Air Freighter Schedule Planning

A Dynamic Programming Optimisation Approach

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by

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Preface

This work is the capstone of my master's degree, my studies and my time in Delft. The past ten months have been characterised by many challenges, highs, and lows, and has proven to stretch my limits and extend them. Above all, it has been an unforgettable experience, made possible by the people involved along the way.
I am grateful for the opportunity to have conducted my research in collaboration with Airbus, spending time at Hamburg Finkenwerder. Working together with the Airline Sciences Team – Petros, Eida, and Dan in particular – has been a great experience, attributing both to the work itself and the joy involved. Furthermore, being able to interact with marketing and strategy as my 'customer' allowed me to show relevance, and make a business impact next to the academic contribution. This ultimately led to me presenting in Toulouse, which has been a great experience.
Thank you, Bruno, for the support, ever-critical eye, and pushing me to work hard and aim for the best possible result. Every meeting has brought me new insights, solutions to problems I was facing, and of course new challenges.

Finally, I want to thank my family, girlfriend, and friends for the (sometimes little) time spend together, for celebrating the highs, and helping me through the lows. The coffee breaks have been great, guys from ATO.

I'm excited to find out what the future holds.

T.L.M. Woudenberg

Delft, October 2019

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List of Acronyms

ATK	Available tonne kilometre
ATM	Air traffic management
BE	Break even
BH	Block hour
BELF	Break even load factor
DOC	Direct operating cost
DP	Dynamic programming
FC	Flight cycle
KPI	Key performance indicator
LCC	Low-cost carrier
LDR	Lift-to-drag ratio
LF	load factor
LP	Linear programming
MILP	Mixed-integer linear programming
MTOW	Maximum takeoff weight
NB	Narrow-body
OD	Origin-destination
OEW	Operating empty weight
OR	Operations research
PAX	Passengers
RFS	Road feeder service
RTK	Revenue tonne kilometre
SFC	Specific fuel consumption
TRT	Turnaround time
ULD	Unit load device
WB	Wide-body

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Paper

Air Freighter Schedule Planning: A Dynamic Programming Optimisation Approach

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Margins for cargo airlines that were already thin have been put further under pressure, which stresses the importance of operating a profitable schedule. Research on modelling passenger operations has proven that integrating different steps in the schedule planning process can yield a significant increase in profit. For cargo operations no integrated model exists that can provide an integrated schedule planning from scratch within reasonable computation time.

The model proposed in this work aims to integrate schedule design, fleet assignment, aircraft routing and cargo routing for both express freight- and general freight airlines. A dynamic programming optimisation framework is introduced that decomposes the schedule planning problem for a week of operations into sub-problems, that each aim to optimise the rotation of an individual aircraft. The model takes important operational constraints and airline requirements into account, such as maintenance and a minimum service frequency per flight leg, while optimising for minimum cost, maximum profit, or connectivity.

Tests were conducted on three real-life case studies, that reflect the applicability of the methodology developed. The results show that the generated schedules meet imposed requirements and reflect real airline operations, according to industry experts. Furthermore, the model provides results in reasonable computation time, which for a small airline is under 10 minutes.

Key words: Aircraft Maintenance Routing, Aircraft Rotation, Air Cargo Routing, Dynamic Programming, Fleet Assignment, Fleet Planning, Schedule Planning

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1. Introduction

Air freight is paramount to the globalised economy as it provides the ability to transport goods, often of high value, in a reliable and fast way. Due to a modal shift from air to sea during the last decade, air cargo growth has slowed (Seabury 2014). However, as the demand for air cargo mainly follows global trade volumes (Kupfer et al. 2011), an annual traffic growth of 4.2% is still expected over the next five years (IATA 2019a). This provides opportunities for both new and existing cargo airlines to start or expand their operations. While margins are thin in the entire airline sector, profit margins for cargo airlines are currently under even more pressure due to stagnating yield, rising fuel cost and falling load factor (IATA 2019a). Therefore, cargo airlines can only remain in business and seize these opportunities by operating a profitable schedule. Since this also impacts aircraft manufacturers, this research is conducted in collaboration with Airbus.

Many airlines have used Excel based tools to aid in making (part of) their schedule planning decisions, and strikingly still do today (Belobaba, Odoni, and Barnhart 2009), despite the high complexity of their operations. This is especially the case for cargo airlines as their operations vary more from one airline to another, making it more difficult to develop appropriate models. Operations research has made great contributions in the development of dedicated optimisation models for simulating airline operations. These models have a major impact on an airlines financial performance, both reducing cost and improving revenue (Eltoukhy, Chan, and Chung 2017). However, the vast majority of the models developed focus solely on passenger operations.

1.1. Standard Scheduling Approach

Schedule planning for both passenger and cargo operations involves making strategic and tactical decisions regarding the use of a fleet of aircraft, with the goal to efficiently transport cargo on flights between airports on a route network. These decisions reflect the four steps below that are typically followed by airlines in modelling their operations (Belobaba, Odoni, and Barnhart 2009, Antes et al. 1998). For each step, recent research is presented that provides a more in depth introduction and the current state of the art in literature.

- **Schedule design:** Defining the frequency that each flight leg is operated per time period (e.g. a week) and specific departure times for each flight. Abdelghany, Abdelghany, and Azadian (2017)
- **Fleet assignment:** Assigning a an aircraft type to each flight. Boudia et al. (2018)
- **Aircraft rotation planning:** Also known as tail number assignment, it involves flowing an individual aircraft over the network by assigning it to (a series of) flights, often while meeting maintenance requirements. Marla, Vaze, and Barnhart (2018)
- **Crew planning:** Assigning a specific crew to a series of flights. Saddoune et al. (2011)

These steps each represent a planning problem which are commonly solved consecutively and evaluated upon completion. A desired overall solution is found iteratively by repeating this process. In this work, we do not consider crew planning as it is less suitable for integration due to the difference in time horizon compared to the other steps above.

Solving one sub-problem of the scheduling process at a time may not lead to an optimal solution to the overall problem. In fact, a solution to a sub-problem may not even yield a feasible solution to the consecutive sub-problem. Integration therefore is a logical step (Barnhart et al. 1998). The benefit of this integration is later quantified by Jiang and Barnhart (2009), Haouari et al. (2011), Sherali, Bae, and Haouari (2013b), who report profit improvements between 2% and 5% for passenger airlines.

The vast majority of integrated methods use a linear programming formulation, for which tailored (decomposition) methods are developed to speed up computation time (e.g. Sherali, Bae, and Haouari 2013b, Tang, Yan, and Chen 2008, Shao, Sherali, and Haouari 2017). In a literature review, Eltoukhy, Chan, and Chung (2017) present an overview of these techniques for different integrated methods and features. However, many of these techniques only adopt a daily planning horizon, preventing the potentially exponential increase in computational complexity of a weekly planning horizon. For schedule planning purposes, such a weekly planning horizon is much more realistic, especially for international airlines (Liang and Chaovalitwongse 2013).

To furthermore keep model complexity manageable, virtually of the models that integrate schedule design with fleet assignment (and aircraft rotation planning) only allow for incremental schedule changes (Lohatepanont and Barnhart 2004), with the exemption of work by Yan and Tseng (2002). These incremental optimisation models require an existing schedule as an input, together with a list of mandatory flights and optional flights that may or may not be covered depending on what is most favourable to the model's objective (e.g. Sherali, Bae, and Haouari 2013a,b, Kenan, Jebali, and Diabat 2018). For integrated cargo schedule planning, Derigs and Friederichs (2013) report that decreasing the number of mandatory flights in the input schedule while increasing the number of optional flights, can dramatically increase computation time to reach a solution with a similar optimality gap. However, this incremental approach "involves too much subjective judgement and decision making in the process" (Yan and Tseng 2002) and therefore integration of planning steps is key.

1.2. Modelling Air Cargo Operations

Schedule planning for cargo operations has received considerably less attention compared to passenger operations. This can be explained by the fact that cargo operations are considered to be more complex (Feng, Li, and Shen 2015), discussed as follows.

Although airlines engage in long-term contracts with freight forwarders that reserve capacity 12 to 6 months in advance, the actual amount of revenue cargo can vary significantly up until several days before departure, as forwarders themselves only allow booking from several weeks in advance (Amaruchkul and Lorchirachoonkul 2011). Adding to this volatility and uncertainty in demand, the aircraft capacity is constrained both in weight and in volume while cargo is often consolidated in standardised unit load devices (ULD's) constraining dimensions (Leung et al. 2009)). Furthermore, cargo does not have a preference for a specific itinerary as passengers do, while keeping timely delivery in mind. This allows for a higher level of freedom in flowing cargo over the flight network. Other than offering direct flights only, carriers operate hub-and-spoke network and en-route stops (Morrell 2012). These complexities require solving the additional cargo routing problem when evaluating a schedule during the planning process.

While this problem is often considered in revenue management research (e.g. Amaruchkul and Lorchirachoonkul 2011, Wada, Delgado, and Pagnoncelli 2017), very little work is available in conjunction with schedule planning. Yan, Chen, and Chen (2006), Derigs, Friederichs, and Schäfer (2009) incorporate cargo routing as a multi-commodity flow problem with schedule design, fleet assignment, and aircraft rotation planning on the level of single flight legs. Derigs and Friederichs (2013) consider the same problem, including basic maintenance constraints, for sequences of connecting flights called lines of flying.

1.3. Problem Statement

Similar to passenger operations, cargo airlines require decision support tools that aid in making complex schedule planning decisions in reasonable computation time. An integrated approach is desired as this prevents a time consuming iterative process where results may lead to infeasible results in the consecutive planning steps. Although an approach that integrates planning steps exists, it cannot provide results for both new and extended operations that require a weekly schedule designed from scratch while capturing technical and economical operational requirements.

1.4. Dynamic Programming Solution Approach

In this paper we present an integrated schedule planning model for cargo airlines based on dynamic programming (DP) that meets most cargo airline's requirements. While DP has a longstanding history of successful application in other fields such as finance (Kraft and Steffensen 2013), energy resource management (Cheng and Powell 2018), and other forms of transportation (Tong et al. 2018), its potential for the airline industry is little explored.

The methodology introduced here builds on an existing research stream (Rubbrecht 1989, Wang 2016) that, while integrating schedule planning steps, focuses on fleet planning. A dynamic optimisation framework is introduced that relies on the principle of dividing the complex schedule planning problem into smaller sub-problems that are much easier to solve. This is a myopic approach, meaning that by optimising one sub-problem the solution quality of future sub-problems can be negatively impacted. However, while the model does not provide a global optimal solution, it provides a solution close enough to optimality in low computation time.

1.5. Contribution

The main contributions of this work are summarised following three categories:

1. Methodological

- The model presented is the first DP model suitable for weekly planning problems. Furthermore, the model follows reality more closely by incorporating operational requirements for maintenance, airport slot constraints, and potential minimum service frequencies per route.
- A novel method is presented to characterise the size and demand-supply dynamics of an origin-destination (OD) market.

2. Application domain

- For the first time, an integrated air cargo schedule planning model is presented that generates schedules from scratch in reasonable computation time.
- The model is suitable to different cargo business models for transporting general freight and express freight with the corresponding network characteristics.

3. Practical

- The model can cope with input parameters and constraints that are specified in various level of detail and is therefore suitable for both existing and new operations.
- Different modelling elements, such as objectives and constraints can be easily switched on and off depending on the problem at hand.
- The model formulation is a DP framework, that is flexible to the introduction of additional model features.

1.6. Outline

The remainder of this work is structured as follows. In Section 2, the dynamic optimisation frame work is introduced along with a formal formulation of the DP optimisation model. Section 3 then presents the computational results of several case studies. Finally, in Section 4 we summarise the work, draw conclusions, and identify areas for future work.

2. Methodology

In this section, the dynamic optimisation framework is introduced that aims to provide a schedule with corresponding aircraft rotations for an entire airline from scratch. The high-level model architecture is presented first (2.1), after which we go more into detail on the different building blocks of the model (2.2). Next, objectives, constraints and other modelling elements are introduced that aim to provide a high degree of applicability and realism of the model (2.3). Finally, the dynamic programming optimisation model is formulated (2.4), which follows a widely accepted structure (Powell 2011). The concepts described in the remainder of this section are formulated by using the nomenclature in Appendix A.

2.1. Dynamic Optimisation Framework

Key for the dynamic optimisation approach, is defining an appropriate decomposition of the schedule planning problem. Rubbrecht (1989) introduced a decomposition based on individual aircraft, as it was intended for fleet planning purposes. However, this decomposition is very natural and suitable for providing aircraft schedules and rotations as problem complexity drops when only a single aircraft is considered. The same high-level methodology is therefore adopted and discussed first, of which an overview is presented in Figure 1.

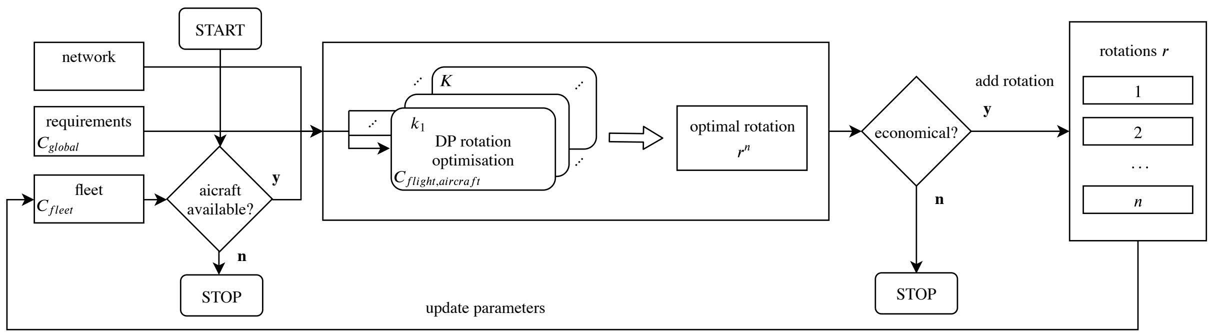


Figure 1 High-level architecture of the dynamic optimisation framework.

As inputs to the model we include a network consisting of (potential) destinations and flight legs, a fleet of aircraft, and both technical and airline imposed market requirements, which will all be discussed further into detail in the next section (2.2).

First, model parameters are pre-computed for constraints, costs, and potential revenues. Then, the model aims to add aircraft to the schedule one at a time while there are aircraft available and while it is economical or mandatory due to the requirements posed. It is considered economical to add an aircraft when the objective value is higher than an input threshold (e.g. 0 for profit, or a maximum break-even load factor).

For each aircraft that is added, an exact optimal rotation is computed by the DP rotation optimisation block for all aircraft types of the available fleet of aircraft. The optimal rotation is subsequently selected, the corresponding aircraft and rotation are added to the schedule, and input parameters are updated.

As can be seen from the figure, each block has its corresponding set of constraints. While many of these constraints are applicable to a single flight, rotation, or aircraft, some global constraints transcend the optimisation of a single rotation and must be evaluated at a schedule level.

2.2. Model Building Blocks

In this section, four high level building blocks that have been introduced in the previous section are discussed further into detail. First, inputs are discussed for the network, fleet and requirements, after which the working principle of the DP rotation optimisation algorithm is introduced. This algorithm is formulated in Section 2.4, after we introduce all model features.

2.2.1. Network

The input network involves a set of airports and (potential) flight legs, with technical and economical parameters that can vary for different aircraft times and time of the day. A single airport serves as the main operations base for a carrier. As all cargo airline operate both in hub-and-spoke point-to-point network types, one or multiple hub airports can be designated for transshipment of cargo.

Technical parameters constitute of i.e. runways length, curfew times and slot availability for airports and the distance between airports. Economical parameters include take-off and landing fees, ground handling charges, and navigation cost. Furthermore, environmental surcharges for noise abatement outside of regular operating hours are considered. to cope with time of day related parameters for all airports, the model takes time zones into account.

2.2.2. Fleet

The model takes a fleet input that consists of one or multiple types of aircraft. The number of aircraft available from each type can be specified to simulate an airline's current or prospective fleet by constraining the aircraft that are added by the model. Technical parameters that are taken into account include payload range characteristic to accurately compute fuel burn and mission capabilities for each flight leg. Furthermore, maintenance requirements are taken into account as will be discussed in Section 2.3.6. In terms of economic parameters, both operating cost and financing costs are are computed based on an average yearly utilisation of the aircraft, and the specific flight leg considered.

2.2.3. Requirements

Cargo airlines, just as passenger airlines, determine their schedule by the needs of their customers. While the optimisation model generates schedules from scratch, operational constraints and market requirements are therefore usually to be considered.

The importance of imposing such constraints can be explained by the key drivers for a cargo airline its customers. According to Feng-Yeu Shyr and Lee (2012), "freight forwarders are most sensitive to the price charged, delivery time and flight frequency, rather than service quality". While the model aims to enable cargo airlines to offer competitive prices by operating an optimised schedule, for delivery time and flight frequency requirements are introduced in.

Cargo airlines generally transport cargo with multiple OD's on a single flight, relying on hub connections or en-route stops. We therefore consider a schedule planning model that not only offers capacity on a flight level, but also on a network level. As cargo airlines can have long-term contracts with forwarders, they wish to offer sufficient capacity to transport the contracted OD cargo. Therefore a minimum OD capacity requirement is introduced.

As both flight frequency and OD capacity requirements must be adhered to on a network level, these are considered global constraints.

The model aims to serve a variety of different all-cargo airlines, for which their respective operations and needs for a decision support tool highly vary (Airbus 2019a). Therefore, input requirements can be posed or omitted depending on the airline considered.

