Machine Learning Based Aircraft Recovery Optimization

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Extended Abstract

For aircraft recovery problem (ARP), existing exact methods are too time-consuming — constructing and solving the resulting integer linear programming problems requires too much computational time to be operationally useful. Therefore, existing literature focuses on approximation-based approaches such as solution heuristics and problem size reduction methods that provide a trade-off between computation time, problem size and problem complexity. However, most heuristics that are fast enough suffer from poor solution quality.

In this research, supervised machine learning is employed to expedite optimization. The core idea is to try to identify components of optimal solutions to new problem instances by leveraging their similarity with alternative (historical) problem instances presented in the offline model-training phase. Our approach prunes the decision space by using machine learning algorithms that are trained using the network-wide optimal decisions for similar scenarios.

Problem Formulation

First, we employ a commonly used modeling approach for characterizing aircraft recovery decisions, based on the concept of flight strings. A flight string is a sequence of flights operated by a single aircraft of a particular fleet type. Next, we present the sets, parameters and decision variables and the ARP formulation itself.

Sets and Parameters

\( S^g_{agt} \): Set of strings corresponding to aircraft group \( g \in G \) that begin at airport \( a \in A \) before the beginning of period \( t \in T \)

\( S^g_{agt} \): Set of strings corresponding to aircraft group \( g \in G \) that end at airport \( a \in A \) before the beginning of period \( t \in T \)

\( I_{fs} \): Indicator parameter (1 if flight \( f \in F \) is in string \( s \in S_g \), \( \forall g \in G \) )

\( N^g_{agt} \): Number of available aircraft of aircraft group \( g \in G \) at airport \( a \in A \) at the beginning of period \( t \in T \)

\( N^g_{agt} \): Number of aircraft for aircraft group \( g \in G \) that need to be at airport \( a \in A \) at the beginning of period \( t \in T \)

Decision Variables

\( x_{gs} \): The assignment of aircraft group to strings (1 if string \( s \in S \) is operated by aircraft group \( g \in G \) )

\( y_f \): Defines the cancelled flights (=1 if flight \( f \in F \) is cancelled)

Constraints

\[ \sum_{g \in G} \sum_{s \in S_g} I_{fs} \times x_{gs} + y_f = 1, \forall f \in F \] (1)

\[ \sum_{s \in S_{agt}} x_{gs} \leq N^g_{agt}, \forall g \in G, \forall t \in T, a \in A \] (2)

\[ \sum_{s \in S_{agt}} x_{gs} \geq N^E_{agt}, \forall g \in G, \forall t \in T, a \in A \] (3)

\( x_{gs} \in \{0,1\}, \forall g \in G, \forall s \in S_g, y_f \in \{0,1\}, \forall f \in F \)

Objective Function

\[
\text{Min} \left( \sum_{f \in F} y_f \times c_f^{\text{cancel}} + \sum_{g \in G} \sum_{s \in S_g} x_{gs} \times [c_{gs}^{\text{operate}} + c_{gs}^{\text{delay}} + c_{gs}^{\text{spill}}] \right)
\]

The objective function is the sum of cancellation cost and assignment cost - the latter is the sum of operating cost, spill cost, and delay cost. Constraints 1 ensure that each flight is either covered by a flight string or cancelled. Constraints 2 and 3 ensure flow balance and aircraft availability at the beginning and ending of the recovery horizon respectively.
The methodology consists of two main components: one offline and one online. The offline component should be run before the day of operations. The online component should be run in real-time, between the time when a disruption situation is identified and the time when the airline must decide its recovery actions. The goal is to identify and exploit the similar solution components (flight pairs) between these previously solved offline instances and the online one that manifests on the day of operations, to inform solution of the previously solved offline instances and the online one that takes only the disrupted aircraft into consideration. This solution resembles the immediate solution that an airline controller would find during operations as described in Vink et al. (2021). SA is the Selection Algorithm – a heuristic that iteratively considers a selection of aircraft, as described in Vink et al. (2021). CGR is the Column Generation Heuristic at root node. CGA is the Column Generation algorithm at all nodes. ML_LR is our proposed machine learning method using logistic regression classifier for learning and ML_RF is our machine learning method using random forest classifier. Table 1 shows the optimality gap – with respect to the true optimal obtained by solving the problem directly using CPLEX over a much longer time period – of all the approaches for different time thresholds. We notice that at all time thresholds, one of our machine learning-based approaches achieves the lowest optimality gap. Specifically, we establish the superiority of our machine learning-based approaches compared to the other baselines considered for each time budget whether we need to make a very quick decision (30 sec objective) or when the decision can be taken with a maximum of two minutes of available runtime budget (120 sec objective).

<table>
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<tr>
<th>Approach</th>
<th>30 sec Runtime</th>
<th>60 sec Runtime</th>
<th>120 sec Runtime</th>
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<tr>
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Table 1 Comparing optimality gaps of approaches w.r.t true optimal cost at different time thresholds (averaged over 20 test instances)

Conclusion

Our results, demonstrate the consistently high performance of our approach on the tested instances when compared to state-of-the-art approaches under various runtime budgets. While much more exploration, experimentation and close scrutiny is warranted of these machines learning based approaches, we find that they do exhibit a potential to generate fast and high-quality solutions of complex recovery optimization problems faced by airlines.

References
