

# A two-stage algorithm on Intelligent Flight Schedules Adjusting

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## ABSTRACT

Sichuan Airlines Co.,Ltd was established on August 29,2002 and its headquarters is located in Chengdu with branches in many other provinces of china. Both the number of the passengers served and the number of the new routes established by Sichuan Airlines have shown a gradual upward trend. When severe weather and aircraft fault happened, how to reschedule flights and reassign aircraft in real time with minimized recovery cost after disruptions occur becomes a great challenge. This report presents an implementation of a multi-commodity time-space network flow model, which is tailored to the Sichuan Airlines' scenario.

In Sichuan Airlines aircraft recovery scenario, options include delaying flights, canceling flights, and changing (swapping) the aircraft for flights. There may be some idle aircrafts at the operating base that can operate the subsequent flight so that the subsequent flight is not affected by the delay of previous flight. If idle aircrafts are used, we assume that they must return to their base at the end of the day, thus they will not be influenced the next day. The cost of switching operation base after a day for each aircraft is extremely high, thus it is a wise choice to set the recovery horizon to one day. Our algorithm consists of two stages, which are identified in Fig. 1 below. In the first stage, the aircraft schedule recovery problem is solved, wherein flights are re-scheduled and aircrafts are re-routed with the objective of minimizing the sum of flight cancellation costs and flight delay costs. Passenger transfer are ignored at this stage, in the second stage, flight rescheduling problem is solved wherein aircraft rotations obtained from Stage 1 are fixed and passenger itineraries are considered, where the objective is to reschedule flights such that the number of disrupted itineraries is minimized. As in normal aircraft recovery problem, there is a minimum turnaround time of each airport for each type of aircraft. However, this is a soft constraint, the planned turnaround time can be at most less than 1/3 of the minimum, meanwhile the number of the flights that dissatisfy the standard of the turnaround time cannot be

greater than 1/20 of the total number of flights on the day. Though different exchange of aircraft type is allowed, we found same type exchange already can generate high quality solution and can speed up total calculation process.

## CCS CONCEPTS

• General and reference~General conference proceedings

## KEYWORDS

Aircraft recovery, Time-space network, Severe weather, Flight rescheduling

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## 1 Literature review

There is a rich literature for the airline recovery problem, Yan and Lin proposed a time-space network flow model [1], where the arcs in the network represent flights, grounded flights and overnight connections. Moreover, flight delay arcs were also created, with associated delay costs, indicating different delay options. In Thengvall et al. [2], two multi-commodity network flow models were proposed to consider the aircraft schedule recovery problem for multi-fleet types. Most recently, Zhang et al. [3] developed a math-heuristic algorithm for recovering aircraft and passengers together. The algorithm carries out an aircraft recovery first; then, flights are re-scheduled and passengers are re-accommodated iteratively until a tolerance limit is reached.

Different from network flow based models, Rosenberger et al. [4] formulated a set partitioning model for rerouting aircraft with a heuristic for pre-selecting the aircraft which are to be rerouted. Selected aircraft are allowed to swap with disrupted aircraft and are included in a route generation procedure. Andersson and Värbrand [5] developed an approach based on a set packing formulation, which is derived from Dantzig-Wolfe decomposition. LP relaxation and a Lagrangian heuristic were proposed for the master problem; two column generation heuristics are implemented for the subproblems. However, maintenance is

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not considered in their model. Eggenberg et al. [6] introduced constraint-specific recovery network for solving the problem. In the network, continuous timeline is discretized into time windows whose width is a parameter that needs to be tuned.

As mentioned above, after solving the aircraft recovery problem, airlines solve the crew and passenger recovery problems to obtain a complete recovery solution. In recent years, with the improvement of modeling approaches and computing capabilities, various methods have been developed to solve the two or three recovery problems in an integrated way.

## 2 A two-stage algorithm

As aforementioned in Section 1, the proposed algorithm consists of two stages, which are identified in Fig. 1 below. In the first stage, the aircraft schedule recovery problem is solved, wherein flights are re-scheduled and aircrafts are re-routed with the objective of minimizing the sum of flight cancellation costs and flight delay costs. In fact, passenger cancellation and passenger delay costs can also be considered in stage one, no passenger transfer is considered in this process. In the second stage, aircraft rotations obtained from stage one is fixed and then we try to consider transfer those canceled passengers in stage one.

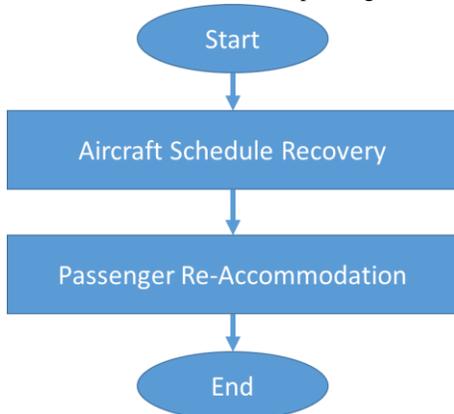


Fig. 1 The two-stage algorithm

A time-space network is defined by a set of activity nodes and a set of arcs. There are two types of arcs, flight arcs and ground arcs, which are directed arcs connecting any two activity nodes in the network. In this following discussion, details regarding flight arcs, ground arcs and activity nodes are described.