2.2.4. DP Rotation Optimisation

The DP rotation optimisation algorithm involves flowing a single aircraft over the airports in the network through time, for which the time-space network representation is adopted, introduced by Hane et al. (1995) and shown in Figure 2. The planning horizon is discretized into the time steps, which are typically chosen at 5 minutes interval to reflect actual airline schedules. Each grey dot in the figure represents therefore both a time step and a location.

Following the DP approach, the rotation planning problem is further decomposed into these time steps, called stages. In each stage that the aircraft is located at an airport and is available for operations, the system is characterised by a state. At a minimum, a state features the location of the aircraft. The optimisation model subsequently determines the optimal decision at each state. This decisions represent either flying to another airport (a flight arc) or staying at the current airport (a ground arc), which are shown in the figure by the coloured dashed lines. A flight arc not only encompasses the flight time and taxi time, but also the required turnaround time (TRT) that the aircraft is ready for operations at the end of the arc. As the model aims to build a rotation, the history of decisions from the start of the planning horizon is stored for the aircraft and is represented by the black solid line.

The model incorporates a multi-day planning horizon, where 7 days is common practice by airlines in actual operations for both passenger and cargo airlines (Liang and Chaovalitwongse 2013, Derigs and Friederichs 2013). Each aircraft must start and end its rotation at the airline's base, the airport where a large part of the airline's resources are located and from which a large portion of its operations are conducted. To simulate reality, the starting moments for these rotations are

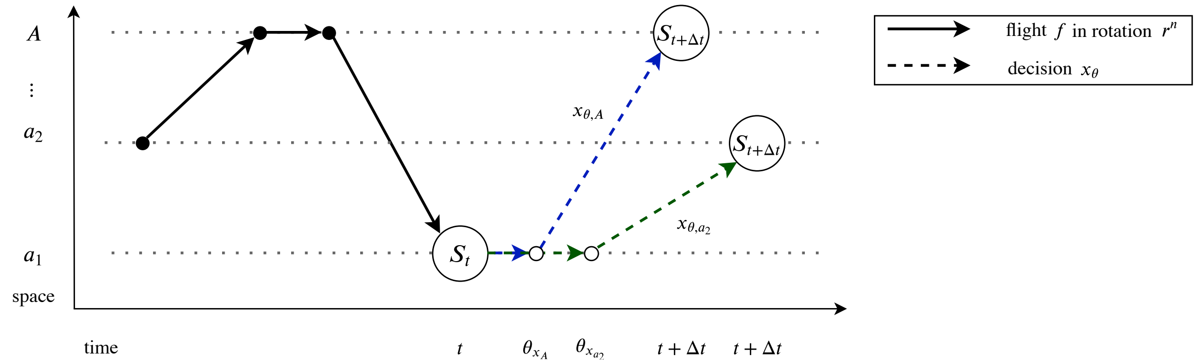


Figure 2 **Time-space diagram to visualise rationale for optimal decision making at airport a_1. Adapted from Wang (2016).**

staggered over the planning horizon by 1 day. Furthermore, the start moment is assumed to be 12:00 such that an aircraft is not obliged to visit the base at 00:00, the schedule start time of many passenger focused models (e.g. Wang 2016). This is important since cargo operations are mostly conducted during nighttime (Morrell 2012). The approach is shown in Figure 3 for 7 aircraft, for a 7 day (168 hour) planning horizon, and includes wrap around arcs for schedule continuity with the next planning horizon.

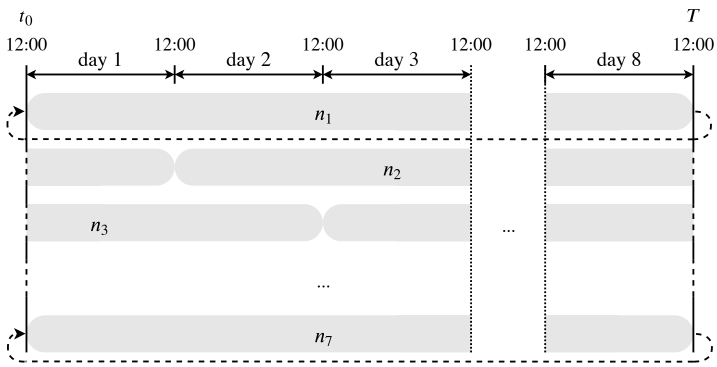


Figure 3 **Shifted schedule start times of individual aircraft within the planning horizon.**

2.3. Problem formulation

In this section, the DP rotation optimisation problem is formulated. First, we introduce the drivers for operating a flight leg. These are split into revenue and a global minimum service frequency (2.3.1), the definition of connectivity (2.3.2), and cargo routing and a global minimum OD capacity (2.3.3). Next, we introduce three objective functions to the model (2.3.7) that incorporate these aspects. Finally, we introduce constraints which can the divided into operation constraints (2.3.1), flight timing constraints (2.3.5), and maintenance constraints (2.3.6).

2.3.1. Yield, Revenue and Minimum Service Frequency

The revenue that a cargo flight captures depends on effective capacity offered, OD distance, and the cargo yield. The latter is defined as the rate charged to customers to transport 1 tonne of cargo of a specified commodity over 1 km. Most carriers charge not by actual weight, but by chargeable weight (Morrell 2012): a metric that combines weight and volume. While this rate differs for general freight and express freight, for simplification we consider airlines that offer either solely general freight or solely express freight, so a single commodity is assumed in the problem.

Demand forecasts with sufficient levels of accuracy are hard to obtain across the entire industry, and even for airlines themselves. While this is the case for passenger operations, it is even harder for cargo operations due to the high variability in cargo demand, as described in Section 1.2. This can be address by introducing a stochastic demand that captures this uncertainty, as has been researched for passenger operations (e.g. Kenan, Jebali, and Diabat 2018, Şafak, Çavuş, and Selim Aktürk 2018). However, this has proven to drastically increase the model's outcome space and therefore computation time, rendering it useless as a decision support tool. So, instead of using an unrealistic fixed and limited demand, or a stochastic demand as an input, a model is introduced that characterises the mechanics of an OD market.

This model is based on a decreasing demand function that is used in micro-economics (Varian 2006). The marginal yield of an OD market of a single commodity can be characterised by an exponentially decaying function (1), represented by the solid blue curve in Figure 4. The lower the yield, the more cargo is available to be transported. This curve can be created by observing the total revenue and transported weight of cargo in the market, incorporated in the market size parameter MS_i. Furthermore, the maximum available yield for this commodity is observed together with the yield for the cheapest modality of transport (e.g. sea). For this yield, all cargo in the market would be transported by air.

$$h_i = (h_i^{max} - h_i^{min}) MS_i^{\omega} + h_i^{min} \tag{1}$$

The revenue potential $q_{n,\theta,i}$ for making the decision to transport a quantity of cargo y can be computed by integrating the yield curve (1) for an OD i, and subsequently multiplying by the OD's distance D_i (2). The left limit for the integration is the cargo that has been transported for the OD at time t, $w_{t,i}$. The right limit is equal to the quantity of cargo that is decided to be transported on this OD ν_{θ,p_i}, added to the left limit, such that it this limit is equal to $w_{t,i} + \nu_{\theta,p_i}$.

$$q_{n,\theta,i} = D_i \int_{w_{t,i}}^{w_{t,i}+\nu_{\theta,p_i}} h_i(\omega) dw_i \tag{2}$$

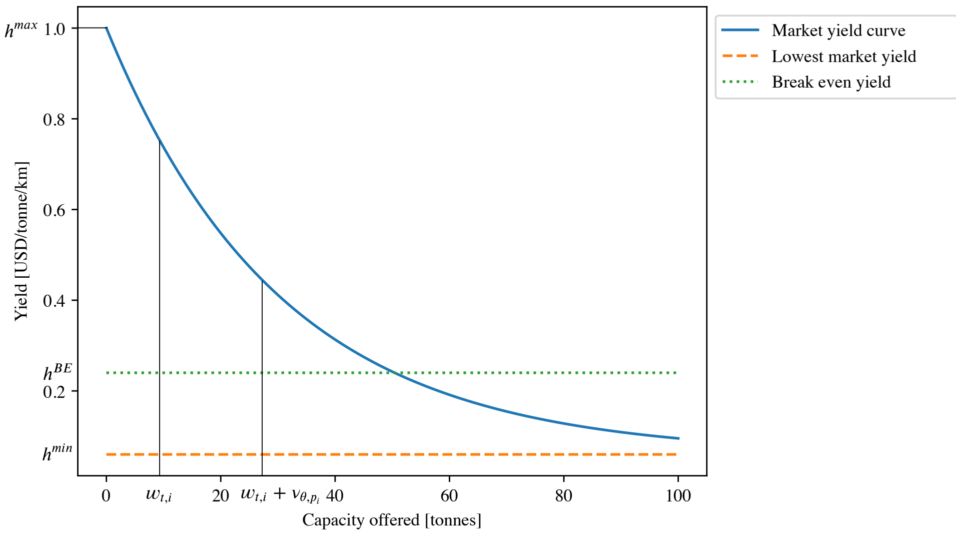


Figure 4 **Example of a decreasing marginal yield curve for a single OD market.**

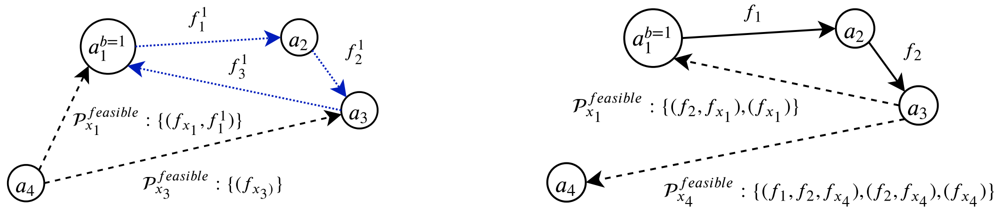
A minimum route frequency is required to obtain, or maintain, a desired market share, similar to passenger operations (Pita, Barnhart, and Antunes 2013). As this global constraint is not applicable to the DP rotation optimisation individually, contributions towards adhering to this constraint may be made. For this purpose, an artificial reward is incorporated intro the model. This reward is a large positive number (big M), that is granted through binary variable $e_{t,i}$ and regulated by a switching constraint (3). When the operated frequency of a flight leg with OD i in all previous and rotations and the current rotation combines is lower than its minimum service frequency Z_i^{min}, the constraint is active ($e_{t,i} = 1$) and the reward is granted. When the operated frequency is equal to or higher than the minimum service frequency, the constraint is inactive ($e_{t,i} = 1$) and no reward is granted.

$$(Z_i^{min} - z_{t,i} - \chi_{\theta,a})e_{t,i} \geq 0 \qquad \forall t \in \mathcal{T}, \forall i(y_t, \chi_{\theta,a}) \in \mathcal{L}, \forall a \in \mathcal{A} \tag{3}$$

2.3.2. Connecting Itineraries

We want to define potential itineraries for two reasons. First, to be able to flow OD cargo over the network to meet minimum OD cargo capacity requirements, which will be further discussed in Section 2.3.3. Second, as we know that demand data is hard to obtain, we introduce a standard goal to maximise the number of OD's served.

The potential itineraries to transport OD cargo depend on the airline's network structure and business model. While some carriers both offer hub transshipment and en-route stops next to direct flights, we consider these separately for simplification reasons and further define express- and general carriers. Both carrier types are respectively illustrated in Figure 5 (a) and (b), furthermore presenting connecting itineraries for each available decision. An express freight carrier can connect two flights, performed by possibly different aircraft, by transshipment through its single hub. A general freight carrier can offer (multiple) en-route stops in a line of flying for the loading and unloading of cargo carried on a single aircraft.



(a) Sample network for an express freight carrier with hub $a_1 \in \mathcal{A}_{hub}$.

(b) Sample network for a general freight carrier that allows for 2 en-route stops.

Figure 5 Choosing potential cargo itineraries for two sample networks when allowing for different connection types.

Cargo does not have a preference for a specific itinerary as passengers do, allowing for a higher level of freedom in allocating OD cargo capacity to flights. However, some practical requirements must be adhered to. For express freight, a minimum time is required for cargo to be transferred from one aircraft to the other at a hub, similar to passenger operations. For general cargo, the number flights that cargo can be transported on may be limited as each stop causes an increase in direct cost per unit of cargo to to additional fuel burn at takeoff and increase is distance travelled. As one of the important drivers for customers in choosing an airline is delivery time, highlighted in Section 2.2.3, a total maximum transit time is imposed. For express freight this is generally around 1 to 2 days, while for general freight this is several days up to a week (Derigs and Friederichs 2013).

For general freight, a feasible path p_i potentially consists of the last ϕ flights in the rotation r_n with increasing departure time t^{dep}. It must meet the following conditions:

- The number of flights in the path must not exceed the maximum number of flights FL^{max} such that $\phi \in \mathbb{R}^+ \leq FL^{max}$
- The same airport cannot be visited twice within the same path such that $a^d_{f_\iota} \neq a^d_{f_\iota} \quad \forall f \in r_n, \forall \iota \in \{1, 2, .., F^{r_n}\}$
- The maximum transit time $T^{transit}$ cannot be exceeded such that $t^{arr}_{f_\iota} - t^{dep}_{f_\iota} \leq T^{transit} \quad \forall f \in r_n, \forall \iota \in \{1, 2, .., F^{r_n}\}$

For express freight, a feasible path p_i consist of two flights f, potentially being operated by different aircraft. Two cases are defined for when the current decision is either a flight arriving at the base or departing from the base. The following conditions must be met for a connecting path to be feasible:

- The path consists of only two flights such that $|p_i| = 2$
- The origin of the path should not be equal to its destination such that
  $a^o_{f_\iota} \neq a^d_{f_\iota} \quad \forall f \in \mathcal{F}, \forall \iota \in \{1, 2, .., F\}$
- The flights in the path must connect at the base such that
  $a^o_{f_\iota} = a^d_{f_\iota} \in \mathcal{A}^{base} \quad \forall f \in \mathcal{F}, \forall \iota \in \{1, 2, .., F\}$
- The minimum transfer time $T^{transfer}$ must be guaranteed such that
  $t^{dep}_{f_\iota} \geq t^{arr}_{f_\iota} + T^{transfer} \quad \forall f \in \mathcal{F}, \forall \iota \in \{1, 2, .., F\}$
- The maximum transit time $T^{transit}$ cannot be exceeded such that
  $t^{arr}_{f_\iota} - t^{dep}_{f_\iota} \leq T^{transit} \quad \forall f \in \mathcal{F}, \forall \iota \in \{1, 2, .., F\}$

Being able to transport cargo for a single OD combination on multiple paths by combining loads on each flight, provides two clear advantages compared to offering direct flights only. First, the frequency of serving an OD combination can be increased. Second, the overall number of OD combinations can be dramatically increased by being able to capture OD markets that otherwise are physically out of range and OD markets that are otherwise too small to make a profit. Especially for airlines that wish to operate within small markets, having a highly connected network is key.

2.3.3. Cargo Routing and Minimum OD Capacity

With feasible paths defined, the cargo routing problem can be integrated in the DP rotation optimisation framework. By taking a decision $\nu_{\theta,p}$, cargo capacity is allocated to paths p that serve an OD combination i, available when taking decision $\chi_{\theta,a}$ to fly to another airport at time step θ. While in reality cargo is mostly consolidated in ULD's, due to the strategic and tactical scope of the model, we assume cargo is divisible by weight such that a single unit of cargo β is equal to 0.1 tonnes. To account for the volume effect of ULD's and irregular volume of general cargo, we assume a maximum load factor LF_n for each aircraft type.

In order to meet minimum OD capacity requirements, an approach is followed that is similar to that for adhering to the global constraint for minimum route frequency. A large artificial reward (big M) is introduced that is granted when contributing to the minimum OD capacity requirement. Each tonne of cargo capacity offered provides a contribution of $1M$ until the minimum contracted capacity CC_i^{min} is reached. This is regulated by the binary variable j and a switching constraint (4). To ensure aircraft capacity is not exceeded, two additional constraints (5, 6) are introduced. These respectively limit the cargo capacity allocated to the flight leg covered by taking decision $\chi_{\theta,a}$, and the cargo capacity allocated to all other flights in both the rotations of the aircraft currently under evaluation and previously routed aircraft. In order to do so, for each decision $\chi_{\theta,a}$ a set of feasible paths $\mathcal{P}_{\chi_{\theta,a}}^{feasible}$ is determined, where the resulting flight is subject to the conditions posed in Section 2.3.2.

$$(CC_i^{min} - w_{t,i} - \nu_{\theta,p})j_{t,i} \geq 0 \qquad \forall i \in \mathcal{I}, \forall p \in \mathcal{P}_{\chi_{\theta,a}}^{feasible} \tag{4}$$

$$\sum_{p \in \mathcal{P}_{\chi_{\theta,a}}^{feasible}} \nu_{\theta,p} \leq CAP_{n,i} \cdot LF_n \qquad \forall \chi_{\theta,a} \in \mathcal{X} \tag{5}$$

$$\sum_{\{p \in \mathcal{P}_{\chi_{\theta,a}}^{feasible} | f \in p\}} \nu_{\theta,p} + g_{t,n,f} \leq CAP_{n,i} \cdot LF_n \qquad \forall \chi_{\theta,a} \in \mathcal{X}, \forall f \in \mathcal{F} \tag{6}$$

Solving the DP optimisation algorithm with the decision variables $\nu_{\theta,p}$ in the objective function would lead to the state space blowing up along with the computation effort required (Powell 2011). As cargo path allocation is a typical problem that can be formulated as a multi-commodity flow problem, it can be solved optimally and relatively easily by an expensive commercial solver such as CPLEX (Derigs, Friederichs, and Schäfer 2009). However, here we propose an allocation algorithm, Algorithm 1 in Appendix B, that does not require such a solver. This algorithm provides a cargo capacity allocation $\nu_{\theta,p}$ for paths p that are used by the flight resulting from taking decisions $\chi_{\theta,a}$. The algorithm gives preference to the allocation of cargo capacity to direct itineraries.

