A simheuristic approach for solving the Aircraft Recovery Problem with stochastic delays

Daniel Guimarans[1], Pol Arias[2], Wenjing Zhao[1]

[1] Amsterdam University of Applied Sciences
Weesperzijde 190, 1097 DZ Amsterdam, Netherlands
d.guimarans.serrano@hva.nl, w.zhao@hva.nl

[2] Loughborough University
Epinal Way, Loughborough LE11 3TU, United Kingdom
p.arias@lboro.ac.uk

Abstract

Air transport operational disruptions arise when operations deviate from the original plan. Due to airlines network configuration, delays are rapidly propagated to connecting flights, substantially increasing unexpected costs for the airlines. The goal in these situations is therefore to minimise the impact of the disruption, reducing delays and the number of affected flights, crews and passengers. However, the reach of a specific disruption is not normally known or it is difficult to assess, increasing the complexity of the problem. In this work, we introduce a methodology based on a Large Neighbourhood Search metaheuristic and a Constraint Programming formulation to tackle the Aircraft Recovery Problem with stochastic delays. We use simulation to help guiding the search, account for system's variability, and evaluate solutions' behaviour. We present some preliminary results on a set of instances with different sizes and characteristics, including some instances originating from real data.

1 Introduction

A flight schedule includes all flights serviced by a given fleet within a certain period of time. They contain the scheduled departure and arrival times, expected flight durations, and turnaround times. Flight schedules are usually made several months prior to the actual day of operation. Specific aircraft are normally assigned closer to the departure date. However, changes often occur in the period from the construction of the plan to the day of operation. These changes may include unforeseen delays due to weather phenomena, turnaround operations, air traffic control, mechanical failures, etc.

Operational disruptions are deviations of originally planned operations due to unexpected events. If these disruptions are not properly managed, they can cause a large impact on operations, not only locally but also through the airline network. The costs associated to them have gained more and more importance with the increase of fuel costs and the punctuality policies that airlines have been forced to implement in order to maintain competitiveness [4].

Among the different elements involved in a disrupted scenario (aircraft, crews and passengers), aircraft have received most attention from the research community, since it is normally considered the scarce resource. In this work, we focus on the Aircraft Recovery Problem (ARP), which is regarded to be NP-Hard [1]. When perturbations occur, the main goal for the airline is to restore the flight schedule as quickly as possible, minimising the number of cancellations and the total delay. Given an original flight schedule and one or more disruptions, the ARP consists of changing aircraft-to-flight allocations and introduce slight schedule modifications to produce a revised flight schedule. These changes may involve delaying or cancelling flights, swapping aircraft between flights, or use of standby aircraft.

These strategies are particularly effective depending on the airline network configuration. For example, Low-Cost Carriers (LCC) can benefit from them due to the nature of their operations [2]. LCCs generally use only one fleet family with the same seat configuration. This strategy helps reducing maintenance and certification costs. It also adds the possibility for swapping aircraft with minimum impact on operations, since the fleet will have homogeneous capacity and all crews will be properly certified. Additionally, LCCs usually operate short-haul flights with short scheduled turnaround times. This allows

LCCs to increase aircraft productivity, but also reduces rotation times and adds opportunities for aircraft swaps in case of disruption. Moreover, these flights are usually scheduled as point-to-point operations. Therefore, a change in the schedule will have limited or no effect on potential connecting passengers. Finally, they aim at reducing costs by using a limited number of bases (usually in secondary airports), where aircraft return for overnight operations. Hence, aircraft can generally be swapped with minimum disturbances on their maintenance cycles.

As a variety of tasks have to be performed to ensure that an aircraft is ready to depart, many sources may introduce variability to the system. Therefore, the nature of the ARP may be considered stochastic. In addition, any variation may rapidly propagate due to the network configuration. In a previous work [3], we tackled this problem by means of a methodology combining Large Neighbourhood Search (LNS) with a Constraint Programming (CP) model. This approach includes Monte Carlo (MC) simulation at different stages of the search process. This way, we are able to improve solutions' behaviour in different situations, since solutions are only accepted if they perform better than the incumbent in a variety of simulated scenarios. In this work, we increase system's variability by introducing stochastic delays to reproduce real-life operations. In general, the duration of delays or the extent of a disruption is not fully known at the time when decision making takes place. We also consider situations where delays and their propagation in the network are not independent, e.g. ground crew may shorten turnaround operations for an aircraft arriving late, trying to mitigate delay effects. This dependent operations require a more sophisticated delay propagation model and a revised CP formulation, introduced in this work. In addition, simulation and its utilisation during the search process becomes critical, since deterministic values provide a less accurate representation of real operations. This methodology has been assessed on a set of instances with different characteristics, some of them obtained from real data provided by a Spanish airline. We apply this approach to a set of scenarios with stochastic disruptions, which is a better representation of realistic operational situations.

