A Methodology Combining Optimization and Simulation for Real Applications of the Stochastic Aircraft Recovery Problem

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***Abstract* - The Aircraft Recovery Problem appears when external events cause disruptions in a flight schedule. Thus in order to minimize the losses caused by the externalities, aircrafts must be reallocated (rescheduled) in the best possible way. The aim of this paper is to develop a suitable methodology that combines optimization techniques with a simulation approach to tackle the so-called Stochastic Aircraft Recovery Problem. The approach solves the problem through the rescheduling of the flight plan using delays, swaps, and cancellations. The main objective of the optimization model is to restore as much as possible the original flight schedule, minimizing the total delay and the number of cancelled flights. By applying simulation techniques, the robustness of the given solution is assessed. The proposed methodology is applied on a medium-sized scenario based on real data provided by a commercial airline. The obtained results show that the methodology described in the paper is capable of producing a feasible and robust solution for this problem.**

Constraint Programming, flight schedule, disruption, simulation, robustness, optimization, Aircraft Recovery Problem

I. Introduction

Operational disruptions are defined as a deviation from originally planned operations. The airline industry is notably one of the most affected industries regarding operational disruptions. 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 [1]. Due to these and other emerging restrictions that the aeronautical industry is facing nowadays, the optimization of resources has become an important issue in the aeronautical agenda [2]. Furthermore, flight plans are usually made several months prior to the actual day of operation. As a consequence, changes often occur in the period from the development of the schedule to the day of operation. Those changes may include unforeseen delays due to weather phenomena, air traffic control delays, cascade propagation delays, ground operations, etc. These problems make evident the need of decision support tools that help decision makers to cope with operative problems under stressed situations.

On the one hand optimization-based methods and tools have proved its efficiency to deal with operative problems in complex fields such as logistics or manufacturing problems but there is a discussion about the lack of flexibility when modelling operational problems. In most cases, the stochasticity inherent to systems is not included in the developed models, thus reducing its applicability for real scenarios. On the other hand, simulation approaches have great flexibility and allow the modeller to face the problem under a different scope including not only stochastic elements in the models but also the interactions between entities that generate emerging dynamics which influence the behaviour of the real system. Nevertheless, in most simulation-based cases the level of optimization achieved depends on the number of scenarios evaluated, which in general are just a small fraction of the whole available configurations. Thus, optimality is not ensured with the standalone simulation approach likewise suitability is not ensured with the standalone optimization approach.

In this paper we present a methodology that aims at overcoming these shortcomings combining optimization techniques with simulation. The combination of both

978-0-7695-5073-2/13 $26.00 © 2013 IEEE
DOI 10.1109/EUROSIM.2013.55

techniques allows evaluating the robustness of the solutions provided by the optimization method under real conditions.

In order to minimize the consequences of the delays, the main objective is to restore the flight schedule as much as possible using the existing aircrafts, i.e. minimize the number of cancellations and the total delay. Given an original flight schedule and one or more disruptions (i.e. flight delays), the optimization approach generates a solution through delaying or cancelling flights, and swapping aircrafts to flights allocations, in order to create a feasible flight plan that minimizes the impact of the delays as much as possible. Such plan considers all flights scheduled within a certain period of time by a given fleet including the original departure, the expected flight durations, and the connections between airports. This challenging problem is known as the Aircraft Recovery Problem (ARP) and regarded to be NP-Hard [3]. Introducing variability in the values associated to the problem, i.e. flights duration or delays, the Stochastic Aircraft Recovery Problem (SARP) arises. In order to evaluate the robustness of the solution provided by the optimization method the stochasticity of the problem is simulated making variations of the original scenario according to the identified variations. Recent studies analyse the robustness of the final re-schedule [4], in contrast with previous airlines' priorities of just minimizing total delays. The principal argument is that in networks with a large number of connecting flights, delays can propagate very rapidly throughout the scenario. This increases the recovery costs of the airlines and has a larger impact on their profit.