After the minimum capacity requirement is fulfilled for the direct flight leg (procedure 1, 2 in Appendix B), the remaining aircraft capacity is allocated to the paths that serve indirect routes. For cargo transported on a sequence of flights, preference is given to paths that involve the least number of flights (procedure 3 in Appendix B).

For cargo transported with a transfer at the base, we assume priority of capacity allocation is based on the value of cargo. As yield is, next to OD distance, the main driver for cargo revenue, we make use of the decreasing market yield curve proposed in Subsection 2.3.1. In Figure 6, an example is presented for 3 OD's that can be served by operating a flight leg. For each curve, only a section is displayed such that the starting point in the graph represents the amount of OD capacity already allocation. As aircraft capacity is allocated to the highest yield cargo, the top curve represents the OD capacity is allocated to. From the intersection points and maximum aircraft capacity, 3 regimes (I-III) can be distinguished where each represents another OD. Aircraft capacity is also discretised into units of weight β and allocated one unit at a time (procedure 4 in Appendix B).

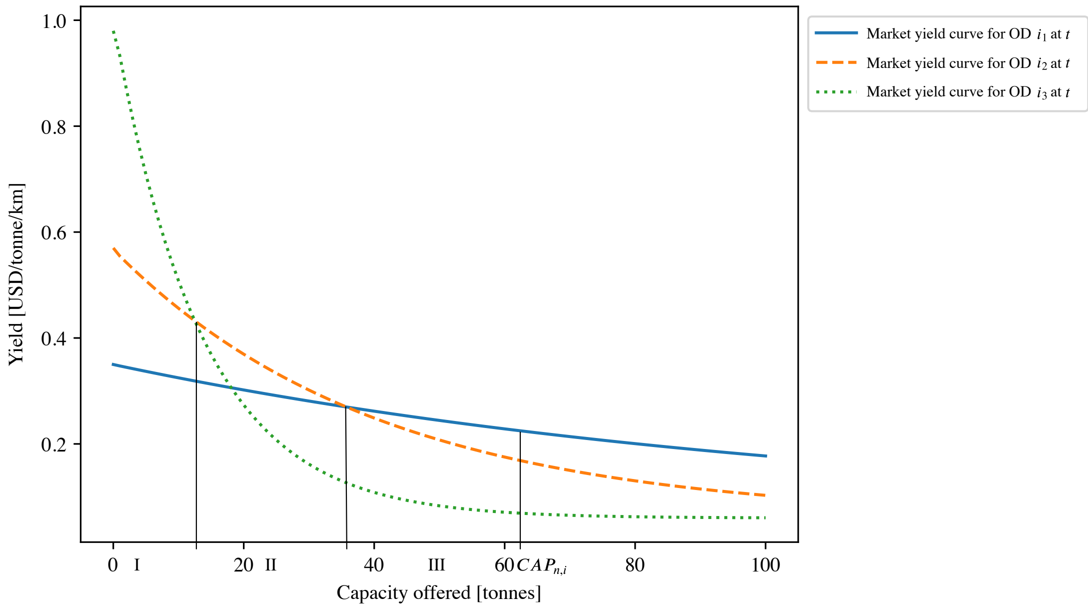


Figure 6 **Example of remaining aircraft capacity allocation to 3 OD itineraries with transfers, based on the decreasing market yield curve.**

This approach is myopic for two reasons: First, cargo is only allocated to complete paths so there is no incentive to operate the first leg of a connecting itinerary. Wang (2016) proposes a methodology that transports high revenue connecting passengers to the hub, without regarding if they are connected to their final destination at the moment the allocation decision is made. While this could also work for transfer cargo, it does not for transporting cargo on a chain of flights. Second, the approach does not consider future paths to allocate capacity to. To solve this, all paths are updated after the rotation of each aircraft and all cargo is re-allocated according to the same logic as proposed in Algorithm 1.

2.3.4. Operational Airport & Flight Leg Constraints

Operational constraint are both technical requirements and airline imposed requirements, that apply to each flight leg that is operated. On an airport level, these constraints involve curfew limits, aircraft type compatibility (e.g. runway length and apron dimensions) and slot unavailability. On a flight leg level, a constraint is introduced to guarantee that a flight leg is operated by a specified aircraft type (e.g. Airbus A330(-200F)) or body type (wide-body (WB), or narrow-body (NB)).

To reduce complexity in the set of constraints, the binary parameter $u_{\theta,i}$ is introduced to indicate whether operating a flight leg i is possible with aircraft n at departure time θ. This parameter is pre-computed during the initialisation step, and combined with a very large penalty (big M^2), an approach similar to that of adhering to the minimum service frequency introduced in Section 2.3.1. Following the formulation below, a flight leg will be granted a penalty when it cannot be operated ($u = 1$). While treated as a soft constraint, in practise these constraint are always adhered to in the DP optimisation model proposed.

$$u_{n,\theta,i} = \begin{cases} 1, & \text{if infeasible} \\ 0, & \text{otherwise} \end{cases} \qquad \forall i \in \mathcal{L}$$

2.3.5. Flight Timing Constraints

Aligning the timing of flights in the planning horizon with the requirements of (prospective) customers is vital to airlines for operating a profitable schedule. Based on the market and commodity characteristics for each flight leg, flight departure days and times are planned.

Following real air cargo operations (Feng, Li, and Shen 2015), requirements are posed based on cargo being not available for transport before an earliest departure time and having to arrive before a latest arrival time. These time windows are more strict for express freight carriers than for general freight carriers. Rather than to add a series of candidate flights, as it is performed in incremental schedule improvement models (Rexing et al. 2000, Derigs and Friederichs 2013), multiple time windows (τ^{from}, τ^{to}) can be defined for each flight leg. If a flight that is operated as the result of taking decision $\chi_{\theta,a}$, has a departure time t^{dep} or arrival time $t^a rr$ outside these time windows, the decision would not be feasible. These time constraints are captured by the parameter $u_{n,\theta,i}$ proposed in the previous section.

Furthermore, we introduce a constraint (7) that ensures a minimum time separation T^{sep} between flights that cover the same flight leg. Spreading the flights over the planning horizon enables airlines to capture a larger portion of the total weekly market for each flight leg. A decision to operate a flight going to another airport can not be made if a flight that covers that flight leg is operated within T^{sep} before, or T^{sep} after the departure time θ. This hold both for flights in the current rotation and the flights in the rotations operation by other aircraft.

$$max\{t_f^{dep} \in \mathcal{F} | \sum_{a \in \mathcal{A}} \chi_{\theta,a} a = a_f^d\} + T^{sep} \leq \qquad \forall \chi_{\theta,a} \in \mathcal{X} \tag{7}$$

2.3.6. Maintenance & Turnaround Time Constraints

Incorporating maintenance in the aircraft routing problem prevents infeasible maintenance rotations and contributes to airline cost savings (Papadakos 2009). This effect is amplified for freight operations as aircraft are not necessarily parked overnight as is the case for passenger operations, allowing time for maintenance (Gopalan and Talluri 1998). As the scope of this planning model is strategic to tactical, maintenance requirements are addressed by allowing for sufficient time for maintenance actions during the weekly planning horizon, rather than to plan for the requirements of a specific aircraft, similar to work by Liang and Chaovalitwongse (2013). The maintenance actions under consideration here are daily checks, mandated by the regulator. The time required for weekly maintenance actions T_n^m depends on the type of aircraft n and can either be conducted in one block or split into B^m blocks of whole hours with a minimum duration of τ_1^m (Airbus 2019b) such that:

$$\mu_n = \{\tau_1^m, \tau_2^m, ..., \tau_{T^m}^m\} \cdot T^{resolution}$$

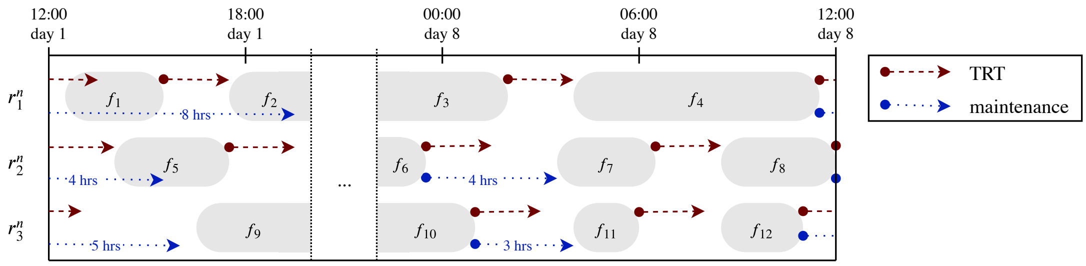


Figure 7 **Example of rotations with maintenance time (total of 8 hours) and turnaround time (2 hours each) between flights. Rotations 1 and 2 do not meet requirements for maintenance.**

Maintenance can only be conducted at the base $a \in \mathcal{A}_{base}$, and continuity of the planning horizon is taken into account as visualised for feasible and infeasible rotations in Figure 7. In this figure, 3 rotations are presented, where turnaround time is indicated by red dashed arrows and maintenance blocks indicated by blue dotted arrows. After the last flight in the planning horizon, the remaining required maintenance block is added, which continues at the start of the planning horizon. While rotation 1 and 2 do not adhere to maintenance requirements, rotation 3 does as can be observed from the figure.

The following constraints are required to adhere to minimum maintenance time (8), through a maximum number of blocks (9).

$$m_{t,\chi_{\theta,a}}^{time} + T^{plan} - t_{\chi_{\theta,a}}^{arr} + t_{\chi_{\theta,a}}^{dep} \geq T^m \qquad \forall \chi_{\theta,a} \in \mathcal{X} \tag{8}$$

$$m^{blocks}_{\chi_{\theta,a}} \leq B \qquad \forall x \in \mathcal{X} \tag{9}$$

While turnaround time between flights is guaranteed as it is incorporated in each flight arc, discussed in Section 2.2.4, an additional TRT constraint (10) must be applied to ensure rotation continuity between the end and start of the planning horizon. For the first flight in the rotation, a fixed TRT is not incorporated, as it is determined dynamically at the end of the planning horizon. For each decision to operate a flight leg, the interval between the arrival time of this operated flight leg and departure time of the first flight in the rotation is determined. Subsequently, this interval is compared to the minimum TRT and still required maintenance time. A flight leg cannot be operated when it does not allow for sufficient time for both. In Figure 7, we can observe how TRT requirements are posed from the end to the start of the planning horizon, and that rotation 1 does not provide sufficient TRT.

$$T^{plan} - t^{arr}_{\chi_{\theta,a}} + t_{\chi_{\theta,a}} \geq T^{TRT} \qquad \forall x \in \mathcal{X} \tag{10}$$

2.3.7. Objectives

For making the set of decisions x_t, 3 different objective functions are presented. These objectives are chosen such that they cater to the needs of many different cargo airlines, that have various degrees of market information available.

Objective 1: cost minimisation

The first objective is both suitable for situations where the airline lacks knowledge on future revenue as well as for situations where revenue has been determined for a series of defined flight legs, such that the cost need to be minimised. The costs $c_{\theta,i,n}$ that are incurred when operating a flight leg on OD i with aircraft n at time θ are discussed in 2.2. These cost are split up into departure related cost, flight related cost, and arrival related cost, as is presented below. The method for computing these costs is largely analogous to the method proposed by Wang (2016) and will therefore not be discussed further.

$$c_{\theta,i,n} = c^{dep}_{\theta,a^o_i,n} + c^{leg}_{\theta,i,n} + c^{arr}_{\theta,a^d_i,n}$$

Using these cost per OD and taking the penalty for infeasible operations into account, we formulate the first objective as a maximisation of negative cost.

$$\Phi_1(y_t, \{\chi_{\theta,a}\}^A_{a=1}) = \sum_{a \in \mathcal{A}} \left[\chi_{\theta,a}(-c_{\theta,i(y_t,a),n} - u_{\theta,i(y_t,a),n} \cdot M^2)\right] \tag{11}$$

Objective 2: profit maximisation

Objective 1 is appended with revenue and artificial rewards to come to the objective of maximising profit. OD revenue is introduced for the cargo located to each path and depends on the amount of cargo served previously on that OD. Furthermore, the rewards are added for adhering to global constraints for minimum service frequency and minimum OD cargo capacity offered. Note that the penalty for infeasible flight legs is always a magnitude larger than the minimum frequency reward.

$$\Phi_2(y_t, w_{t,i}, \{\chi_{\theta,a}\}_{a=1}^{A}, \nu_{\theta,p}) = \sum_{a\in\mathcal{A}} \left[\chi_{\theta,a}(-c_{\theta,i(y_t,a),n} - u_{\theta,i(y_t,a),n}\cdot M^2) + e_{\theta,i}\cdot M\right] + \sum_{p\in\mathcal{P}_{\chi_{\theta,a}}^{feasible}} \nu_{\theta,p}\cdot(q_{\theta,i}(w_{t,i}) + j\cdot M) \quad (12)$$

Objective 3: connectivity maximisation

Optimising for connectivity can be seen as a 'standard' objective, used when no data on demand is available. It involves maximising the number of OD itineraries that are offered for a given network structure, containing potentially feasible flight legs. Connectivity is therefore measured in the total number of feasible paths that connect an origin to a destination, made available by taking decision $\chi_{\theta,a}$.

$$\Phi_3(\{\chi_{\theta,a}\}_{a=1}^{A}) = \sum_{a\in\mathcal{A}} |\mathcal{P}_{\chi_{\theta,a}}^{feasible}| \quad (13)$$

2.4. DP Formulation

In this section, the rotation optimisation problem is formalised by adopting the DP framework. This framework consists of the 4 following elements which are described in the next sections: state space description, (2.4.1), decision space (2.4.2), state transition (2.4.3), and optimisation model (2.4.4).

2.4.1. State Space

The state of the system at a give time step t can be defined by its current features as well as relevant historic information on previous states. The state vector (14) is comprised of three types of state features. Type 1 provides information on the aircraft that is considered and type 2 considers aspects that are presented for each OD. Finally, type 3 features provide the rotation history for both the current aircraft and for aircraft which' optimal rotations have been added to the schedule.

$$s_t = (\underbrace{y_t, m_t^{block}, m_t^{time}}_{\text{1: aircraft}}, \underbrace{w_{t,i}, z_{t,i}}_{\text{2: OD}}, \underbrace{\{r_{t,n}\}_{n=1}^{N+1}, \{\{g_{t,n,f}\}_{f=1}^{F_n}\}_{n=1}^{N+1}}_{\text{3: rotation history}}) \quad (14)$$

For some features, initial conditions that arise form both model requirements as well as the schedule of all previously routed aircraft are set for the initial state s_{t_0}. For the global requirements, the service frequency per flight leg and OD capacity offered the values are set equal to those of the final state S_T of the previously routed aircraft as follows:

$$z_{t_0,i} = z^N_{T^{plan},i} \qquad \forall i \in \mathcal{L}$$

$$w_{t_0,i} = w^N_{T^{plan},i} \qquad \forall i \in \mathcal{I}$$

Similarly, initial conditions for the rotation history $r_{t,n}$ and cargo to path allocation $g_{t,n,f}$ are set:

$$r_{t_0,n} = r_{T^{plan},n} \qquad \forall n \in \mathcal{N}$$

$$g_{t_0,n,f} = g_{T^{plan},n,f} \qquad \forall f \in r_{T^{plan},n}, \quad \forall n \in \mathcal{N}$$

2.4.2. Decision Space

At each stage, the decisions that can be made relate to the location of the aircraft and the amount of aircraft capacity allocated. Decision $\chi_{\theta,a}$ involves either remaining at the airport it is located at time t, or flying a flight leg to another airport. Decisions $\nu_{\theta,p}$ involves the allocation of aircraft capacity to the feasible OD paths $\mathcal{P}^{feasible}$ that are available. Both decisions are described by the decisions vector (15).

$$x_t = (\{\chi_{\theta,a}\}^A_{a=1}, \{\nu_{\theta,p}\}^P_{p=1}) \tag{15}$$

Each $\chi_{\theta,a}$ is a binary decision variable with the following properties:

$$\chi_{\theta,a} = \begin{cases} 1, & \text{remain at, or fly a flight leg to, airport } a \text{ at time step } \theta \leq t \\ 0, & \text{otherwise} \end{cases}$$

2.4.3. State Transition

After a decision is made in stage t, the system evolves from state s_t to state $s_{t+\Delta t}$ as a consequence of decisions x_t. This transition is characterised by the transition function (16). Note that for the entire transition function, no exogenous information becomes available and no other stochastic parameters are considered. The system therefore is assumed to be fully deterministic.

$$s_{t+\Delta t} = \mathcal{S}^{trans}(s_t, x_t) \tag{16}$$

When the decision is made to operate a flight leg, the system does not advance to stage $t+1$ but to the stage $t+\Delta t$ where the aircraft is again ready for operations (see Figure 2). Using the aircraft (type) dependent average flight time per flight leg $T_{n,i}^{flight}$, taxi time T_n^{taxi} both before takeoff and after landing, and required turnaround time T_n^{TRT}, we define Δt as follows:

$$\Delta t = \begin{cases} (\theta - t) + T_{n,i}^{flight} + T_n^{TRT} + 2 \cdot T_n^{taxi}, & \text{if } y_t \\ 1, & \text{otherwise} \end{cases}$$

The transitions for all features in the state are described next, following the classification introduced in the previous section.