(1) Flight arcs: Flight arcs are created to represent flight legs, and a flight leg can correspond to multiple flight arcs. Each flight arc indicates one specific delay option of its corresponding flight leg, where the departure time of a flight arc is the actual departure time of its corresponding flight leg in addition to its associated delays. (The arrival time of a flight arc can be calculated in a similar manner). For example, in Fig. 2, the flight arcs 3U8621 and 3U8621-1 are both generated by the flight leg 3U8621, with the 3U8621-1 option having an additional time delay as compared to 3U8621. Additional constraints are incorporated in the model to guarantee that at most one flight arc is selected for each flight leg (a flight leg is defined as a direct flight connecting one airport to

another without any intermediate stopovers. Each flight leg is assigned a flight number, an origin airport, a destination airport, a scheduled departure time and a scheduled arrival time).

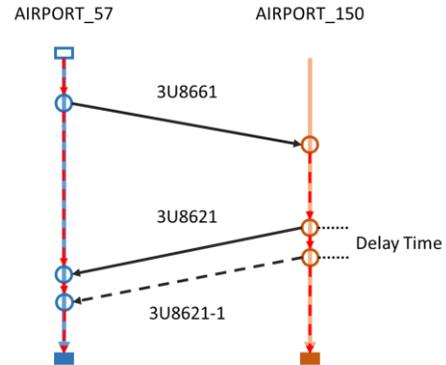


Fig. 2 The flight arc and flight legs

Note that every flight arc corresponds uniquely to one time-space network. In other words, while two flight arcs in different networks might correspond to the same flight leg and delay option, for the purposes of our modeling, they are regarded as two different flight arcs.

(2) Activity nodes: Before defining activity nodes, we first need to define events, which are essential elements in the time-space network flow model. In our case, there are four types of events: departure events, arrival events, aircraft input events and aircraft output events. These events are represented using flight arcs and aircrafts. Each flight arc creates one departure event (at its origin airport) and one arrival event (at its destination airport), and the time of a departure (or arrival) event is set as the actual departure (or arrival) time of the corresponding flight arc. Moreover, each aircraft creates one aircraft input event, and the location and time of an aircraft input event is the location and ready time of the corresponding aircraft. Furthermore, for each airport, there is one aircraft output event at the end of the recovery time window. The purpose of creating aircraft output events is to maintain the necessary flow balance constraints. (In Fig. 2, there are two airports leading to two aircraft output events).

Now, an activity node is a generalized node for events sharing the same location at the same time. Therefore, there might be multiple events corresponding to one activity node, and the following seven characteristics are required to uniquely define an activity node: (a) location; (b) time; (c) input flight arc list; (d) output flight arc list; (e) input ground arc; (f) output ground arc; and (g) aircraft input. In Fig. 2, all activity nodes are denoted as either circles or squares.

(3) Ground arcs: Each ground arc connects two consecutive activity nodes at the same airport. For example, in Fig. 2, there are five activity nodes at AIRPORT\_57 airport and correspondingly, four ground arcs are generated at this airport. Once a ground arc is generated, the output ground arc (at the head node) and the input ground arc (at the tail node) are updated and stored.

As described above, for each aircraft (commodity), a single-commodity network flow model is built, and a multi-commodity network flow model is then obtained by integrating all these networks into one large, single network. Several classes of bundle

constraints are added to guarantee airport capacity limitations are satisfied. We are now ready to formulate the multi-commodity network model as detailed below:

$$\min \sum_{fc \in FC} C_{fc} * X_{fc} + \sum_{f \in F} Cancel_f * Y_f$$

s.t.

$$Input_n + \sum_{fc \in FC_{fcin}^n} X_{fc} + \sum_{ga \in GA_{gin}^n} Z_{ga} =$$

$$\sum_{fc \in FC_{fcout}^n} X_{fc} + \sum_{ga \in GA_{gout}^n} Z_{ga} \quad \forall n \in Node$$

$$\sum_{fc \in FC_f} X_{fc} + Y_f = 1 \quad \forall f \in F$$

$$\sum_{fc \in FC_s} X_{fc} \leq Cap_s \quad s \in Slot$$

$$X_{fc} = 1 \quad \forall fc \in FC_m$$

### 3 Conclusions

In this report, we gave a brief description of Sichuan Airlines aircraft recovery scenario, and then reviewed two types of algorithm, which are the most efficient and popular to solve this problem. One is network-flow based models, which is easy to program and able to deal with very huge number of decision variables. The other is path-based models. The subproblem of the aircraft recovery problem model is the same as vehicle routing problem, which is elementary shortest path problem with resource constraint. In Sichuan Airlines aircraft recovery scenario, the multi-commodity time-space network flow model is a good choice as we assumed the recovery horizon is one day and the total number of aircrafts are only about one hundred. We build the total model into the Commercial solver GUROBI and solved to a very qualified solution in about 2-3 minutes.

### ACKNOWLEDGMENTS

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