We applied the presented methodology to a problem based on real data provided by a commercial airline. The obtained results are encouraging, being able to demonstrate the robustness of solutions obtained by means of the developed optimization method. The robustness of the methodology is proved by finding the optimal solution for most of the tested scenarios even when the stochasticity values are introduced.

The remainder of the article is organized as follows. In subsection A the state of the art of the problem is presented. The proposed approach is further discussed in section II. The results are presented in section III leading to interesting conclusions that we outline in the final section.

A. Literature Survey

Teodorvic and Gubernic [5] are the pioneers of the ARP. Given that one or more aircraft are unavailable, their objective is to minimize the total passenger delay by flight re-timing and aircraft swaps. The algorithm is based on a branch-and-bound framework where the relaxation is a network flow with side constraints.

The literature contains several works on different aspects of the ARP. Many of them are based on a multi-commodity flow problem solved on a time-band network, Jarrah et al. [6] use a network flow model for cancelations and re-timings. Yan and Yang [7] work is based on network models, which are formulated as pure network flow problems or network flow problems with side constraints. Yan and Young [8] formulated several strategic models as multiple commodity network flow problems. Argüello et al. [9] and Bard et al. [10] use a time-band model to solve the ARP. Yan and Lin [11] and Yan and Tu [12] use a time-line network in which flights are represented by edges. Thengvall et al. [13] present a model in which deviations from the original schedule are penalized in the objective function. Again, Thengvall et al. [14] introduce a multi-commodity flow model based on a time-band network to solve the ARP after a hub closure. Bard et al. [10] present an heuristic based on an integral minimum cost flow in the time-band network.

A most recent work by Dunbar et al. [5] is focused on the robustness of the solution by integrating aircraft routing and crew pairing. Lan et al. [15] develop a robust aircraft routing model to minimize the expected propagated delay along aircraft routes. They use an approximate delay distribution to model the delay propagation and use a branch-and-bound technique to solve their MIP. Instead of estimating delay propagation, Wu [16] used a simulation model to calculate random ground operational delays and airborne delays in an airline network. Wu [16][17] shows that delays are inherent in airline operations due to stochastic delay causes.

II. Proposed approach

A. Optimization method

The optimization method is based on the Constraint Programming (CP) paradigm. CP is a modelling and solving paradigm that uses constraints to describe the relations between the different problem variables. It differs from programming languages, as it is not necessary to specify a sequence of steps to generate the solution, but rather the properties. The main applications areas to date are scheduling, routing, planning and resource configuration among others [18]. In CP, different methods may be applied to solve problems in order to find a feasible solution satisfying all the constraints. This class of problems are known as Constraint Satisfaction Problems (CSP), and the main mechanism for solving them is *constraint propagation* [19]. Constraint propagation works by reducing variables' domains removing unfeasible values, strengthening constraints, or creating new ones. This leads to a reduction of the search space, guiding the search quicker towards feasible regions. Basically, constraint propagation generates the consequences of a decision. There are strategies to increase the efficiency of the technique; one of them is the addition of redundant constraints to further prune the search tree. We take advantage of this characteristic in our formulation of the ARP, thus modelling the problem with two sets of variables: predecessors and successors. This formulation is inspired on the Vehicle Routing Problem formulation by Kilby and Shaw [20]. These variables allow us modelling the same search space from two different perspectives, while the redundant constraints propagate decisions made in any of the two sets to the other one. Following this strategy, the search space is explored more efficiently. We use an exact branch-and-bound algorithm [21] to solve the problem, so we can guarantee optimality for the solutions. Although in general regarded as a slow method, it perfectly fulfils our purposes according to the real instances at hand.

The ARP model provides solutions through reallocations of aircrafts performing swaps (Figure 1), delays (Figure 2), and cancellations. The goal is to minimize the total delay and the number of cancelled flights, while restoring as much as possible the original flight schedule. The use of CP introduces flexibility to our approach, aiming at extending the model to more complex scenarios in the future. Although this methodology has the presented advantages, it also has some limitations as only permits tackling deterministic scenarios. For this reason, we combine it with simulation techniques in order to cope with stochastic scenarios.