Aircraft related state features

The location of the aircraft $y_{t+\Delta t}$ is equal to the binary $\chi_{\theta,a}$ multiplied by the airport a. This new location of the aircraft is used in the remainder of state transition formulations for legibility.

$$y_{t+\Delta t} = \sum_{a \in \mathcal{A}} \chi_{\theta,a} a$$

In order to add a maintenance block, we evaluate the time between the last flight F_n in the current rotation $r_{t,n}$ with $n = N+1$, and the time θ of the decision to fly to another airport. The largest feasible maintenance block τ_k^m is then added to the current maintenance time m_t^{time}. We assume assume a single airport where maintenance can be conducted: the airline's operations base $a \in \mathcal{A}_{base}$. If τ_k^m is added, the number of blocks is incremented by 1.

$$m_{t+\Delta t}^{blocks} = \begin{cases} m_t^{blocks} + 1, & \text{if } m_{t+\Delta t}^{time} > m_t^{time} \\ m_t^{blocks}, & \text{otherwise} \end{cases}$$

$$m_{t+\Delta t}^{time} = \begin{cases} m_t^{time} + max\{\tau_n^m \in \mathcal{T}_n^m | \tau_n^m \leq \theta - t_{F_{(N+1)}}\} & \text{if } y_t \neq y_{t+\Delta t} \wedge y_t \in \mathcal{A}_{base} \\ m_t^{time}, & \text{otherwise} \end{cases}$$

OD related state features

The cargo capacity offered for each OD, $w_{t,i}$ is increased by the sum of all aircraft capacity allocated $\nu_{\theta,p}$ to the paths p that serve that OD.

$$w_{t+\Delta t,i} = w_{t,i} + \sum_{p \in \mathcal{P}^i} \nu_{\theta,p} \qquad \forall i \in \mathcal{I}$$

With set $\mathcal{P}^i$ containing all feasible paths p that serve OD i when taking decision $\chi_{\theta,a}$:

$$\mathcal{P}^i = \{p \in \mathcal{P}_{\chi_{\theta,a}}^{feasible} | i_p = i(y_t, y_{t+\Delta t})\}$$

The operated service service frequency for an OD, $z_{t,i}$, is increased with 1 if the decision to fly to another airport, $\chi_{\theta,a}$, leads to operating a flight leg on that OD.

$$z_{t+\Delta t,i} = \begin{cases} z_{t,i} + 1, & \text{if } i = (y_t, y_{t+\Delta t}) \\ z_{t,i}, & \text{otherwise} \end{cases} \qquad \forall i \in \mathcal{L}$$

Rotation history related state features

The rotation $r_{t,n}$ for the currently routed aircraft $N+1$ is updated when the decision is made to fly to another airport, adding that flight f to the rotation.

$$r_{t+\Delta t,n} = \begin{cases} r_{t,n} \cup f(y_t, y_{t+\Delta t}, \theta)), & \text{if } y_t \neq y_{t+\Delta t} \\ r_{t,n}, & \text{otherwise} \end{cases} \qquad \text{for } n = N+1$$

When cargo capacity is allocated to a path, $\nu_{\theta,p}$, the aircraft capacity of all flights f in that path p is reduced by the amount of cargo allocated. This feature is updated after the expansion of the rotation $r_{t,n}$ described above.

$$g_{t+\Delta t,n,f} = \begin{cases} g_{t,n,f} + \nu_{\theta,p}, & \text{if } f \in \{p \cup f(y_t, y_{t+\Delta t})\} \\ g_{t,n,f}, & \text{otherwise} \end{cases} \qquad \forall f \in r_{t,n}, \quad \forall n \in \{\mathcal{N}\}$$

2.4.4. Optimisation model

In order find the optimal rotation for the current aircraft, a policy is defined to optimise the decisions to be made at each stage. The approach is myopic as the policy does not explicitly attempt to capture future effects of the decisions made now (Powell 2011). Bellman's optimality equation (17, Bellman (1958)) provides the value function for the current stage $V_t(s_t)$, which is maximised by making optimal decision x_t and the value of being in the resulting state $V_{t+\Delta t}(s_{t+\Delta t})$. When solved recursively for each state $s_t \in \mathcal{S}_t$ and time step $t \in \mathcal{T}$, this function (17) can be used to find such an optimal policy.

As the problem has a finite horizon, a backward induction approach is used to solve the recursive relation (17). This means the algorithm moves backwards from stage $T^{planning}$ to the initial stage t_0, finding the optimal decisions for each state s_t at each stage t.

$$V_t(S_t) = \max_{x_t}(C_t(s_t, x_t) + V_{t+\Delta t}(S_{t+\Delta})) \tag{17}$$

The direct influence of a decisions on the value function is determined by the contribution $C_t(s_t, x_t)$. The contribution function (18) is described by an objective $\Phi_(y_t, \{\chi_{\theta,a}\}_{a=1}^{A}, \nu_{\theta,p})$, which is either one of three objective introduced in Section 2.3.7.

$$C_t(s_t, x_t) = \Phi(y_t, \{\chi_{\theta,a}\}_{a=1}^{A}, \nu_{\theta,p}) \tag{18}$$

This objective is subject to the constraints (3 - 10) introduced in Sections 2.3.1 - 2.3.6, and additional constraints (19, 20) to guarantee continuity between the end and start of the planning horizon, partly discussed by Wang (2016). Finally, the nature of all variables is defined (21)

The following set of constraints ensures that at each time step, an aircraft can only move to, or stay at, a single airport:

$$\sum_{a \in \dashv} [\chi_{\theta,a}] = 1 \qquad \forall \theta \in \mathcal{T} \tag{19}$$

The location of the aircraft at the start of the planning horizon should be equal to the location at the end of the planning horizon:

$$y_{t_0} = y_{T_plan} \tag{20}$$

The variables introduced meet the following conditions:

$$e_{t,i} \in \{0,1\}, \chi_{\theta,i} \in \{0,1\}, u_{n,\theta,i} \in \{0,1\}, j_{t,i} \in \{0,1\}, g_{t,n,f} \in \mathbb{R}^+, \nu_{\theta,p} \in \mathbb{R}^+ \tag{21}$$

2.5. Computational Complexity

Following the high-level model hierarchy presented in Figure 1, the computational complexity is given by (22):

$$\overbrace{\sum_{n \in \mathcal{N}^{available}}}^{\text{add aircraft}} \overbrace{\sum_{\{k \in \mathcal{K} | n_k > 0\}} n^k}^{\text{compare aircraft types}} \overbrace{\prod_{t_0 \in T^{plan}} \sum_{a \in \mathcal{A}} \sum_{\{i \in \mathcal{L} | a_i^o = a\}} ai}^{\text{optimise a single rotation}} \tag{22}$$

The first two parts of (22) indicate how many times the dynamic programming routine is performed and, at a maximum, depends on the total number of available aircraft $N^{available}$, where for each evaluation of an additional aircraft all available fleet types K are evaluated. The number of dynamic programming routines is stopped when no more aircraft are added to the fleet.

The third part of (22) defines the total number of outcomes that must be evaluated. Not considering cargo routing, finding the optimal decision calls for evaluating all available decisions to fly to another airport or remain.

The number of available decisions depends on the airline's network structure and, at a maximum, is given by the number of other airports $A - 1$. As soft constraints are used that assign a large penalty to infeasible flights, the number of available decisions is not limited further. For each time step, the number of outcomes is equal to the total number of routes, L.

3. Numerical Case Studies

This section aims to demonstrate the versatility and applicability of the dynamic optimisation model on real life scenarios. Table 1 provides an overview of the objectives and constraints introduced in the previous section and identifies sensible combinations. These combinations have been selected based on the meaningful results of the outcomes, and the availability of demand and revenue forecasts to an airline. For example, a minimum OD capacity constraint is introduced for long-term contracts, without knowing what revenue cargo will actually be present at the time of operations. Another example, only minimising cost for a given fleet does not lead to any operations as there is no motivation to operate flights on any flight legs.

As is the case in real airline operations, the constraints presented are usually combined, leading to a large number of potential combinations for which its meaningfulness must be evaluated individually. The case studies presented in the remainder of this section are key examples of such meaningful combinations.

Table 1 Meaningful combinations of objectives and constraints.

Constraints	Objectives		
	Min. cost	Max. profit	Max. connectivity
Given fleet		✓	✓
Minimum utilisation	✓	✓	✓
Maxmimum BELF	✓	✓	✓
Minimum service frequency	✓	✓	✓
Minimum OD capacity	✓		
Combination	...	...	...

Three case studies have been provided by Airbus that have been based on two airline requests for future operations. Two cases studies are presented on an African cargo airline and the third case study involves a South American cargo airline. The inputs for these case studies have been collected from manufacturer's aircraft manuals, and databases published by IATA[1] and ICAO[2]. Although no real operations have been conducted for these case studies as of now, validation of the results has been carried out in consultation with Airbus. At the end of this section, the model performance is evaluated, demonstrating how computation time scales for different problem sized and model features. The model is implemented using Python and does not require an external solver. The tests have been run on a regular computer with a 2.9 GHz i5 processor and 16 GB of memory installed.

[1] International Air Transport Association

[2] International Civil Aviation Organisation

3.1. African Airline: A

The goal of this first case is to operate a weekly minimum service frequency per route at minimum cost, with the most appropriate aircraft type, while adhering to operational constraints. The resulting aircraft rotation is then compared with to the lines of flying proposed by the airline. After finding an initial schedule, we furthermore evaluate the impact of a typical user input made by a schedule planner after observing the initial results. The requirements are further described below, together with the assumptions made.

The network consists of 15 predefined flight legs, with each a minimum service frequency, that connect 9 airports (including a fuel stop), as can be seen in Figure 8. Furthermore, a minimum time separation between same OD flight legs of 24 hours is introduced. No current fleet is present, so new aircraft are to be chosen from two fleet types (Airbus A300-600F, Airbus A330-200F), while adhering to a minimum average utilisation of 8 hours per day per aircraft and maximum BELF per flight leg of 80%. For both aircraft types, a TRT of 2 hours and total maintenance time of 8 hours are assumed. For the latter, maintenance can be conducted at the airline's base (NBO) in two of the following blocks of hours: $\{0, 3, 4, 5, 8\}$.

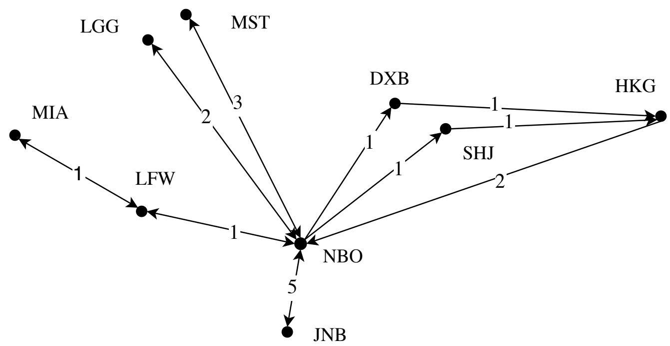


Figure 8 African Airline network structure with corresponding one-way service frequency per flight leg.

Using this is a base case, the input is to limit take off and landing time windows to avoid peak hours for passenger operations. For each airport, a limit is imposed on the hourly flight movements, above which a take off or landing is restricted in the model. This limit, mov^{max}, is equal to the mean number of movements per hour plus a multiple α of the standard deviation σ, such that $mov^{max} = \mu + \alpha\sigma$.

3.2. African Airline: B

This second case study aims to provide a minimum cost flight schedule with corresponding cargo routing for the same airline as discussed in the previous Subsection. However, the driver of flying in this case study is a set of long-term contracts for which a minimum amount of OD capacity must be offered, presented in Table 2. Note that no requirements are specified for OD's with origin or destination MIA. This input is obtained using the airline's proposed lines of flying, shown in Table 5. While operating the same set of airports, no fixed flight leg network is given, i.e. all airports can potentially be connected with a direct flight leg, which we define as a 'free' network. The carrier only transports general freight which can be transported on both direct flights and a series of flights involving 2 en-route stops. The maximum transit time of each unit of cargo is assumed to be 3 days. The remainder of requirements and assumptions are equal to those presented for the other African Airline case study.

Table 2 African Airline minimum OD cargo capacity requirements [tonnes].

		Destination						
		NBO	MST	JNB	LGG	SHJ	HKG	DXB
Origin	NBO		137	140	92	30		30
	MST	36		99				
	JNB	30						
	LGG	23		66				
	SHJ	9						
	HKG	84				3		6
	DXB	6					3	

3.3. South American Airline

The third case study involves a South American airline that transports primarily express freight, and aims to maximise connectivity. A set of potentially profitable flights legs have been identified by the airline, and serve as an input. In order to find the best type of operations for the airline, connectivity is compared for (combinations of) different itineraries to transport cargo, involving direct flights only, transshipment at a hub, and en-route stops. For simplicity, we assume that cargo involving multiple flights can be transported either on an itinerary that connects through a hub, or on an itinerary involving en-route stops, but not a combination of both. The network consists of 47 flight legs which serve 17 airports. Two of those airports have a high degree of incoming and outgoing flight legs, respectively 24 and 18, of which the first is the airline's base. Due to the high degree of this other airport, the influence of allowing for connection through this secondary hub, in addition the base, is examined.

For feasible itineraries, we assume a maximum transit time of 2 days, a maximum of 2 en-route stops and a minimum cargo transfer time at the hub of 2 hours. For this case study, the fleet is given and fixed, and consists of 2 aircraft types (2 Airbus A330-200F, 3 Airbus A321-P2F). The maintenance requirements are equal to those presented in Section 3.1 for the A330-200F, and are assumed as follows for the A321-P2F: two blocks of hours from $\{0, 3, 4, 7\}$, with a total of 7 hours.

3.4. Results

The resulting schedules and aircraft rotations for the three test cases are discussed by means of common industry specific key performance indicators (KPI's). These are compared, where possible, to real operations for a week in October 2017 (IATA 2019b) to infer the validation of the results obtained.

3.4.1. African Airline: A

The results of the Kenya Airways case study are presented in Table 3. Furthermore, all operational requirements such as the minimum service frequency have been adhered to and no infeasible flights were performed. First, the fleet choice is discussed after which we closer examine KPI's of the individual aircraft. The model has chosen two aircraft of the A330-200F type, for which we compared the obtained results to those for the same case, but now with a fixed fleet of 2 aircraft of the A300-200F and relaxation of minimum utilisation and maximum BELF assumptions. These results are presented in Table 4. Both results covered the same set of flight legs. While the operating cost for the A300-200F were 36.8% lower, the A330-200F was still chosen. This can be explained by the difference in payload-range characteristics of the two aircraft and high BELF of the A300-600F. Besides that the A300-600F has a lower maximum payload, its payload range characteristics are inferior to the larger A330-200F as the two aircraft respectively offer a capacity equal to 29.8 % and 68.9 % of their maximum payload on the longest distance route.

At yields as observed in the market, the A300-600F would not be able to operate at a profit while the A330-200F has an average break even LF (BELF) of 66.4%. Compared to a worldwide average industry BELF of 63.9 % (IATA 2018), with even higher values in the carriers most dominant geographical regions, we show furthermore show that the model reflects real life operations in terms of economics.

Table 3 African Airline case study A: KPI's for aircraft type A330-200F.

Aircraft number	Operating cost [k US $]	Average utilisation [BH / day]	Average utilisation FC / day	ATK [k tonnes km]	Average market yield [US $ / tonne / km]	BELF [%]	Industry average LF [%]	BE yield [US $ / tonne / km]
1	1,050.33	16,43	2,71	5,999.76	0.34	64.3	69.2	0.26
2	719.74	11,02	1,57	3,805.41	0.32	70.0	69.2	0.26
Fleet aggregate	1,770.06	13,72	2,14	9,805.17	0.33	66.4	69.2	0.26

Table 4 African Airline case study A: KPI's for aircraft type A300-600F.

Aircraft number	Operating cost [k US $]	Average utilisation [BH / day]	Average utilisation FC / day	ATK [k tonnes km]	Average market yield [US $ / tonne / km]	BELF [%]	Industry average LF [%]	BE yield [US $ / tonne / km]
Fleet aggregate	1,293,44	13.66	2.14	5,304.34	0.33	132.2	69.2	0.38

Evaluating the individual aircraft of the A330-200F type, we observe that utilisation is unbalanced and, for aircraft 1, high compared to the industry average of 11.0 block hours (BH) per day (IATA 2019a) due to the 'greedy' nature of the DP algorithm. However, with unbalanced utilisation, and schedule start moment for the second aircraft separated by one day, a schedule must allow for sufficient swapping opportunities for maintenance and schedule recovery Liang et al. (2018), Burke et al. (2010), and equal wear of the aircraft. Although the model does not explicitly takes these swapping opportunities into account, the resulting schedule provides 4 over the weekly planning horizon, which is sufficient. Evaluating the sequence of flights in the schedule, all lines of flying proposed by the airline in Table 5 are covered. While this again was not a requirement, it shows that results are comparable to those proposed by experienced schedule planners.

Table 5 Lines of flying with weekly frequency proposed by African Airline. * denotes a fuel stop without (un)loading of any cargo.

Line of flying	Weekly frequency
NBO - MST - NBO - JNB - NBO	3
NBO - LGG - NBO - JNB - NBO	2
NBO - SHJ - HKG - NBO	1
NBO - DXB - HKG - NBO	1
NBO - LFW* - MIA - LFW* - NBO	1

We furthermore introduced the flight movement cut-off limit to avoid an airport's busy hours, for which aircraft 1 and aircraft 2 have an average daily utilisation of 14.7 and 12.8 hours. The most appropriate cut-off limit with α equal to 0.6 has been found empirically. From these results, we observe that utilisation is now more evenly distributed among the two aircraft. The mean time between flights, without regarding the time at the base at the end of the planning horizon, increases by 62% from 2.2 hours to 2.5 hours. This can negatively impact the total transit time for cargo that is transported through multiple en-route stops. Therefore, despite the more even distribution of utilisation, additional operations requirements should be posed by an airline's schedule planner. Interacting with the model in this way is possible due to the low computation time of 8 minutes and 27 seconds.

