Utrecht University

Dynamic Airline Scheduling

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October 24, 2019

Universiteit Utrecht

Agenda

Introduction

Dynamic Airline Scheduling

Model

Case study

Conslusion

Paper

This presentation is based on:

Hai Jiang & Cynthia Barnhart. "Dynamic airline scheduling". In: *Transportation Science* 43.3 (2009), pp. 336–354.

Recent trends in Flight schedules

→ Hub and Spoke

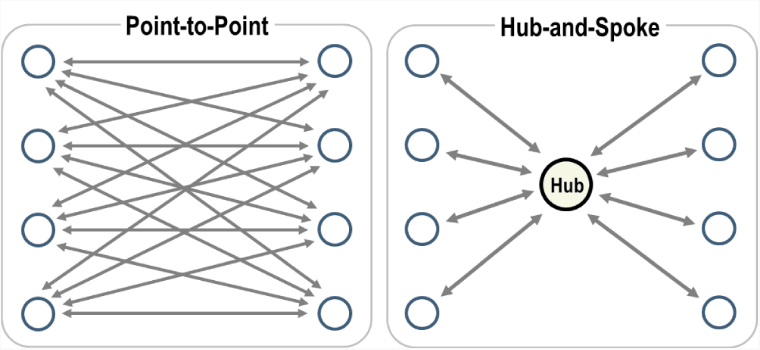

Figure 1: Point-to-Point and Hub-and-Spoke Networks [2]

Recent trends in Flight schedules

→ Depeaking / Debanking

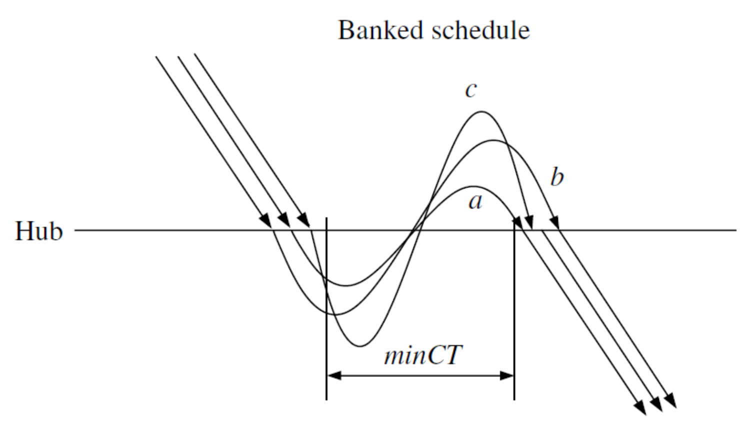

Figure 2: Banked Schedule [1]

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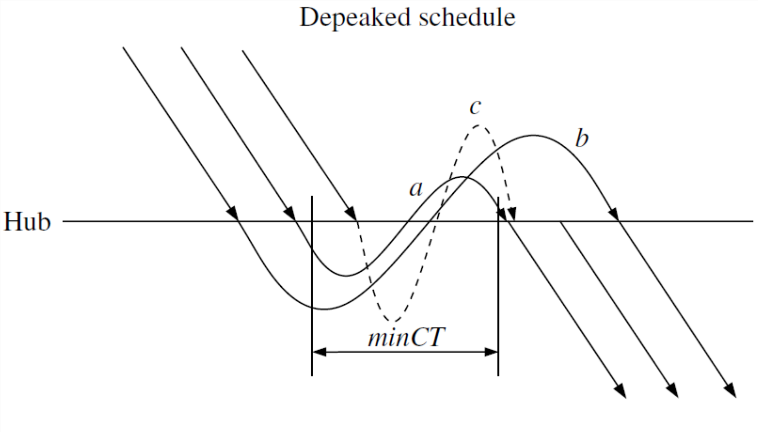

Figure 3: Depeaked Schedule [1]

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Definition (Dynamic Scheduling)

Reoptimize the flight schedule at a given reoptimization point based on demand changes.

Two types of dynamic scheduling:

- → Refleeting
- → Retiming

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- → Service guarantee to booked passengers.
- → Number of aircraft of each type at each airport must remain the same at begin and end of the day compared to original schedule.

Refleeting

Definition (Fleet family)

Set of crew-compatible aircraft types for which a pilot qualified to fly one type in the family is qualified to fly all other types in that family.

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Definition (Refleeting)

Changing the used aircraft type for a flight leg within a *fleet family*.