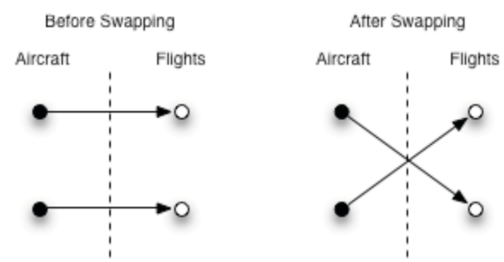

Figure 1. Swapping Movement.

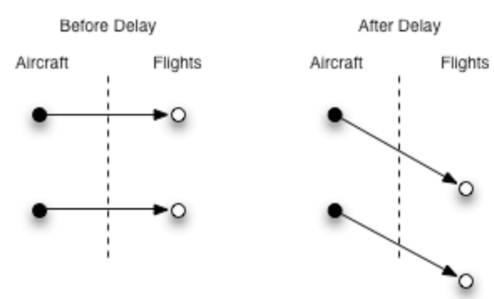

Figure 2. Delay Application.

B. Simulation approach

When the ARP is extended with stochasticity, the resulting problem becomes more challenging. This problem is the so-called Stochastic Aircraft Recovery Problem (SARP). There are some variations of the SARP due mainly to the nature and origin of the variations. The case studied in this work provides solutions for variations that appear in flight time and turnaround times caused by local disruptions.

When the stochastic times are included in the original ARP, it becomes necessary to develop an approach that takes into account this variability. In general, an optimal solution for a deterministic problem may not be optimal, or even feasible, for the stochastic case. For this reason, we combine optimization and simulation techniques in order to develop a suitable methodology for the SARP. In this approach, we use simulation to assess the robustness of the solutions obtained by means of the optimization method. Hence, the developed methodology is able to deal with real scenarios, where stochasticity is inherent to the system.

The proposed methodology, illustrated in Figure 3, is structured in the following steps:

1) The stochastic problem is simplified to a deterministic instance by using the average values of the adjusted probability distributions of the different processes.

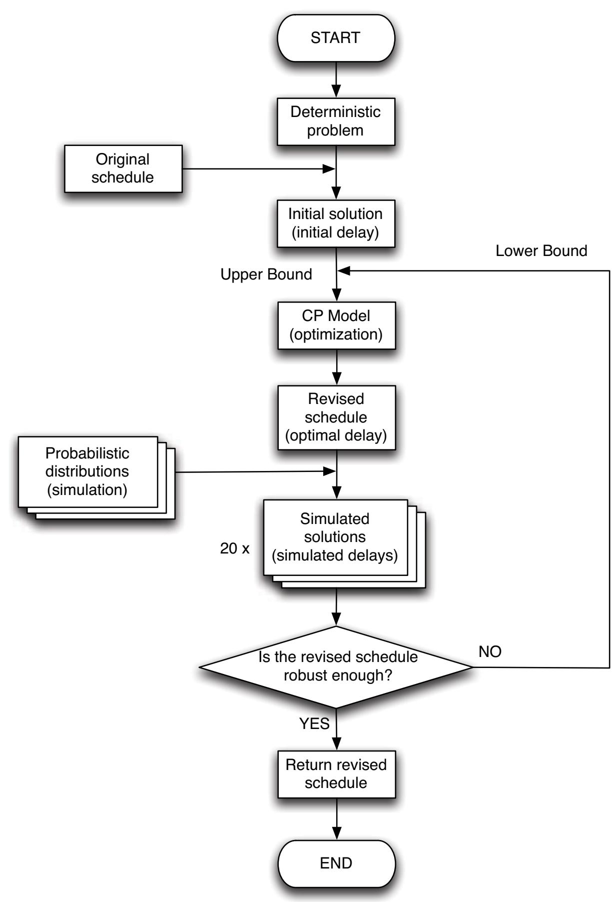

Figure 3. Flow diagram of the proposed methodology.