3.4.2. African Airline: B

In Table 6, the KPI's for the schedule plan and cargo routing are presented for this case study, designated by the free network type. Additionally, the schedule plan of case study A is used for comparison in combination with the cargo allocation proposed by the airline.

Table 6 African Airline KPI's for different network structures and en-route stops under minimum OD capacity constraints.

Network type	En-route stops	Flights	Operating cost [k US $]	Ferry flights	Total utilisation [FH]	ATK [k tonnes km]	Average LF all flights [%]	Average LF payload flights [%]	RTK [k tonnes km]	Inefficiency [%]
Fixed	2	26	1,492	0	160.5	8,751	59.0	59.0	5,163	5.38
Free	0	32	2,031	9	215.5	12,035	40.7	51.2	4,899	0
Free	2	29	1,619	6	170.8	9,395	48.7	60.0	5,637	15.05

First, we compare the results for the 'free' network types. It immediately becomes apparent that operating a schedule with en-route stops performs significantly better than that with direct flights only. To offer the same OD capacity, the schedule with direct flights involves 25.4% higher cost, caused by the higher number of (ferry) flights, and on average significantly longer flights.

When comparing both 'free' network types to the fixed network type, the difference in operating cost is mainly attributed to the higher number of ferry flights and a significant number of flights that have a load factor below 15%. We furthermore characterised the routing inefficiency, i.e. the difference in distance between the most direct route and performed route that cargo is transported. As expected, when no en-route stops are made, cargo is transported on direct paths only. Comparing both en-route stops networks, the airline proposed schedule also outperforms the model on inefficiency.

There are two main drivers for this lack in performance. First, due to the myopic nature of the DP rotation optimisation algorithm, only the cargo for which a complete itinerary is available can influences the decisions made. The model therefore primarily considers direct cargo. Second, due to the greedy nature of the cargo routing algorithm, where direct cargo receives priority, the cargo allocation may not be optimal.

As both 'free' network types require the evaluation of all flight legs, computations times are longer compared to the fixed network. For the direct and 2 en-route cases, results were respectively obtain in 37 and 42 minutes.

3.4.3. South American Airline

For this case study, the key characteristics of the results obtained for all combinations of hubs and connection types are presented in Table 7, with each column representing a schedule planning of 175+ flights. The results for the direct flight legs only case and direct flight legs with en-route stops case are identical for both number of hubs.

Table 7 South American Airline key characteristics of results.

	1, 2 hubs		1 hub		2 hubs	
	Direct	Direct, stops	Direct, transfer	Direct, transfer, stops	Direct, transfer	Direct, transfer, stops
Flights NB	157	146	134	147	131	148
Flight WB	44	40	44	44	44	44
OD Itineraries	201	248	1828	1705	1674	1677
Unique OD's	26	54	128	134	118	108
Direct unique OD's	26	25	27	27	31	29
En-route stop unique OD's	0	42	0	52	0	22
Transfer unique OD's	0	0	101	96	95	124
Average utilisation NB [BH/day]	15.4	15.7	16.2	16.2	15.2	15.1
Average utilisation WB [BH/day]	15.7	17.4	16.1	16.1	16.0	16.1

Comparing the 1 hub and 2 hub cases, the first provided better results, against the expectations. However, this can be explained by the fact that for the 2 hub case, more direct flights were performed, lowering the total number of unique OD itineraries. Closer evaluation furthermore showed that the number of flight movements at the secondary hub did not increase from the 1 hub to the 2 hub case. The model aims to provide the largest number of itineraries, for which connecting at the base provides better results due to the higher degree of adjoining flight legs.

Without regard of any cargo flow, the best results for this network were obtained by using a hub-and-spoke structure. Moreover, allowing for both hub transfers and en-route stops to transport OD cargo in a standalone manner, negatively impacts the number of unique OD's served.

Evaluating the fleet of aircraft, we observed that utilisation is very high for both aircraft body types, while already adhering to maintenance requirements. The next for an airline schedule planner would be to further constrain the model, by imposed operational requirements, such as proposed for the African Airline in Section 3.4.1.

In terms of computation time, results for the single base only case were obtained in 97 minutes. For the case with both direct flight legs and en-route stops, computation time was marginally higher with 100 minutes. For all cases involving transfers, the model provided results in 113 minutes, without significant differences among the individual cases.

3.5. Computational Complexity

In order to find out how computation time scales for other case studies than those presented in the previous section, sensitivity analysis is performed. The parameters that influence computation time (22) are varied for a case without cargo routing and the results are compared to a reference case as shown in Table 8. The results show that only the number of aircraft influences the computation time per outcome of decision $\chi_{\theta,a}$ significantly. Computation time scales linearly for all other parameters.

Table 8 Computation time sensitivity to parameters influencing model complexity. The reference case consists of a 1 day planning horizon, 10 routes, 1 aircraft, and 1 fleet type. The values are averages from 5 equal experiments.

	Reference case	Planning horizon [days]		Routes		Aircraft		Fleet types	
Parameter	-	3	7	15	30	5	10	2	4
Time / outcome [ms]	2.27	2.25	2.51	2.69	2.48	3.76	4.03	2.39	2.57
Deviation from base [%]	0	-0.9	10.7	18.5	9.2	65.7	77.7	5.3	13.4

Closer evaluation of the sensitivity to a change in the number of aircraft does not show a non-linear increase in computation time, but a jump after the first aircraft. This is explained by the fact that the existing rotations are evaluated during each iteration, and no such rotation exists when the first aircraft is evaluated. We observe that when additionally paths are generated, computation time p(the slope of the curve) is still constant. Finally, when the fleet is limited, computation time per per aircraft falls as some types of aircraft become unavailable as is shown by the discontinuities in the curve at aircraft 5 and 8.

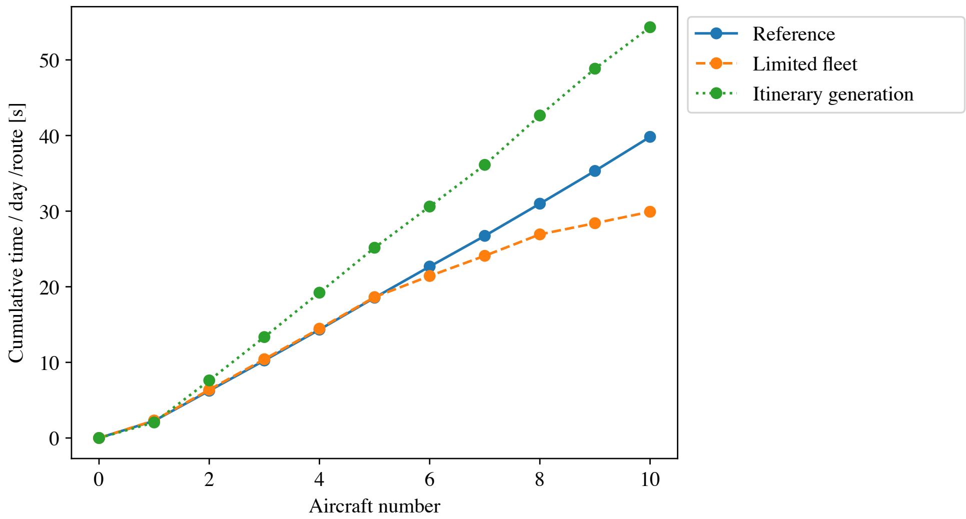


Figure 9 **Scaling of computation time of different experiments over the number of aircraft added to the fleet. The reference case consists of an unlimited fleet of 3 types.**

4. Conclusion and Recommendation

This work shows the successful application of a dynamic programming optimisation approach to the schedule planning problem of cargo airlines. The method proposed integrates schedule design, fleet assignment, aircraft rotation planning with maintenance consideration, and cargo routing, for both express freight- and general freight airlines with corresponding network characteristics. Weekly schedules are generated from scratch and in reasonable computation time, which is not possible for traditional linear programming models. The model can cope with many degrees of input requirements that reflect both exploratory and more advanced stages in schedule development. We present a decision support tool that is flexible to the introduction of novel modelling features and versatile in its applications.

The dynamic programming optimisation framework presented decomposes the schedule planning problem into rotation problems for individual aircraft, for each of which the optimal solution is found. Each rotation is optimised for either maximum profit, minimum cost, or for maximum connectivity. Airline imposed requirements are introduced, which represent a minimum service frequency per route, and a minimum origin-destination capacity that must be offered. This capacity can be offered either direct, connecting through a hub, or on a series of consecutive flights, each with its limitations and requirements. To handle unavailability of demand data, an micro-economical approach is presented to simulate market characteristics.

The model has been applied to three real-life case studies, from an African and South American airline, representing very different operational- and airline imposed requirements for future operations. As no comparison to actual operations could be made, validation has been carried out through the consultation of industry experts and initial solution proposed by the airline. First, results for a cost minimisation case with minimum frequency requirements are presented. These show a high unbalance in aircraft utilisation when no additional flight timing restrictions are posed, revealing the greedy nature of the model. After introducing restrictions that reflect the actions an airline schedule planner could take, a schedule is provided that better represents real operations. Furthermore, results were presented for a case involving a general freight carrier aiming to offer a certain OD capacity. While given priority to direct flights, the models successfully allocates OD capacity to a chain of multiple flight legs when spare aircraft capacity is available. Third, results for a larger case study were presented that show how a standard connectivity maximisation objective can be used to optimse a schedule. Finally, analysis of the computational complexity show that computation time scales linearly in the following three dimensions: the number of aircraft, the number of aircraft types, and the flight legs in the network.

The methodology developed is the first DP optimisation model that is able to capture required dynamic of the schedule planning process and is the first method to fully integrate all schedule planning steps for air cargo operations from scratch. While the results show the model's potential to serve as a decision support tool, opportunities for future work present themselves.

First, further validation is required to quantify the solution quality for a historic planning case, evaluating the solution found by the airline and potentially a related linear programming model. Furthermore, the model's applicability can be enhanced by allowing for the transportation of cargo on a combination of hub connections and series of connecting flights. Finally, better integration of cargo routing in the flight decision process, a forward induction based solution approach such as approximate dynamic programming should be investigated

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Appendix A: Nomenclature

Parameters

a	Airport
a^d	Destination airport of a flight f
a^o	Origin airport of a flight f
A	The number of airports in the network
B	Maximum number of maintenance blocks
$c^{arr}_{n,\theta}$	Arrival cost for aircraft n at time θ
$c^{dep}_{n,\theta}$	Departure cost for aircraft n at time θ
$c^{leg}_{n,i}$	Operating cost for aircraft n for a single flight leg on OD i
$CAP_{n,i}$	Cargo capacity of aircraft n for operating a single flight on OD i
CC^{min}_i	Minimum OD capacity to be transported
D_i	Great circle distance for an OD i
f	A single flight
F	Number of flights
F^{p_i}	Number of flights in a path p_i
$F^{r_{t,n}}$	Number of flights in a rotation $r_{t,n}$
FL^{max}	Maximum number of flights cargo can be transported on
h^{max}_i	Maximum yield in the market for an OD i
h^{min}_i	Minimum yield in the market for an OD i
l	Flight leg
L	Number of unique flight legs
LF_n	Average load factor for aircraft n
M	A very large number
MS_i	Market size parameter for yield on OD i
n	A single aircraft
N	Total number of aircraft added to the fleet
$N^{available}$	Total number of aircraft available
S	Number of states
t	A single time step
T	The number of time steps in the planning horizon
t_0	The first time step in the planning horizon
t^{arr}	Arrival time of a flight f
t^{dep}	Departure time of a flight f
T^m	Number of possible maintenance blocks
T^{res}	Model time resolution in time steps per hour
$T^{flight}_{n,i}$	Flight time for operating a single flight on OD i with aircraft n
T^{TRT}_n	Turnaround time time for aircraft n
T^{taxi}_n	Taxi time for aircraft n

$T^{transit}$	Maximum time cargo can be in transit
$T^{transfer}$	Minimum time cargo requires to be transferred at the base
T^{sep}	Minimum time separation between flight legs operating the same OD
Z_i^{min}	Minimum service frequency requirement for flight leg i
β	Weight of a single unit of cargo
Δt	Time required for an aircraft to be ready again for operations from time t
ϕ	Last number of flights in rotation r
ι	Index parameter for flights
μ	Mean flight movements per hour
θ	Departure time of a flight
τ_i^{from}	Earliest departure time step for a single flight on OD i
τ_i^{to}	Latest arrival time step for a single flight on OD i
τ_n^m	Maintenance time block for aircraft n
ω_i	Market yield curve parameter for OD i

Sets

$\mathcal{A}$	Set of all airports $\{a_1, a_2, ..., A\}$
$\mathcal{A}^{base}$	Subset of $\mathcal{A}$ containing the base airport a_{base}
$\mathcal{A}^{hub}$	Subset of $\mathcal{A}$ containing (the) hub airport(s) a_{hub}
$\{$	Set of all operated flights $\{f_1, f_2, ..., F\}$
$\mathcal{I}$	Set OD combinations $\{i_1, i_2, ..., I\}$
$\mathcal{L}$	Subset of $\mathcal{I}$ containing direct flight legs
$\mathcal{N}$	Set of aircraft $\{n_1, n_2, ..., N+1\}$
$\mathcal{P}$	Set of paths $\{p_1, p_2, ..., P\}$
$\mathcal{P}_{\chi_{\theta,a}}^{feasible}$	Set of feasible paths $\{p_1, p_2, ..., P\}$ under decision $\chi_{\theta,a}$
$\mathcal{R}$	Set of aircraft routings $\{r_1, r_2, ..., R\}$
$\mathcal{S}$	Set of states $\{s_1, s_2, ..., S\}$
$\mathcal{X}$	Set of decisions $\{x_1, x_2, ..., X\}$

Decision related variables

$\chi_{\theta,a}$	Binary decision for airport location a
$\nu_{\theta,p}$	Cargo quantity allocation to path p
$x_{n,t}$	Decision vector

State related variables

y_t	location
$C_t(s_t, x_t)$	Contribution of taking action x when in state s
e	Binary variable to indicate whether the minimum frequency constraint is active or not
$g_{t,n,f}$	Cargo quantity allocation to flight f performed by aircraft n
$h_i(w_{r,\theta,i}, y_{n,\theta,p})$	Yield for OD i, based on cargo capacity allocated $w_{r,\theta,i}$ and $y_{n,\theta,p}$
j	Binary variable to indicate where the minimum OD capacity constraint is active or nor
m_t^{time}	Maintenance time conducted at time t
m_t^{blocks}	Maintenance blocks allocated at time t
p_i	Path with OD corresponding to i
$q_{n,\theta,i}$	Revenue potential of operating a single flight on OD i with aircraft n at time
$r_{t,n}$	Rotation, a sequence of flights f
s_t	State
$u_{n,\theta,i}$	Binary variable that indicates feasibility for operating a single flight on OD i
$w_{t,i}$	Cargo capacity allocated to OD i at time t
$z_{t,i}$	Operated service frequency on flight leg i at time t
Φ	Objective of optimisation model

Others

$\mathcal{S}^{trans}$	State transition function
$V_t(s_t)$	Value of being in state s_t

Appendix B: Algorithms

Algorithm 1 Cargo capacity allocation

procedure 1 INITIALISE VARIABLES:
  Set $CAP^{rem}_{\chi_{\theta,a}} = CAP_{n,i} \cdot LF_n$ ▷ Current aircraft capacity remaining
  Set $CC^{rem}_{i} = max(0, CC^{min}_{i} - w_{t,i})$ ▷ Capacity still required to be offered
  go to procedure: 2

procedure 2 ALLOCATE DIRECT CARGO:
  $\nu_{\theta,p} \leftarrow max(CAP^{rem}_{\chi_{\theta,a}}, CC^{rem}_{i})$ ▷ Allocate cargo capacity
  $CAP^{rem}_{x_{\theta,l}} \leftarrow CAP^{rem}_{x_{\theta,l}} - y_{p_i}$
  $CC^{rem}_{i} \leftarrow CC^{rem}_{i} - y_{p_i}$
  if $CAP^{rem}_{x_{\theta,l}} > 0$ **then**
    go to procedure: 3 or 4 ▷ Choose procedure appropriate to problem

procedure 3 ALLOCATE INDIRECT CARGO ON A SEQUENCE OF FLIGHTS:
  for $p \in \mathcal{P}^{feasible}_{\chi_{\theta,a}}$ where p is ordered such that $\{|p_1| \leq |p_2|\}$ **do**
    $AL_p \leftarrow max(CAP^{rem}_{f,p}, CC^{rem}_{i_p})$ ▷ Allocate cargo capacity to path
    $y_{p_i} \leftarrow y_{p_i} + AL_p$
    $CAP^{rem}_{f} \leftarrow CAP^{rem}_{f} - AL_p \qquad \forall f \in p_i$
    $CC^{rem}_{i} \leftarrow CC^{rem}_{i} - AL_p$

procedure 4 ALLOCATE INDIRECT CARGO WITH TRANSFER:
  let I^{cov} be the itineraries covered by the set of feasible paths $\mathcal{P}^{feasible}_{\chi_{\theta,a}}$
  for $\zeta = \{\beta, 2\beta, ..., CAP^{rem}_{\chi_{\theta,a}}\}$ **do**
    $h^{max}_{i} \leftarrow max(\{(h(w_i + \zeta) : i \in I^{cov}\})$
    $CAP^{rem}_{f} \leftarrow CAP^{rem}_{f} - \beta \qquad \forall f \in p_{i_{h^{max}}}$
    $CC^{rem}_{i} \leftarrow CC^{rem}_{i_{h^{max}}} - \beta$

II

Literature Review

previously graded under AE4020

1 Introduction

The airline industry is characterised by highly complex and costly operations, where planning decisions have a large impact on an airline's profitability. These decisions reflect an optimisation problem that, even for a very small airline, can hardly be solved by hand. Many airlines have used Excel based tools to aid in making (part of) their planning decisions, and some still do today. However, history has proven that dedicated optimisation models for simulating real airline operations have a major impact on an airline's financial performance, both reducing cost and improving revenue.