Retiming

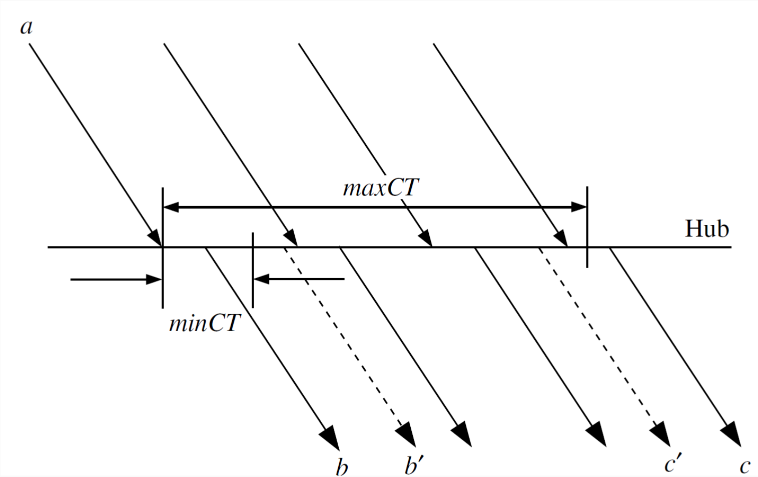

Figure 4: Retiming flightlegs [1]

Dynamic scheduling synergy

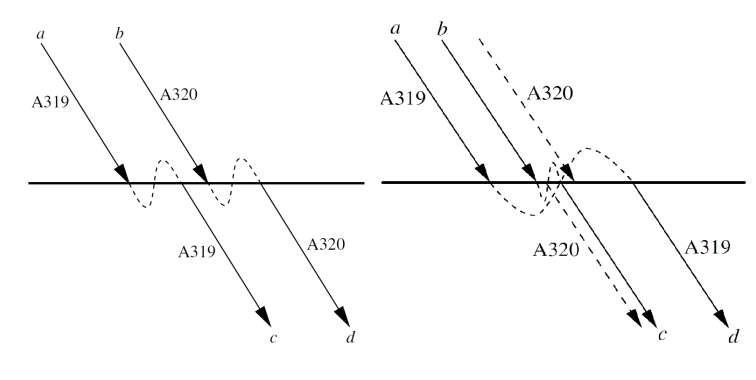

Figure 5: Example synergy [1]

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Definition (Passenger group)

Set of passengers and a market with average fare.

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Solve following (simplified) ILP for maximum revenue. Decision variable:

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\max \sum_{m \in M} \mathrm{fare}_m \sum_{r \in R(m)} x_{mr} & \\
\text{s.t.} \sum_{r \in R(m)} x_{mr} &\leq \mathrm{Demand}_m \\
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Remarks

- Aircraft use is constant
- Assumes perfect forecasting

Reoptimization model

Important changes:

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→ Model is no longer deterministic

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$\rightarrow$ Model is no longer deterministic

New decision variable:

$$f_{lk\pi} = \begin{cases} 1 & \text{fleet } \pi \in \Pi \text{ is used to fly copy } \langle l, k \rangle \text{ with } k \in \mathcal{C}(l), l \in L \\ 0 & \text{otherwise} \end{cases}$$

Objective function

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Objective function PMM

$$\max \sum_{m \in M} \sum_{r \in R(m)} \text{fare}_m x_{mr}$$

New objective function

$$\max \sum_{m \in M} \sum_{r \in R(m)} \text{fare}_m^F x_{mr} - \sum_{l \in L} \sum_{k \in \mathcal{C}(l)} \sum_{\pi \in \Pi} c_{lk\pi} f_{lk\pi}$$

Interesting constraints

New objective function

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$\rightarrow$ Each flight leg should be covered once

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→ Each flight leg should be covered once

→ Limit the number of available seats after reschedulding

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$\rightarrow$ Each flight leg should be covered once

$\rightarrow$ Limit the number of available seats after reschedulding

$\rightarrow$ Can't change used fleet compared to original schedule

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- → Each flight leg should be covered once
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- → Can't change used fleet compared to original schedule
- → Number of departures and takeoffs per time window is limited

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→ Each flight leg should be covered once
→ Limit the number of available seats after reschedulding
→ Can't change used fleet compared to original schedule
→ Number of departures and takeoffs per time window is limited
→ Keep service guarantee

Solution Approach

Solved using computer program, programmed in C and CPLEX library.

Case study: Daily schedules

Large American airline, banked hub-and-spoke schedule, 1000 daily legs, serving 100 destinations. One major hub is origin/destination for over 600 flight legs.

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1. Depeak the schedule using *depeaking model* [3]
2. Seven flight copies are created in 30-minute interval
3. Pick a reoptimization point
4. Solve reoptimization model

Case study: Daily schedules - Results

Two forecasts:

A Perfect information (Upper bound)
B Based on historic data (Lower bound)

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Profit increase:

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On average annually between \$18 and \$36 million profit increase.

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On average annually between $18 and $36 million profit increase.

Synergy is between 10% and 37%.

Future research

$\rightarrow$ Multiple reoptimization points

$\rightarrow$ Flexible booking

Conclusion

Dynamic Airline Scheduling

$\rightarrow$ Refleeting
$\rightarrow$ Retiming

Results

$\rightarrow$ 2.6% – 5.3% profit increase

Slides: `https://github.com/TeunDr/STT-Presentation-TD`

References

Hai Jiang and Cynthia Barnhart. "Dynamic airline scheduling". In: *Transportation Science* 43.3 (2009), pp. 336–354.

Jean-Paul Rodrigue, Claude Comtois, and Brian Slack. *The geography of transport systems*. Routledge, 2016.

Hai Jiang. "Dynamic airline scheduling and robust airline schedule de-peaking". PhD thesis. Massachusetts Institute of Technology, 2006.