2) As the original flight schedule is known, we compute the total delay (the objective function) associated to this solution. This provides an initial value for the total delay, which is used as an upper bound for the objective function in the local search process performed by the CP optimization method.
3) The CP model is then used as a local search process to improve the initial solution allowing flights to be delayed, swapped, and cancelled if necessary. An improved flight schedule reducing the total delay is found as the result of this step.
4) The optimized solution is then checked using simulation to verify its robustness: a set of 20 stochastic instances is generated using the probability distributions for the processes. Maintaining the improved flight schedule returned by the CP model, we compute the total delay for each instance. This way, a single solution is evaluated in 20 different scenarios. The results are analysed in order to determine the level of robustness of the obtained solution. At this stage, different criteria can be considered to determine whether a solution is robust or not. First, a solution may be considered to be robust if the standard deviation of the simulated solutions is proportional to the variation of the used probabilistic distributions and its expected propagation due to problem's size. Second, a solution may be considered robust if the gap between the average of the simulated solutions and the deterministic solution falls within a tolerance interval. Third, we may define the criterion as the number of solutions whose gap to the deterministic solution is smaller than a given value. Finally, operational considerations such as the number of swapped flights / aircraft allocations may be introduced. In the practical case presented in this work, we use the first criterion to determine the robustness of the obtained solutions.

If the solution is not robust, its objective function value is used as a lower bound and the optimization/simulation process is repeated. Using this strategy a worst solution may be found but with a better robustness. Otherwise, the solution is accepted and the algorithm ends. Thus, the methodology returns either the optimal deterministic solution, if it is robust enough, or a quasi-optimal one whose properties are more suitable for the stochastic problem at hand.

III. APPLICATION

The tests were conducted in a standard personal computer with an Intel Core i5 processor at 2.5 GHz and 4Gb RAM. For the optimization process, we used the CP platform ECLiPSe 6.0 [22]. In order to generate the different stochastic scenarios, an Excel sheet was used.

Aiming to test the presented methodology, we used real data to define a SARP instance. The flights information was provided by a Spanish airline through a confidentiality agreement. We shall refer to this airline, when applicable, as "the airline". The airline has a main hub at Madrid's airport and secondary hubs in Barcelona and Palma de Mallorca. This fact is observed in their flights distribution summarised in Table I. Madrid (MAD) hosts 15 flights, while Barcelona (BCN) and Palma de Mallorca (PMI) host 8 and 5 flights, respectively.

A total of 51 flights have been used, with 13 airports and 11 aircrafts. This scenario has a flights/planes ratio of 4.63, compared to a ratio of 4.3 for Thengvall et al. [14], and 7.2 for the biggest ratio of an instance reported in the survey of Clausen et al. [23]. Due to the size of the graph, it is not possible to show all the connections between airports and the aircraft to flight allocation.

TABLE I. LIST OF FLIGHTS AND AIRPORTS

Airport	# Flights
ACE	2
AGP	5
AMS	2
BCN	8
BIO	1
CDG	3
FCO	3
LGW	2
MAD	15
MXP	1
ORY	1
PMI	5
TFN	3
Total	51

In order to simulate a local disruption, we introduce a delay of 120 minutes to the first 5 flights departing from Madrid airport. In addition, some stochasticity is added to the duration of each flight. We simulate this fact by considering a normal probability distribution whose mean value is the estimated flight duration. The standard deviation is set to be 5 % of the flight duration. A 5% is chosen as no distribution can be adjusted due to the lack of samples. By using this deviation, we introduce some reasonable variation to our system. This permits validating the obtained results and the robustness of our solutions. According to this variation and the size of the considered scenario, we consider a solution to be robust if the standard deviation obtained from the simulated scenarios is less or equal to 15%.

Table II and Table III summarize the results obtained for both the deterministic and stochastic scenarios, respectively. Since the first solution obtained accomplishes the defined robustness criterion, only the results for this solution are reported.