This literature survey forms the foundation for a MSc. thesis project that follows up on earlier work conducted at the Delft University of Technology. This work involves a strategic model that integrates different stages of the airline planning process, which will be discussed in further detail in section 4.2.3. The project is conducted in collaboration with Airbus, and its goal is to increase real-world applicability of the model. Therefore, a real-world case study on air cargo operations is provided.

The main goal of this report is to provide insight in modelling different stages of the airline planning process for both passenger- and air cargo operations. Going further into detail, it aims to provide the reader an understanding of modelling different aspects of airline operations by discussing the most significant contributions from literature. While doing so, special attention is paid towards the particular optimisation algorithms used and their performance in specific case studies. Furthermore, the work aims to introduce dynamic programming applied this domain as an alternative to the more widely used linear programming and to show its value for integrating multiple stages of the planning process by discussing strengths and limitations. Finally, the reader will be aware of state of the art and current challenges of the research field.

The scope of the project is in part determined by the collaboration with Airbus and earlier work, and the goal posed above. This led to limiting the scope to the tactical stages of the airline planning process. Distinction is made based on the time (gap) between the different stages and the time before actual operations. The most strategic fleet planning stage and the operational crew scheduling stage are therefore considered out of scope. With regard to modelling optimisation problems, the focus lies predominantly on deterministic methods: linear programming and dynamic programming. In terms of application area, modelling passenger operations is the reference due to the large volume of available literature, and air cargo specific models are discussed separately.

The literature collection procedure involved searches over a combination of different axis: by planning stage, by application area (air cargo and passenger operations, and other industries), and by optimisation technique.

The remainder of this work is structured as follows. In Chapter 1, an overview of the airline planning process is given. Chapters 3 and 4 present different modelling approaches, through linear programming and dynamic programming respectively. While Chapters 2 to 4 focus on passenger operations, Chapter 5 considers cargo both in properties and modelling approaches. In Chapter 6, a conclusion of the literature review is drawn and areas for further research are identified. Finally, the structure for the consecutive MSc. thesis project is presented.

2

Planning in the airline industry: an overview

This Chapter has the objective to introduce the reader to the airline planning process. Therefore, an overview of the different planning steps and their interrelations is presented.

2.1. The planning process in the airline industry

Although technological development of aircraft took off from the 50's, it wasn't until the late 70's that the airline industry was economically liberalised through deregulation. This led to an increase in competition, a subsequent drop in ticket prices and ultimately, an explosive passenger growth. This allows for more efficient operation, but requires careful management of operating cost. Next to the high degree of competition, the airline industry is characterised by large capital investments, variable passenger demand and strong safety regulations. These factors all call for a thoughtful planning process to ensure profitable operation.

Ideally, the entire planing process should be considered at once, which is commonly perceived as impossible due to the magnitude of the problem. Therefore the typical airline planning process can be decomposed into three major consecutive stages: fleet planning, route planning and schedule planning, according to Belobaba et al. (2009). Moving closer to the flight departure date, other operational and sales decisions need to be made such as scheduling crew and ticket pricing. The reason for step-wise segregation of the planning process is mainly driven by the difference in time horizon and ability to provide a tractable and realistic solution for the corresponding model. An overview of all steps can be found in 2.1 where the different planning steps are depicted, along with their characteristics in terms of time horizon and decision type - ranging from strategic to tactical. It is important to note that all planning stages are highly interrelated, and often iteration is required to provide a final planning.

2.1.1. Fleet planning

One of the most long-term strategic decisions to made made by an airline is its fleet composition: the number and type of different aircraft in its fleet. As the available aircraft essentially determine the airline's operating capabilities thought-full trade-off is required between technical, financial and other aspects such as environmental, political and trade issues. Main technical, and techno-economical criteria include: capacity, range, fuel consumption, operating cost and maintenance. Fleet commonality, that is having aircraft that are of the same or closely related series, plays a major role in the reduction of crew and maintenance cost due to reduction in training of personnel and total required number of personnel and spare parts in inventory. Some financial criteria include aircraft purchase price and possible discounts, and type of ownership, e.g. lease, that allows for more flexibility in change of aircraft, at a premium. The most challenging part of fleet planning is the inherent uncertainty of having a planning horizon of up to 10 years. Uncertainty in air travel demand and fuel prices are the main sources of uncertainty, and must be taken into account when constructing a robust fleet plan that is suitable for use in most likely future scenario's. In terms of modelling, two approaches are distinguished by Belobaba et al. (2009) which are touched upon here but not discussed in detail any further.

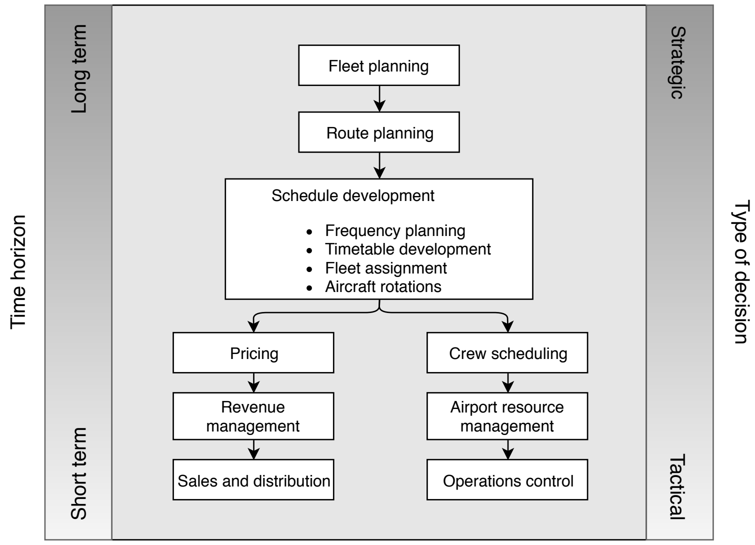


Figure 2.1: The airline planning process. Adaptation from Lohatepanont (2002) as published by Belobaba et al. (2009).

Top-down or macro approach approach
This approach is used for high-level aggregate analysis of (sub-)networks to produce a future fleet plan. It is sometimes formulated in a spreadsheets that incorporate traffic forecasts, aircraft characteristic and estimates of aircraft operating profit, and allows for rapid evaluation. Many different scenario's that emerge by long-term uncertainty in market condition and operating cost (e.g. fuel prices), can be evaluated by (simulation) models.

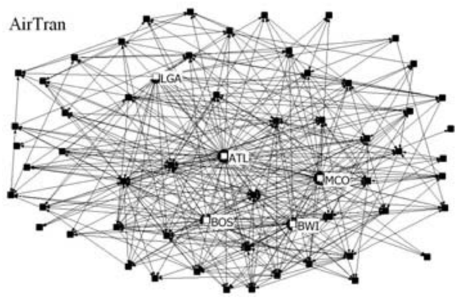
Bottom-up or micro approach
In contrast, the bottom-up approach provides a detailed forecast of future operation and fleet requirements. It requires detailed forecasts of origin-destination market demand, aircraft characteristics, and routes and schedules to provide the operating cost per flight. Furthermore, competition needs to be taken into account, which is very difficult in practise. This approach therefore requires very advanced models and still offers no guarantee for satisfactory results in the future.

2.1.2. Route planning

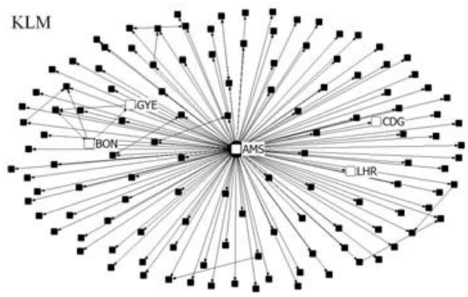
This step determines which routes to be flown, based on demand- and revenue forecasts. Its goal is to identify profitable routes that can be operated by aircraft in the fleet in terms of operating characteristics (e.g. range range and capacity), and forms an important part of the airline's strategy. The ability to make a profit is furthermore highly dependent on competition and network structure. The latter determines how origin-destination (OD) market demand can be served, and can vary with different airline business models. Two network structures, point-to-point and hub-and-spoke, are discussed below and examples shown in Figure 2.2.

Point-to-point network structure
The point-to-point network offers passenger that want to travel from A to B, direct flights from A to B, without connection. Although direct flights have traditionally only profitable on high demand routes, the low cost carrier (LCC) business model has proven that (former) less dense routes can be operated profitably. This can be explained by a drastic reduction in operating cost one one hand, and an increase in travel demand, driven by low fares, on the other.

Hub-and-spoke network structure
The hub-and-spoke network serves many low demand origin-destination city pairs through a connection at a hub. By accumulating passengers on flights from and to a hub, a legacy carrier can operate fewer flights to and from the spokes. If the cost savings from operating fewer flights is greater than the loss in revue incurred by passengers choosing a direct connection, it is favourable to operate a connecting service. In order to ensure low connection times between flights for passenger, aircraft arrive and depart not at a constant rate throughout the day but in 'banks'.



(a) Point-to-point network for US carrier AirTran



(b) Hub-and-spoke network for Dutch carrier KLM

Figure 2.2: Airline network structure examples, Reynolds-feighan (2010)

2.1.3. Schedule planning

The next stage, after selecting which routes to operate, is schedule planning which begins a year or more prior to the departure date. This stage is further subdivided into the following sequential steps of which the first two are also reffed to as *schedule design*:

- **Frequency planning:** The frequency of flights per route per time period (e.g. day or week).
- **Timetable development:** Providing departure and arrival times for each flight.
- **Fleet assignment:** Assigning an aircraft type to each flight.
- **Aircraft routing:** Also known as tail number assignment, it involves flowing an individual aircraft over the network by assigning it to (a series of) flights, often while meeting maintenance requirements.
- **Crew scheduling:** Assigning a specific crew to a series of flights, often split in two sequential steps: crew pairing, and crew rostering.

These steps are all tactical decisions made by an airline and models that aim to optimise these steps have received great attention throughout literature, as shown in Chapters 3 and 4 where the first four steps are covered in detail. Crew scheduling however, will not be discussed further as it is less suitable for integration with the more strategic planning steps. This is due to the fact that the problem is highly constrained by regulations, and has a large disparity in planning horizon. Next steps in the airline planning process such as pricing and revenue management are more operational of nature and are considered out of scope in this literature survey. Both these steps and crew scheduling are covered by Belobaba et al. (2009).

3

Linear programming models

This Chapter covers the most important stages in airline schedule planning that have been identified in the previous Chapter: schedule design, fleet assignment and aircraft routing. It deals with both deterministic and stochastic planning models and their solution methods. These solution methods are either exact or heuristic of nature. In the first section, the first modelling efforts and a number of outstanding literature surveys are discussed. Hereafter, fundamental modelling approaches are presented that address the stages in schedule planning individually, as well as by integration of two or more stages.

3.1. First modelling approaches

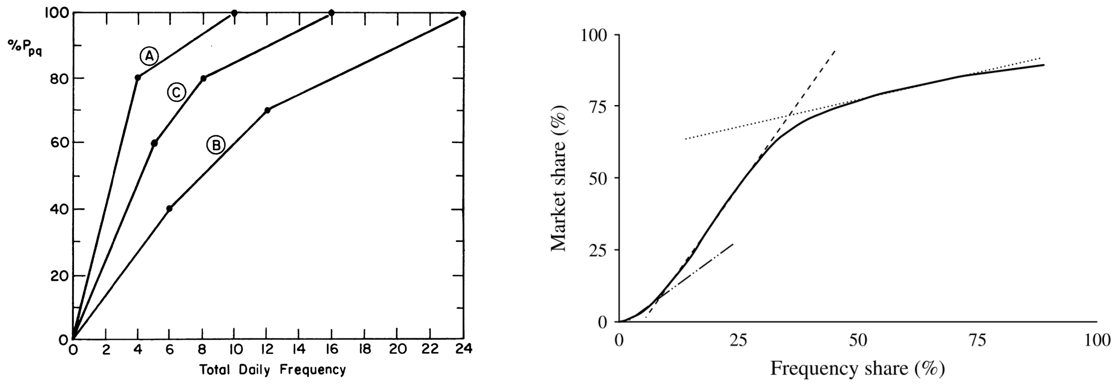
The field of Operations Research has had a longstanding application history in the airline industry. It has been studied by various companies and (academic) research groups ranging from management science to computer science. Similarities amongst airlines have led to the wide application of OR, and early cooperation between airlines to advance the research field. Scheduling of tasks and allocating resources has always been widely studied in other areas within transportation such as busses, shipping vessels and trains, and different domains such as machinery in production. While some literature is available from the 50's, the air traffic that quadrupled in the 60's, ICAO (2013), fuelled the interest in modelling air transportation systems and therefore led to an increase in the amount of papers that were published. Simpson (1969) provides a categorisation of the first modelling approaches and combined different notations of similar formulations for readability.

Ferguson and Dantzig (1954) were the first authors to describe a frequency planning model by using a linear programming formulation. As discussed in Chapter 2, developing a frequency plan is highly intertwined with the fleet planning problem and fleet assignment problem. This holds for Ferguson's work as well, as it assigns aircraft of different types to non-stop routes to meet travel demand. The proposed model serves as a basis of future contributions to the body of literature in the airline industry as well as other fields such as econometrics Markowitz and Manne (1957), and is therefore discussed below.

Ferguson regards a set of non-stop routes between airports with a given daily demand, and a fleet composed of a limited number of aircraft from different types as an input. The primary output of the model is a aircraft type specific frequency plan, on which an initial timetable will be constructed. In terms of objective, the model minimises the direct operating cost (DOC) for a fixed revenue. The objective function features the set of decision variables N_{pqa}, which is the number of flights N between cities p and q with aircraft type a, and is multiplied by an aircraft type specific DOC. The optimal solutions will be the set of decision variables which minimises the objective function, subjected to five constraints: (1) Passenger demand fulfilment, ensures that all travel demand is met. (2) Fleet capacity, limits the number of aircraft used to the number of aircraft that is available. (3) Aircraft balance, conserves the flow of aircraft by setting the amount of daily departures equal to the amount of daily arrivals(4) Minimum frequency, is required because of competitive reasons, traffic generation or management policy. (5) Maximum airport capacity, for airports where capacity quota are present that limit daily activity.

Simpson (1969) provides extensions found in literature that allow for multiple stop-overs, and incorporate competition. Allowing for (multiple) stop-overs was required to more closely capture reality as many flights involved stop-overs for fuel but also for (dis)embarking passengers, resulting in a mix of passenger origins and destination on a single aircraft. This problem is larger in terms of both variables and constraints as it involves a set of arc sequences from cities p to q instead of a single arc. This model assigns aircraft in such way that the load factor is maximised on all legs, which is called "load building". Miller (1963) however argues that only meaningful results are obtained when this problem is formulated as an integer linear program (ILP), where the flight frequency per set of arc sequences is integer. This results in load factors that are below the maximum at some flight segments.

In terms of competition, a minimum frequency is replaced by a more advanced market share curve that relates traffic to daily frequency for each route as shown in an early example in Figure 3.1 (a). Nowadays, a market-frequency share curve is commonly depicted as an S-curve, shown in Figure 3.1 (b). The model's objective is to maximise profit and therefore must include the fare and other possible income (e.g. subsidies from adhering to public service obligations) next to DOC. The success in implementation can stand or fall with the accuracy of the (forecasted) market share model.



(a) (A) long haul routes, (B) short haul routes with competition, (C) short haul routes without competition

(b) S-curve

Figure 3.1: (a) Former market-frequency share curves. (b) Current market-frequency share curve, resp. Simpson (1969), Pita et al. (2013)

3.2. Follow-up research

When considering the problem size for modelling stop-overs that was posed by Simpson (1969) in the previous section, finding a solution would become intractable fast for larger and more complex networks. To reduce problem size, the intermediate stops are divided into mutually exclusive sets, and from each set only a limited number of stops can be incorporated in a route. In general, this is known as the 'Port Linkage Problem'. Etschmaier and Richardson (1972) formulate this as mixed integer linear program (MILP) and opt for a Bender's decomposition solution method.

While some early optimisation methodology has been presented to serve a given network and a corresponding travel demand, Gordon and de Neufville (1973) address the trade-offs that exists in designing the network itself. While their method is based on a model that optimally assigns capacity to a given network, the authors focus on the impact of different aircraft sizes and traffic growth. The guidelines for design state that long haul and dense routes should have higher load factors than short haul and thin routes. In addition, a hub-and-spoke network maximises the overall quality of serve, while a direct network distributes the quality of service more evenly. Pollack (1982) later provides an extension on the trade-off between non-stop and multi-stop routes.

In a literature survey, Etschmaier and Rothstein (1974) praise the progress made in OR within the airline industry, partly enabled by the extensive degree of inter airline cooperation. The authors provide a managerial perspective to the capabilities of OR within the industry at the time, discussed through a functional breakdown of different planning stages. It is noted that 75% of the research focuses on tactical problems, yet a new interest in developing strategic models had commenced.

