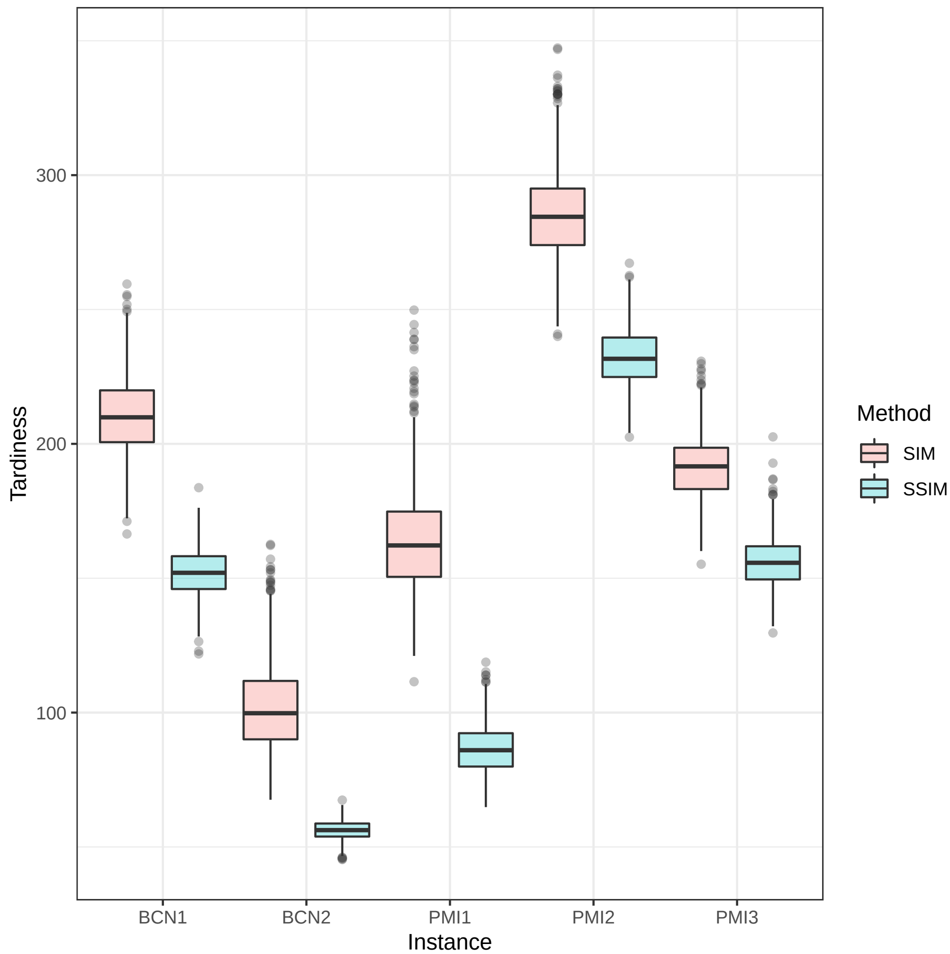


Fig. 4: Turnaround tardiness regarding STD experimented by SIM and SSIM solutions under scenarios with high variability for PMI and BCN instances

5.4. Comparison of the SSIM and an online dispatcher

To assess the quality of the solutions obtained using our approach during the day of operation, we provide a comparison with an online dispatcher algorithm. The dispatcher algorithm is inspired by the parallel scheduling generation scheme (Kolisch and Hartmann, 1999), which is a time-oriented insertion heuristic for solving the resource-constrained project scheduling problem. Available resources are allocated only to the operations that are eligible to be planned/performed at each decision time t. Requirements to consider an activity eligible have been adapted to build a realistic dispatcher close to current operations in most airports. Ground handlers schedule their resources according to the actual arrival of the aircraft (i.e., ATA), and this information is typically known ahead of time, around 30 minutes before arrival. Thus, we schedule at time t the necessary resources to perform operations in all turnarounds such that $ATA - 30 = t$.

Resources are iteratively assigned to the earliest eligible activity not scheduled yet. If more than one resource is available, the closest one is selected. Since tasks can be planned from 30 minutes before the ATA, this assignment is done using deterministic service and traveling times. As per common operational practice, we can include a buffer to absorb delays, so we choose as deterministic values the expected service and traveling times to compare with SSIM in conditions of equality. We have assumed that each vehicle leaves the depot to be at the stand at the planned starting time of the first operation, hence there is no waiting time related to the first visit of the route.

The earliest start time is calculated using the ATA and the expected duration of the precedent operations, and is updated each time a task is planned or completed. An operation is complete when *(i)* t is higher than its actual —simulated— starting time plus its actual duration, and *(ii)* the preceding activities in the turnaround have also been finished. Once a resource is allocated, any other operation cannot be assigned to this resource until the scheduled activity is completed. If all the eligible operations have been planned, or there are no more free resources, t is incremented by one, and the subset of qualified operations is determined again.