TABLE II. RESULTS FOR THE DETERMINISTIC SCENARIO

	Original flight schedule (min)	Improved flight schedule (min)	Gap (%)
Total delay	718	688	- 4.18

As mentioned before, for the deterministic case we take the mean values of the normal distributions. The total delay is calculated as the sum of all delays present throughout the system. As can be observed in Table II, applying the optimization process allows obtaining a revised flight schedule for the new scenario, reducing the total delay in 4.18 %.

Table III shows the results for the 20 generated stochastic instances. For each case, the corresponding optimal solution is reported, as well as the results for the original and revised flight schedules. The optimal solution is computed for each scenario by means of the CP model. As it uses exact methods, the obtained solutions are guaranteed to be optimal. This value is provided for comparative purposes. For each flight schedule, the total delay and the gap regarding the optimal solution are presented. The total delay is calculated by keeping the same flight allocation as in the deterministic case. Therefore, the variations in solutions' value are given by the deviations in the input data for each scenario, i.e. the variations in the flights duration.

As it may be observed in the values presented in Table III, the improved flight schedule presents a more robust behavior than the original one. This can be inferred from the lower gaps regarding the optimal solution. Although the standard deviations of the objective function values are similar, the revised plan is able to match the optimal solution in 14 cases out of 20. On the other hand, the original flight schedule only matches the optimal solution in 3 scenarios. In these three cases, both the original and the revised flight schedules yield the same total delay.

It is also important to notice that the improved flight schedule provides a better solution in all scenarios but one. Thus, the adopted simulation approach assesses the solution obtained by means of the local search process as a good and robust alternative.

TABLE III. RESULTS FOR THE STOCHASTIC SCENARIOS

Scenario	Optimal solution (min)	Original flight schedule		Improved flight schedule	
		Total delay (min)	*Gap (%)*	*Total delay (min)*	*Gap (%)*
1	761	815	7.1	761	0.0
2	789	874	10.8	789	0.0
3	787	837	6.4	787	0.0
4	711	746	4.9	711	0.0
5	835	835	0.0	835	0.0
6	767	791	3.1	767	0.0
7	916	1015	10.8	944	3.1
8	794	847	6.7	802	1.0
9	710	741	4.4	710	0.0
10	809	843	4.2	809	0.0
11	777	803	3.4	803	3.4
12	785	927	18.1	785	0.0
13	701	714	1.9	701	0.0
14	986	1046	6.1	1064	7.9
15	640	691	8.0	661	3.3
16	720	737	2.4	720	0.0
17	934	934	0.0	934	0.0
18	769	823	7.0	769	0.0
19	804	902	12.2	854	6.2
20	769	769	0.0	769	0.0
Average	*788.2*	*834.5*	*5.9*	*798.8*	*1.2*
St. Dev.	*10.4 %*	*11.8 %*		*11.4 %*	

IV. CONCLUSIONS

In this paper we present a combined methodology using simulation and optimization techniques to cope with the Stochastic Aircraft Recovery Problem. The uncertainty associated with this problem turns it into a good candidate for combining both disciplines. Furthermore, in real scenarios the simulation component gains weight, but at the same time better and more robust solutions are needed.

We combine simulation and optimization in a very straightforward way. First, we use a CP-based local search process to get the optimal solution of a simplified version of the problem. Next, we simulate different variants of the tackled instance in order to assess the quality of this solution. Thus, the inherent stochasticity of the problem is naturally introduced in the decision making process. If the so-obtained solution does not achieve some imposed robustness criteria, it is discarded and a new improved solution is generated.

The main contribution of the paper is the methodology combining simulation and optimization approaches where results are easily propagated between both techniques. The solutions obtained from the optimization method are easily perturbed and tested in the simulation scenarios. On the other hand, the information retrieved from the simulation variants may be used to add new restrictions to the optimization model.

Real scenarios involving unpredictable disruptions need a more robust solution that can absorb changes in a solid way. As shown in the results, our methodology is able to find a robust solution, which in most experiments matches the optimal solution. Bigger instances up to 150 flights are currently being tested to further assess the methodology presented.