Magnanti (1981) provides a modelling oriented literature survey, presenting different aspects of vehicle routing and scheduling and their interrelations. According to Magnanti (1981) and Bodin et al. (1983), the majority of research has favoured the development of heuristic algorithms over exact optimisation methods, the latter limited by available computing power. Yet, Magnanti describes some simplifications to the general problem, also made by airlines in reality: (1) Allow vehicles to circulate among service destinations, before returning to a fixed depot. (2) Permit vehicles to visit only the most profiting destinations. (3) Impose a special network structure that limits combinatorial explosiveness of route selection, e.g. a hub-and-spoke network.

Reasons to adopt exact optimisation techniques include performance guarantees, possibility to conduct sensitivity analysis, and when operational profit exceeds computing costs. In subsequent work, Magnanti and Wong (1984) focuses on network design and applicability of solution techniques.

In comprehensive work on routing and scheduling problems, Bodin et al. (1983) provide a classification of different problems by assumptions and inputs, a review of algorithmic techniques and solution methods, and emphasise practical implications of advances in said methodology, illustrated by major applications. While examples from the airline industry are predominantly confined to crew scheduling in the work by Bodin et al. (1983), Etschmaier and Mathaisel (1985) provide a literature survey on flight scheduling.

This work describes the process actually used by airlines at the time, where much calculation work is conducted by computer, yet many decisions and choices are performed by humans. Schedule construction at the time was either step-wise, as discussed before, or direct, adding flights to the schedule one by one. Both required extensive evaluation of the resulting schedule that involve all operations departments of the airline, which is not sustainable for increasing network size. Whereas direct schedule construction had been done in the past by using heuristics to be able to handle the problem size, in 1985 the state of the art was a man-machine interactive environment in which the selection of flights was made by the planner, limiting the set of choices for the computer. The characteristics of an airline such as route- and market structure determine which method yields the best results. The authors conclude that airlines with a large amount of competition and time sensitive demand benefit most from the direct approach.

3.3. Modern models

The rise in computing power in the '90s enabled researchers to solve much larger and more complex problems that were deemed impossible to solve before Bodin et al. (1983), Etschmaier and Rothstein (1974), Magnanti (1981). This resulted in the development of fundamental deterministic models for schedule design, fleet assignment and aircraft routing that are being used today. In search of better representing reality, in the last decade the focus shifted towards to stochastic models that can incorporate uncertainty (e.g. travel demand and competition). In present day literature, the use of deterministics is limited to cases where a new modelling element or solution procedure is adopted. This section discusses literature on different stages of the schedule planning process. Although not discussed here, there is a literature stream that focuses on robust optimisation techniques of which Marla et al. (2018) provides a thorough literature review.

3.3.1. Schedule design

As discussed in the previous Chapter, schedule design is usually decomposed into two sequential steps: (1) frequency planning and (2) timetable development. The purpose of frequency planning is matching supply to anticipated demand for each day or week. In turn, the amount of demand that can be captured depends on the passenger's sensitivity to a higher or lower frequency. Following Belobaba et al. (2009), this sensitivity depends on the type of route (long haul versus short haul), type of passenger (business versus leisure), and competitor's frequency (see Figure 3.1 (a)). The authors provide an example to illustrate this sensitivity, expressed by the schedule displacement: the average difference between a passenger's preferred departure time and the (evenly distributed) departure times over the day. Business passengers are significantly more sensitive to longer schedule displacements compared to leisure passengers, especially on short haul routes. On long haul routes, this sensitivity is lower as the schedule displacements is a smaller portion of the overall trip time.

Next, timetable development is concerned with offering the best departure times, depending on the market, and schedule constraints. Again, business passengers are more demanding when it comes to departure times.

In practice, schedules evolve step-wise over time, period by period, by relatively minor modifications. According to Lohatepanont and Barnhart (2004) this can be explained by the following reasons: (1) Potential unavailability of required data. (2) Operational impracticality due to e.g. limited slot availability and use of connection banks, and high computational effort required or intractability. (3) Frequently changing network structure requires significant investment at airports. (4) Consistency and reliability in offered services, especially for business passengers.

Teodorovic and Krcmar-Nozic (1989) present a method for providing a frequency plan that maximises total profit and passengers flown and minimises total passenger waiting time. This multi-criteria model was a novel contribution that incorporates both passenger and carrier interest while taking into account competition and available fleet. The authors provide a nonlinear integer formulation to the problem, solved rapidly by a heuristic as it is a large combinatorial problem. By applying Monte Carlo simulation, a number of solutions is generated from which the best solution is picked by hand by an experienced schedule designer.

To address the high dimensional nature of timetable optimisation, Berge (1994) discusses an approach that breaks down the network into smaller portions. These sub-networks are defined manually and include candidate flights with different departure times. For each sub-network, the respective timetable is optimised by maximising the number of passengers able to find a path from their origin to destination. Next, the timetable of this sub-network is incorporated in the master timetable and evaluated. These steps are performed iteratively until a satisfactory solution is obtained.

Traditionally, after a draft timetable has been constructed, this timetable is evaluated by performing the next stages in the schedule planning process: fleet assignment and aircraft routing. During these stages operational feasibility is checked, profit maximised, and improvements highlighted. Then, the draft timetable is changed and the process iterates over the two phases until no significant improvements can be made, Etschmaier and Mathaisel (1985).

More recent research efforts have focused on schedule robustness, competition, and the integration of schedule design with fleet assignment. While the impact of competition on designing a schedule is discussed below, the integration of schedule design with fleet assignment is discussed in section 3.3.4. Yan and Tseng (2002) underwrite the need to do so, as employing draft timetables "involves too much subjective judgement and decision making in the process but also reveals an incapability of directly and systematically managing the interrelation between supply and demand".

Providing a robust schedule that can absorb delays, mainly relies on the re-timing of flights during the aircraft routing-, and integrated scheduling and fleet assignment stages of the planning process and will therefore be discussed in sections 3.3.3 and 3.3.4 respectively.

Competition

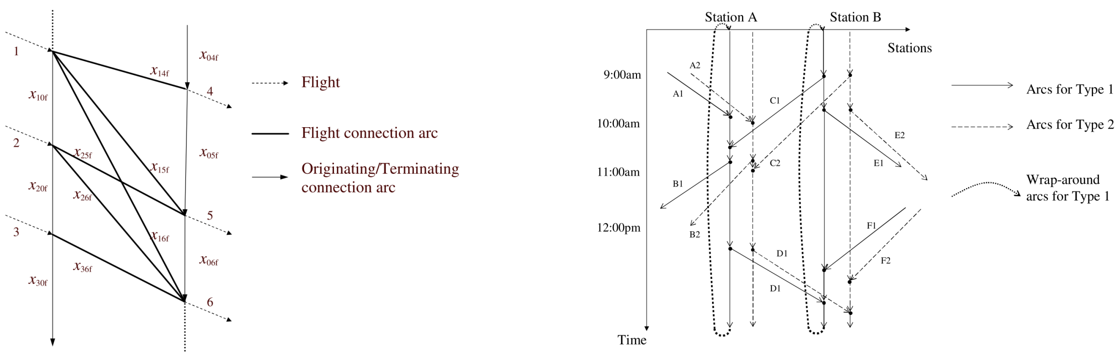
Modelling competition among airlines has received little attention throughout literature due to its complexity, inherent uncertainty and strong causal nature. As a result, most planning models either adopt a fixed demand or basic market share model as input. These include the 'S-curve' as presented in Figure 3.1 (b), and an extension to include weighting factors based other parameters such as number of connections required for an OD itinerary, level of comfort, and airline safety reputation: The quality of service index (QSI), Belobaba et al. (2009).

While the two methods described above provide the required level of detail for devising a long term frequency plan, the ability to capture time-of-day dependent demand and exploit a passenger's willingness to pay can render a schedule profitable. Abdelghany et al. (2017) propose a bi-level optimisation approach that assumes fixed competitors' schedules and a fixed frequency plan of the target airline with a corresponding fleet assignment. In the higher level, the schedule is optimised for maximum profit by discretising given departure windows per flight into smaller intervals, and representing the problem in a time-space network. This optimisation model can also include aircraft routing to ensure that additional operational constraints are met. In the lower level, the market response to the schedules by both the target airline and competitors is evaluated passenger by passenger, according to a passenger choice model originally developed by Yan et al. (2007). This work is further discussed in section 3.3.4. Abdelghany et al. (2017) provide a real validation case on the US market, consisting of 1.75 million served passengers per day. The target airline, which has a 14% market share, offers 3,014 daily flights that serve 61 destinations and 718 city pairs with an average frequency of 4.2 flights per day. The solution, obtained by employing a Genetic algorithm, provides a schedule that underestimates the actual market share by 0.8% points in a time of 15 hours.

Tang and Hsu (2016) consider oligopolic competition with direct flights in a point-to-point network model, where the authors assume that passengers are only sensitive to the departure time. As carriers try to guess each others decisions and respond, departure times vary and prediction is difficult. In contrast to the work by Yan et al. (2007) and Abdelghany et al. (2017), the model proposed by the authors does not rely on competitors' timetable as an input. It features an iterative two-stage approach where in the first stage a time-table for the target airline is determined using the Nash equilibrium, and in the second stage the profitability is evaluated using a basic fleet assignment model. The Nash equilibrium is the solution to a non-cooperative game which can be used under the authors' assumption that all airlines behave rationally and have no desire to change their departure times. A computational study was conducted on a portion of the Taiwanese market that features 1 to 3 competitor airlines on 8 OD pairs between 4 cities. With the target airline offering up to 72 daily flights, a solution time for one month of operations was found on average after 2 hours and 38 minutes with a 2.19% optimality gap. The scope of the work is limited due to the market characteristics and network type, and no further comparison is drawn to actual operations to assess the impact of the solution found.

3.3.2. Fleet assignment

Given a schedule of flights with departure and arrival times, a fare and (OD) demand, fleet assignment determines which aircraft type will covered the scheduled flights. The goal is either to minimise operating cost (OC) or maximise profit and is mostly formulated as a multi-commodity network flow problem.



(a) Connection network

(b) Time-space network

Figure 3.2: Network models for fleet assignment problems, Sherali et al. (2006)

Basic fleet assignment models, introduced by Abara (1989), Hane et al. (1995), minimise operating cost under the following non-trivial constraints: (1) Flight coverage, ensures that each flight is covered by a fleet type, and covered only once. (2) Flow balance, sets the number of arriving aircraft equal to number of departing aircraft. (3) Fleet availability, limits the number of available aircraft of each type. However, the two models differ in underlying network structure and level of detail.

Connection network

The connection network used by Abara (1989), and shown for one airport in Figure 3.2 (a), depicts flights arcs, two types of connection arcs and nodes that represent the arrival or departure time of a flight. The network furthermore features binary decision variables x_{ijf} for fleet type f that indicate if a connection between two flights i and j, or an originating (x_{0jf}) or terminating connection (x_{i0f}) is covered or not. This approach requires that all feasible connections are supplied as an input to ensure a feasible solution, which can dramatically increase problem size to an extend that it is no longer manageable, Sherali et al. (2006).

Time-space network

The time-space network used by Hane et al. (1995), and shown for two different fleet types in Figure 3.2 (b), depicts ground- and flight arcs, wrap-around arcs that guarantee continuity overnight, and nodes that represent a departure- or arrival location and time. The network features binary decision variables x_{fl}, that indicate if flight leg l is covered by fleet type f or not.

The latter of the two network representations is widely used throughout literature as it is more intuitive in capturing the location and temporal nature of fleet assignment while limiting problem size compared to a connection network. Furthermore, the time-space network allows for flight- and turn around times that depend on the aircraft type, in contrast to the connection network. This is especially relevant for making a distinction between short-haul narrow body-, and long-haul wide body aircraft. In an extensive survey on time constrained optimisation, Desrosiers et al. (1995) discuss the use of time-space network and methods for problem size reduction, such as grouping of nodes, in detail. Nodes in a time-space network can be grouped by evaluating them in chronological order. For each flight arrival node with a new flight arrives, a new group is created which includes the subsequent flight departure nodes to ensures that departing flights utilise an aircraft that has already arrived. This can reduce the number of arcs from potentially $O(n^2)$ to (n), next to reducing the number of nodes, depending on the network. A case study by Soumis et al. (1980) illustrates this reduction: the number of arcs have reduced from 1875 to 1050 and the number of nodes from 1250 to 420, grouping them on average by 2.98. Next to size reduction methods, the authors conclude that optimisation algorithms based on the Dantzig-Wolfe decomposition (also known as column generation) are the most powerful solution methods. These techniques will be discussed later in this section, along with a practical case study.

The model developed by Hane et al. (1995) can deal with very large problems due to enhancements in branch-and-bound solution technique, making it two orders of magnitude faster than using default branch-and-bound. These enhancements include fixing the optimal fractional values for decision variables of the interior solution and fixing decision variables with values close to 1, to 1, before the branch-and-bound phase. Furthermore, the branching strategy involves a prioritisation based on the variability of objective function coefficients: the larger the coefficient, the more impact imposing a constraint could have on the objective function.

While the work by Hane et al. (1995) is limited to assigning a fleet type, Rushmeier and Kontogiorgis (1997) also take passenger connectivity into account. The authors utilise a time-space network representation but include rules to formulate subsets of arriving and departing flights. Unlike the heuristic approach by Abara (1989) that selects only the top 5 connections, Rushmeier and Kontogiorgis' approach to handle connectivity is exact. In terms of model performance, the authors state that the addition of connectivity results in possibly exponential growth in solution space. In order to obtain results in a satisfactory computation time, the authors used daily fleet assignments as an initial input to solve for a monthly planning horizon. An integer solution for a real USAir network with 11,480 nodes and 39,475 arcs was obtained after a fixed run time of 2 hours with an optimality gap of 3.6%.

Later work by Barnhart et al. (2002) builds on the model developed by Hane et al. (1995). These authors are the first to offer an itinerary based fleet assignment model that considered the recapture of spilled passengers (passengers that cannot travel on their preferred itinerary) by incorporating a passenger mix model. The objective is to minimise the total fleet assignment costs and spill cost, solved by a row and column generation algorithm. Through a real life case study, consisting of 2.044 flight legs and 9 fleets, a daily profit increase of \$100.000 is achieved mostly by increasing the system load factor. In later work, Barnhart et al. (2009) provide an extension that includes a more realistic revenue function.

Barnhart et al. (2002) are aware of demand uncertainty and distribution within the week, but state that the benefits of modelling network effect outweighs incorporating demand uncertainty and therefore implement a forecasted daily demand. However, in recent work, Boudia et al. (2018) argue that the accumulation of OD demand errors has significant impact on the performance of this approach. As the number of passengers with the same OD itinerary is low, having 3 instead of 5 passengers leads to a 40% deviation of the forecasted demand. The authors propose a method to decrease the sensitivity of individual OD demand forecasts, by grouping itineraries by geographical location. This model is compared to the original itinerary based fleet assignment model by optimising the passenger mix problem for a number of stochastic demand realisation scenario's. For a network on a Saturday consisting of 75 flight legs serving 10,447 passenger (of which 1,545 are connecting), the model showed only significant improvements for high standard deviations. On a similar network on a weekday with a higher percentage of connecting passengers, the fragmentation of itineraries was higher, resulting in a more significant improvement in the objective value with an average of 2%.

When considering the planning horizon, other authors (indirectly) demonstrate that the objective function value for the fleet assignment model can be improved by adopting a weekly planning horizon for both deterministic demand (Bélanger et al. (2006), Pilla et al. (2012; 2008)), and stochastic demand (Dumas et al. (2009)).

3.3.3. Aircraft routing

The final stage under consideration is aircraft (maintenance) routing, or tail number assignment, and concerns assigning individual aircraft to a flight leg. While fleet assignment may include aggregate maintenance constraints, the main goal of aircraft routing is to evenly space maintenance opportunities for each aircraft. Whereas the type and timing of more rigorous maintenance checks (letter checks, ranging from A to D, where A is the lightest and D is the heaviest) depends on the number of flight hours and cycles, the more frequent checks are required both daily and weekly, and take place overnight. The letter checks and weekly checks are conducted at a carriers hub or other maintenance station. It used to be common in the industry to carry out a 'transit check' every 35 to 40 flight hours (Gopalan and Talluri (1998)), resulting in planning horizons of 3 to 4 days. Nowadays, most authors opt for incorporating a weekly planning horizon that covers weekly checks and schedules.

Extensive work by Desaulniers et al. (1998) shows relations between different, more generic time constrained routing models but lacks any computational application. In a literature survey by Gopalan and Talluri (1998), work is presented on a asymmetric travelling salesman problem formulation (Talluri (1998)). Gopalan and Talluri provide a generalised k-day maintenance routing solved by a heuristic algorithm as they state that even a 2 day routing problem can be categorised as NP-complete. The algorithm proposed by the authors relies on fixing a set of daily routings, which are adapted to meet maintenance constraints, and then evaluated to find k-day maintenance routings in polynomial time. While the authors include a small case study, involving 12 aircraft and 12 daily routings, no metrics for determining the optimality of the resulting set of routings, and computation time are presented. In contrast, Clarke et al. (1997) present an exact solution method based on Lagrangian relaxation that adds sub-tour and maintenance constraints when violated. For 11 subsets of a major US carrier's network the model shows mixed results. While some of the sub-network both small (195 arcs and 154 nodes) and large (2,246 arcs and 1,002 nodes) require only 2 and 8 maintenance constraints, 6 out of the 11 sub-networks do not yield a feasible maintenance routing.

Liang et al. (2011) are the first to discuss another approach for aircraft maintenance routing, which is a network flow formulation. This formulation comprises two major differences compared to a time-space network. While the time-space network considers a one-day period for a daily schedule, the network shown in Figure 3.3 uses a D day period in which D is the time between maintenance. Second, instead of time-reversible overnight arcs, maintenance arcs are used that ensure the time between maintenance is limited to D days. Through several real life case studies, this model has been shown to be very compact and scalable and finds an optimal solution considerably faster than the method by Barnhart et al. (1998a).