2 Methodology and Preliminary Results

Large Neighbourhood Search has proved to be an efficient metaheuristic to deal with complex combinatorial optimisation problems. However, LNS is designed to provide high-quality solutions under deterministic scenarios. In some real-life problems, like in the case of the ARP and many air transportation applications, uncertainty is present. In these cases, a deterministic approach may not be accurate enough, since it does not reflect the real stochastic nature of the system. Therefore, it is necessary to extend the deterministic framework to account for the variability of the system.

Algorithm 1: SimLNS

$x^b \leftarrow$ Original schedule x
repeat
  $x' = repair(destroy(x^b))$
  $\bar{x}' \leftarrow$ Simulation(x')
  if $f(\bar{x}') < f(\bar{x}^b)]$ **then**
    $x^b \leftarrow x'$
until stopping condition is met
return x^b

Algorithm 1 depicts our LNS-based approach to tackle the stochastic ARP. For this problem, the *destroy* operator consists of unassigning all flights and connections from a given number of airports (1 to 3 airports, depending on the stage of the search). As a *repair* method, we use a branch-and-bound algorithm combined with the CP model to solve the generated smaller problems to optimality. The process repeats until no further improvements are found by the algorithm.

In our approach, we integrate MC simulation at an early stage in the process. In this case, simulation is embedded in the acceptance criterion instead of being used to just evaluate the final result. The solution obtained after applying the destroy and repair methods is then tested in a set of scenarios before deciding whether it is accepted or discarded. Simulation results may be used to evaluate the solution in different ways. The most common approach consists of accepting solutions which, on average, are better than the incumbent. Hence, we are only accepting solutions whose average behaviour is better than previous solutions.

By moving the simulation step to the acceptance criterion, our goal is to detect earlier in the process solutions with undesired attributes. On the other hand, this increases the number of solutions to be evaluated with respect to a more traditional approach, where simulation takes place at the end of the optimisation process. Thus, the required computational time is expected to increase with respect to a deterministic approach using simulation at the end of the process. These effects can be observed in our results, summarised in Table 1.

Scenario	# Flights	# Airports	# Aircraft	Delay	Det. Sol.	CPU (s)	SimLNS	CPU (s)	Gap Sol. (%)
1	50	10	11	30	216.1	0.972	203.3	1.799	-5.9
1	50	10	11	60	604.2	6.961	560.9	7.072	-7.2
1	50	10	11	90	1130.1	25.987	1045.1	17.094	-7.5
1	50	10	11	120	1644.2	81.495	1600.5	144.159	-2.7
2	110	23	52	30	2301.1	17.303	2235.6	34.489	-2.8
2	110	23	52	60	2519.7	7.671	2446.8	15.427	-2.9
2	110	23	52	90	3174.4	18.433	3150.9	28.865	-0.7
2	110	23	52	120	4746.0	22.323	4672.2	33.655	-1.6
3	110	23	52	30	450.8	5.961	445.3	11.883	-1.2
3	110	23	52	60	901.7	5.865	892.2	12.459	-1.1
3	110	23	52	90	1512.4	8.495	1477.2	33.139	-2.3
3	110	23	52	120	2282.4	17.405	2225.0	43.598	-2.5

Table 1: Results for 3 scenarios with 4 different levels of delay.

We observe that, for the 3 designed scenarios and for different levels of delay, our SimLNS algorithm outperforms the deterministic approach when we account for variability in the system. Therefore, introducing simulation at an earlier stage improves solution's quality in more realistic scenarios, but may increase the required computational time.

In the near future, we are planning to extend this study to include further results and evaluations of our methodology. Current lines of research include the development of a more refined delay propagation model, considering actual operations and mitigation strategies. Furthermore, we are adapting a real schedule from a Spanish LCC to further assess our SimLNS approach. This schedule provides a larger size benchmark to test the validity of our approach.

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