Finally, being an active field for research, the methodology may be extended to tackle more complex variants of the problem. For instance, a joint problem combining ARP characteristics with flight crews' scheduling is under consideration.

ACKNOWLEDGMENTS

NICTA is funded by the Australian Government as represented by the Department of Broadband, Communications and the Digital Economy and the Australian Research Council through the ICT Centre of Excellence program.

REFERENCES

[1] Zhang X, Zhao, M, Kuang, S M., & Du, Q. "Research on Airline Company Fuel-Saving Model Based on Petri Network". Advanced Materials Research, 2013, 616, 1107-1110.

[2] Yu, G. "Operations research in the airline industry ". Kluwer Academic Pub, 1998, Vol. 9.

[3] Arora, S, Barak, B. "Computationals Complexity: a Modern Approach". Cambridge University Press, 2009.

[4] Teodorvic D, Gubernic S, "Optimal dispatching strategy on an airline network after a schedule perturbation". European Journal of Operational Research, 1984,15,178–82.

[5] Dunbar, M., Froyland, G., & Wu, C. L. (2012). Robust airline schedule planning: Minimizing propagated delay in an integrated routing and crewing framework. Transportation Science, *46*(2), 204-216.

[6] Jarrah A, Krishnamurthy N, Rakshit A, "A decision support framework for airline flight cancellations and delays". Transportation Science, 1993,27(3),266–80.

[7] Yan S, Yang D, "A decision support framework for handling schedule perturbations". Transportation Research Part B 1996,30,405–19.

[8] Yan S, Young H., "A decision support framework for multi-fleet routing and multi-stop flight scheduling". Transportation Research Part A, 1996,30(5), 379–98.

[9] Argüello M, Bard J,Yu G, "A grasp for aircraft routing in response to ground ingsand delays". Journal of Combinatorial Optimization, 1997,5,211–28.

[10] Bard J, Yu G, Argüello M, "Optimizing aircraft routings in response to groundings and delays". IIE Transactions, 2001,33,931–47.

[11] Yan S, Lin C, "Airline scheduling for the temporary closure of airports". Transportation Science, 1997,31:72–8.

[12] Yan S, Tu Y., "Multifleet routing and multistop flight scheduling for schedule perturbation". European Journal of Operational Research, 1997,103,155–69.

[13] Thengvall BG, Bard JF, Yu G, "Balancing user preferences for aircraft schedule recovery during irregular operations". IIE Transactions, 2000,32(3),181–93.

[14] Thengvall B, Yu G, Bard J, "Multiple fleet aircraft schedule recovery following hub closures". Transportation Research Part A 2001,35,289–308.

[15] S. Lan, J. Clarke, C. Barnhart, "Planning for Robust Airline Operations Optimizing Aircraft Routings and Flight Departure Times to Minimize Passenger Disruptions". Transportation Science, 40(1),15–28, 2006.

[16] C. L. Wu. "Inherent Delays and Operational Reliability of Airline Schedules". Air Transport Management, 11,273–282, 2005.

[17] C. L. Wu,. "Improving Airline Robustness and Operational Reliability by Sequential Optimisation Algorithms". Network and Spatial Economics, 6:235–251, 2006.

[18] Rossi F, Van Beek P, Walsh T (Eds.), "Handbook of constraint programming", 2006, Elsevier.

[19] Bessiere C, Constraint Propagation. "Handbook of Constraint Programming", 2006, chapter 3, 29-83. Elsevier.

[20] Kilby, P. & Shaw, P. Vehicle Routing. "Handbook of Constraint Programming", chapter 23, 801-836. Elsevier.

[21] Lawler, E.L. & Wood, D.E., "Branch-and-Bound Methods: a Survey". Operations Research, 14(4), 699-719.

[22] Apt, K. & Wallace, M. "Consrtaint Logic Programming using ECLiPSe". Cambridge University Press, 2007.

[23] Clausen J, Larsen A, Larsen J, & Rezanova N. J. "Disruption management in the airline industry—concepts, models and methods".Computers & Operations Research, 2010, 37(5), 809-821.