A comparison of the simulation outcomes of SSIM and the dispatcher algorithm is provided in Table 5. We have considered the most reliable SSIM solution per instance and the one with the smallest fleet size when two solutions have the same reliability. The number of available resources for scheduling operations using the dispatcher has been set according to the expected optimal value obtained by the corresponding SSIM solution. As shown, the schedules obtained by SSIM clearly outperform the dispatcher solutions in terms of robustness and incurred delays. Shorter overall turnaround times are reached by the dispatcher, but at the expense of a considerable increase in the unproductive times of resources. The dispatcher strategy of keeping resources locked once allocated until the activities are completed improves the on-time performance of some assignments, but produce significant delays on other aircraft. The risk of late departures is reduced by increasing the fleet size, leading to a high level of underutilized resources, a typical situation encountered in airports.

Table 5: Simulation results obtained using an online dispatcher and SSIM for PMI and BCN instances.

		Online dispatcher							SSIM						
Instance	#V	$\overline{w}$	$\overline{\delta}$	$\overline{CT}$	r_{15}	D	OT_5	OT_0	$\overline{w}$	$\overline{\delta}$	$\overline{CT}$	r_{15}	D	OT_5	OT_0
BCN1LV	35	8418.53	2198.81	3080.60	0.17	13.6	0.81	0.69	4212.32	1162.73	3166.74	1	0	0.79	0.55
BCN1HV	40	10239.13	2255.02	3107.25	0.67	5.04	0.79	0.58	3655.34	1154.86	3241.31	0.94	0.90	0.75	0.38
BCN2LV	33	5176.00	1661.58	1921.88	0	22.71	0.82	0.68	1474.56	700	1883.41	1	0	0.92	0.78
BCN2HV	36	5727.04	1714.32	1936.28	0	24.5	0.77	0.66	1824.45	724.18	1933.6	0.95	0.86	0.89	0.59
PMI1LV	47	1439.08	1622.29	1852.73	0.06	28.58	0.77	0.74	511.7	395.4	1957.11	1	0	0.83	0.33
PMI1HV	53	1873.76	1676.97	1844.08	0.35	10.38	0.86	0.69	624	428.9	1945.27	1	0	0.79	0.40
PMI2LV	47	12680.80	2999.04	3340.44	0	27.4	0.85	0.66	6312.19	765.26	3506.84	1	0	0.81	0.48
PMI2HV	47	12417.77	3080.09	3387.29	0	28.97	0.81	0.74	6180.53	832.2	3621.46	0.96	0.85	0.70	0.40
PMI3LV	47	10348.07	2312.96	2651.78	0.09	29.87	0.88	0.78	2650.39	588.57	2732.4	1	0	0.81	0.47
PMI3HV	51	11375.04	2397.79	2648.04	0.33	10.27	0.89	0.67	2835.27	639.27	2746.32	0.84	2.47	0.77	0.48

6. Conclusions

In this paper, we have introduced the SGSPP to enhance the robustness of ground support activities in a real-life environment. A set of SVRPTW is sequentially solved considering the different relations between activities and their effect on the defined time windows. The SVRPTWs are solved using a VNS approach, where expected vehicle travel and waiting times are minimized along with the tardiness of turnarounds. To obtain more reliable global solutions, we have developed the SSIM, extending the SIM method introduced by Padrón et al. (2016). MCS is integrated into the SSIM to estimate the behavior of the solutions reached during the search process in stochastic scenarios. The order in which each SVRPTW is solved is iteratively changed considering the number of time window violations of different operations, based on the simulation results. In addition, solutions are only kept if they improve reliability, that is, the percentage of scenarios in which all turnarounds finish on time. The goal is to obtain a set of Pareto solutions that minimize the resources' idle time and the total turnaround time while maximizing reliability.

The proposed methodology has been evaluated utilizing a group of instances based on two Spanish airports flight data in scenarios with low and high variability conditions. Unlike simply using SIM with expected times to design the routes, the simulation component of the SSIM produces more reliable solutions for most instances, while keeping similar fleet utilization rates. Under low variability, turnarounds are mostly on time in all scenarios, whereas delays are notably mitigated in the high variability situation. In other cases, reliability is comparable. However, a higher percentage of aircraft complete the ground activities within the scheduled slot. In general, the actual time required to finish the ground operations is lower when the SSIM is applied. Although the execution time is increased due to the simulation component, we can state that the SSIM yields more realistic plans and is able to reduce the risk of delays under perturbations.

In addition to modifying the sequences of activities, using simulation results to help re-schedule the vehicles would be required to obtain a more reliable plan in some cases. However, integrating MCS at each step of the local search process for all the routing problems is computationally expensive. To reduce the volume of re-optimization steps, by examining the survival functions, we noticed that tardiness could be particularly decreased when only operations with the highest number of time window violations are re-planned. This represents a future line of research aimed to reduce the computational requirements of the presented approach. Another potential action is to solely simulate the most promising schedules. In this case, schedules that are likely to fail could be rejected earlier in the process without consuming simulation budget. To detect them, we can look at undesired attributes, such as vehicles with no to little slack between consecutive visits, or the starting time of the most constrained operations being too close to the end of the time window.

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