Similar to schedule design, research on aircraft routing over the past decade has focused on providing robust models. Marla et al. (2018), provide a literature review on robust optimisation with special focus on aircraft routing. The authors furthermore study the application of three types of models: (1) domain-specific, (2) probability distribution-free and, (3) probability distribution based. Although a computational case study as carried out for comparison, the authors conclude that "the efficacy of any given robust approach is determined not by the approach or model alone, but by the interaction between the model, data (including network structure and delay patterns), and evaluation metrics". Further research on the topic is therefore required to better evaluate the models under different scenario's.

In other work, not covered in the review by Marla et al. (2018), Yan and Kung (2018) distinguish two types of robustness: (1) the ability to fix disruptions and delays, and (2) the ability the prevent disruptions and delays. In the first category, Maher et al. (2014) provide a single day routing model that penalises a set of aircraft rotations with insufficient routes terminating at a base for overnight maintenance. As the planning scope is more operational of nature, this model is not discussed further. In the second category, Yan and Kung (2018) provide a model to minimise the maximum possible total propagated delay, instead of the expected propagated delay proposed by lan et al. (2006). For an arbitrary flight, a delay can have two components: (1) independent delay, only depending on that flight, and (2) propagated delay, which is a the impact of earlier delays on that flight and therefore dependent on the routing. Both are modelled as a stochastic variable, usually based on a historic distribution. The authors demonstrate the capabilities of their row- and column generation solution approach on a real network that involves 106 daily flights and 24 aircraft. The optimal solution was found in 10 minutes and showed a 47% decrease in average total propagated delay to 490.2 minutes, and a 48% decrease in maximum propagated delay to 2,658 minutes. Compared to another stochastic propagated delay model from literature (Dunbar et al. (2014), the reductions were 15% and 18%.

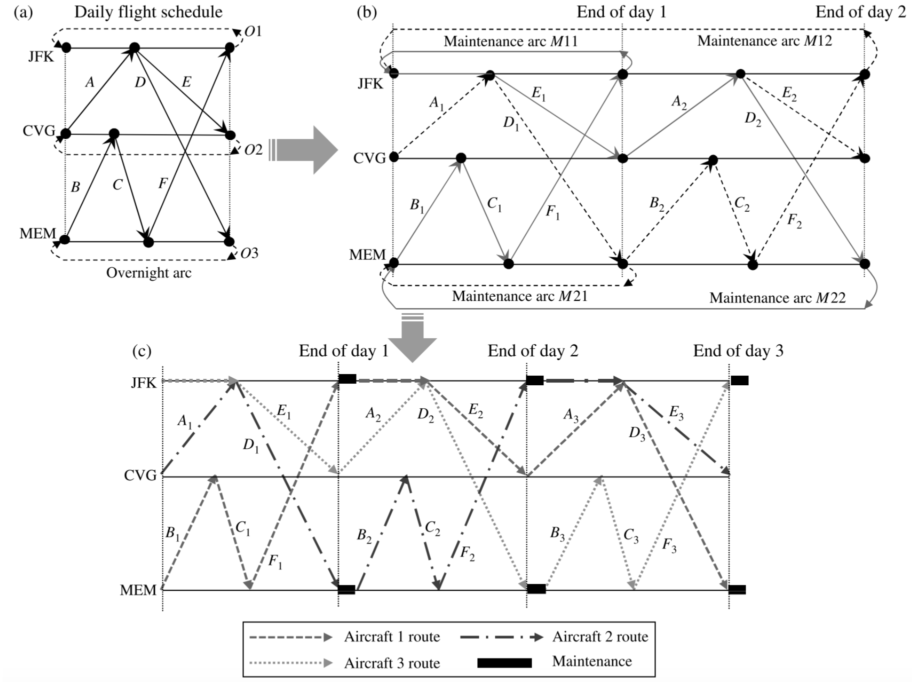


Figure 3.3: Transformation of a daily flight schedule to a network flow maintenance routing with two day maintenance requirement, Liang et al. (2011)

Later work by Ben Ahmed et al. (2017a) demonstrates a hybrid optimisation-simulation method for robust aircraft routing and the re-timing of flights that maximises the aircraft on time performance, minimises the total delay, and minimises the number of delayed passengers while adhering to maintenance. The two-stage process consists of a mixed-integer optimisation model and a Monte Carlo simulation. The former provides routings that meet maintenance constraints, and the latter iteratively adjusts flight departure times based on randomly generated primary delays. In a case study that consist of 3,387 flights and 164 aircraft, the authors present the following comparison to actual airline operations. The on-time performance increased by 9.8–16.0%, the cumulative delay was reduced by 25.4–33.1%, and the number of delayed passengers was reduced by 8.2–51.6%. Although the authors state that computation time is reasonable, for this case study a relaxation heuristic to decompose the problem into smaller sub-problems was required.

Aircraft routing has historically been often combined with fleet assignment as discussed next, and crew scheduling which is considered out of scope for this survey. As details of crew scheduling are not discussed into detail further, Eltoukhy et al. (2017) present an overview of relevant modelling efforts in their literature review.

3.3.4. Integrated approach

Solving one sub-problem of the scheduling process at the time may not lead to an optimal solution of overall problem. In fact, a solution to a sub-problem may not even yield a feasible solution to the consecutive sub-problem. Due to the ability to solve huge integer programming models in the mid 90's, it became possible to meaningfully integrate different steps in the planning process, pioneered by Barnhart et al. (1998a).

On a note, a variety of authors propose heuristics for the integrating of fleet assignment and/or aircraft routing with crew pairing (e.g. Cacchiani and Salazar-González (2013), Cordeau et al. (2001), Mercier and Soumis (2007), Mercier et al. (2005), of which Cacchiani and Salazar-González (2017) provides an overview).

Flight scheduling and fleet assignment

There has been a significant stream of research that focuses on the integration of flight scheduling and fleet assignment as it simultaneously considers both supply and demand as discussed in section 3.3.1.

In this context, Yan and Young (1996) provide a decision support framework to deal with future demand fluctuation, based on a basic multi-fleet time-space network formulation. From this purpose, 3 strategies are modelled: (1) aircraft rental, (2) deletion of multi-stop flight legs, (3) adjustment of flight departure times. The latter is incorporated by adding alternate flight arcs in the time-space representation as shown in Figure 3.4. A Lagrangian based heuristic is proposed to solve the resulting multi-commodity network flow problem.

This paper is later extended by the same author, all featuring case studies on Taiwanese airlines, solved by heuristics. Yan and Tseng (2002) integrate flight scheduling and fleet assignment under a given passenger origin-destination demand. Yan and Chen (2007) discuss a coordinated model under alliance, while Yan et al. (2007) incorporate competition. The latter introduces a passenger choice model that capture major factors in choice behaviour that include frequency, fare, and waiting time.

Finally, Yan et al. (2008) feature a fleet assignment and scheduling model under stochastic passenger and variable market share, for the first time to the author's knowledge. The authors propose both an arc-based and route-based formulation to minimise operating cost, solved by heuristics. Both approaches rely on generating a number of market demand scenario's, according to a demand distribution as seen in real operations. For each deterministic scenario, a solution is found by iteratively adjusting the market share according to a passenger choice model, in a similar manner as the model by Barnhart et al. (2002). The solution found for each deterministic scenario is within a maximum of 5.77% of the optimal solution. The arc-based heuristic utilises the profit and number of occurrences over the different scenario's to select a flight, fixing one or a number of flights at a time. The route-based heuristic iteratively selects routes that best absorb stochastic demand variations. While the arc-based heuristic yields a 0.55% better objective function value than the route-based heuristic, compared to adopting a deterministic market share, both approaches show a significant improvement. However, as the problems are considered to be very hard, a number of very small case study is used that considers a single fleet with 160 flights within one month.

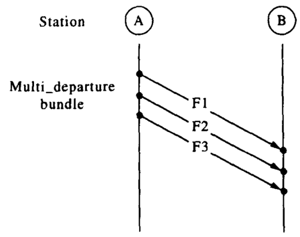


Figure 3.4: Network modifications for a departure time shift, Yan and Young (1996)

In his comprehensive Ph.D. thesis, Lohatepanont (2002) provides a different integration approach and is built upon the itinerary based fleet assignment model by Barnhart et al. (2002). It relies on the schedule from the previous season, extended by a set of optional flights, for composing a master flight list to serve as an input. The author furthermore describes a model to generate a list of potential new flights.

Two variations of the integration model are proposed, which address both constant market share, and variable market share. The latter is simultaneously updated when changes are made to the schedule. The solution procedure is similar to the one by Barnhart et al. (2002), and a testing methodology provided, as shown in Figure 3.5. It can be concluded that a planner is directly compared to the integrated model. Following this methodology, the model shows daily profit improvements with upper bounds of $400,000 for full-size problems.

Pita et al. (2013) propose an extension that takes passenger delay cost into consideration under airport congestion. This is a robust approach, involving slot-constraints and cooperation between airlines. The model is tested by a case study involving Portuguese carrier TAP.

Sherali et al. (2010) also provide an itinerary based integration that can capture demand for multiple fare classes. Their model is formulated as a mixed integer linear programming problem (MILP) for which two solution approaches are provided: One solves a relaxed model directly, the second applies Bender's decomposition. The latter provides the best results and can be further augmented with a heuristic developed by the authors to deal with large scale problems.

In a later extensions, Sherali et al. (2013) include flexibility of departure time and allow for recapture of spilled passengers. In a United Airlines case study, the authors claim an annual revenue increase of $30 million by choosing an integrated approach over a sequential approach.

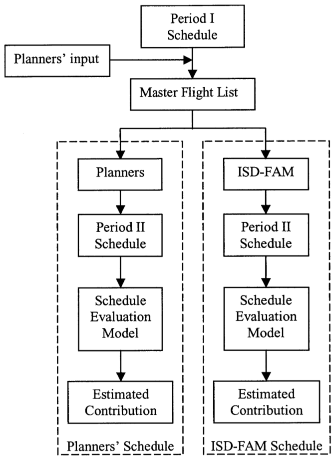


Figure 3.5: Testing methodology for integrated flight scheduling and fleet assignment, Lohatepanont (2002)

Another interesting dynamic re-optimisation approach is proposed by Jiang and Barnhart (2009) that is suitable for tactical to operational decision making. The authors make use of increased accuracy in forecasting stochastic passenger demand for a particular flight, as the departure date approaches. This increased accuracy is achieved by both existing bookings an improved traffic forecasts. Furthermore, the paper discusses trends and opportunities in depeaking hub-and-spoke networks.

Recent work by Kenan et al. (2018) focuses on incorporating demand uncertainty into the integrated flight scheduling and fleet assignment problem through a two-stage stochastic model, for which the stages separated by a time gap in the planning horizon. In the first stage, a aircraft family is assigned to both mandatory and optional flights, while in the second, later stage the exact fleet type assigned. This allows for assigning the aircraft family specific cockpit- and (majority of) cabin crew, while allowing for flexibility in assigning capacity through a specific fleet type. However, the authors do not realise that aircraft rotation is highly intertwined with crew scheduling, which they only mention briefly to include as a future extension.

The authors' contribution is therefore mainly limited to the solution approach used for incorporating stochastic demand. A sample average approximation is used to sample a random subset of all demand scenario's, for which the average objective function is maximised. While increasing the sample size will approach the exact optimal solution, drawing different samples of the same size can be more efficient in providing a near-optimal solution.

A case study is presented which involves 228 flight legs, 45 cities, and a fleet of 59 aircraft divided into 3 aircraft families and 5 fleet types. With 10 samples, each consisting of 100 scenario's, a solution with an optimality gap within 1% can be found in 32 minutes. The authors conclude with a sensitivity analysis for varying sample size and standard deviation of the demand.

With regard to robustness, Cadarso and Marín (2013) provide a passenger oriented approach that optimises a flight schedule and fleet assignment for hub-and-spoke operations. It aims to find a balance between the cost of missed connections due to various stochastic passenger delays (e.g. flight delays, security checks, and terminal congestion), and low aircraft utilisation and passenger dissatisfaction due to long waiting times. The expected probability of an OD passenger that misses the connection is represented by an exponential distribution, providing a deterministic input to the optimisation problem. Furthermore, the objective function is a profit maximisation and the model considers both mandatory and optional flights. A case study is presented, involving a hub-and-spoke network from Spanish carrier Iberia which consists of 23 airports and is served by 3 fleet types. The authors demonstrate the trade-off described above in practice. If aircraft utilisation is to remain high, fewer passengers are served by the robust schedule. If utilisation is reduced, the total number of passengers that is served increases, yet requires more aircraft to provide sufficient capacity.

Fleet assignment and routing

Integrating fleet assignment and routing was a logical step, according to Barnhart et al. (1998a), as then state of the art fleet assignment models by e.g. Hane et al. (1995) did not consider individual aircraft. Solutions found for the fleet assignment problem therefore did not not necessarily lead to a feasible solutions to the aircraft routing problem. This can be explained by the need to implement aggregate maintenance requirements for the entire fleet, possibly causing an unequal distribution of maintenance opportunities. Barnhart et al. propose a string-based model, in which a string is defined as "a sequence of connected flights that begins and ends at (possibly different) maintenance stations, satisfies flow balance". It is connected with a branch-and-price-and-cut solution approach in which both maintenance constraints and through revenues are modelled, so meeting maintenance criteria is guaranteed.

A case study is conducted on a long-haul operation, traditionally associated with little possibilities for maintenance, with a weekly schedule of 1,124 flights, 40 cities and with 90 fleet types which contain a total of 89 aircraft. An integer solution within 1.52% of the LP lower bound was found after 5.5 hours, acceptable for a planning model.

An additional short-haul case study imposes equal wear and tear requirements across the entire fleet. For 190 weekly flights, 6,244 connections, and potentially 500 possible strings, the model provides an optimised solution in 10 hours, which is again acceptable.

In later work, Sarac et al. (2006) extend this problem by involving more operational and resource availability constraints, focusing more on short term planning. As this scope requires fast solution time, the authors aim to improve the branch-and-price algorithm by focusing on the branching technique, column generation, and the stopping rule. The branching technique gives priority to flight legs covered by the aircraft with the least remaining flight hours before maintenance. The same prioritisation is used for adding routes in the column generation routine. The authors test their enhancements on the network of a US airline, featuring 175 daily flight legs operated by 32 aircraft between a total of 19 cities. For this problem, the model finds a solution within 1% of the optimum in 22 minutes.

In pursuit of the same goal as Barnhart et al. (1998a), Liang and Chaovalitwongse (2013) provide an extension to Liang et al. (2011) by means of integrating fleet assignment and maintenance routing. The extension involves the addition of a 'fleet' parameter and aims to maximise fleet assignment profit, neglecting the comparably small maintenance routing cost. Simultaneously, a planning horizon of one week is adopted. For a case study involving 1,006 flights, 62 aircraft and 4 fleets, an optimal solution is found after just 32 seconds. The solution time rises quickly as the number of fleets increases. The authors therefore propose an iterative heuristic that fixes decision variables based on their values in the relaxed solution, similar to the model developed by Hane et al. (1995). A test case, consisting of 1,032 flights, 62 aircraft and 8 fleets, is solved within 0.04% of the optimum in just over two hours, compared to 4 hours for the exact method.

Finally, Haouari et al. (2011) provide a Bender's decomposition solution approach to the integrated fleet assignment and maintenance routing problem. Despite being outperformed by branch-and-price in objective function value, their approach yields high quality solutions in a considerably shorter time. This is demonstrated by a case study on a real TunisAir network consisting of 1,050 flights, 34 aircraft and 8 fleets. While the branch-and-price algorithm yields the optimal solution in 67 minutes, the Bender's decomposition approach is 0.86% of the optimum in just 59 seconds. Next to that, the authors demonstrate the benefit of integrating different planning steps through a numerical study. After modifying the fleet assignment algorithm to ensure feasible rotations could be found, the cost savings of integration amount to 2.07% for this case study. All other case studies performed by the authors also show a cost saving which percentually reduced as the network becomes larger.

Multiple planning stages

As interest in integration of multiple planning stages continues to grow, recent literature has focused on joining schedule design, fleet planning, and aircraft routing.

Within this scope, Gürkan et al. (2016) propose a new method to reduce missed passenger connections through schedule robustness: cruise speed control. While the profit maximisation approach is similar to that by Cadarso and Marín (2013) described earlier in this section, fuel cost and CO_2 emission costs are incorporated in the objective function. These two parameters are influenced by an additional cruise speed (i.e. flight time) decision variable for each each flight and aircraft (type). As fuel cost are non-linear, a second order cone programming algorithm is used, which is not described into detail. Computational results on a published airline schedule consisting of 114 flights are presented, and show a 9% decrease in total cost compared to the same integrated approach without cruise speed control.

In an adaptation by Şafak et al. (2018), the authors present a novel three-stage stochastic model to take both uncertainty in travel demand and delay (non-cruise times) into account with a cost minimisation objective. The decision structure is shown in Figure 3.6. As multi-stage stochastic optimisation models are characterised by rapidly expanding scenario trees, a "scenario group-wise decomposition algorithm" is employed to reduce computation time.

Computational results show a 2.04% average cost saving compared to adding a 30 minute buffer time to each flight. Furthermore, the three-stage model yields an average cost-saving of 2.97%. In terms of computation time, the non-linearity in fuel cost attributes to a long total run time of 19 hours within an optimality gap of 7%. The case study involves a real US network consisting of 114 flights covered by 31 aircraft.

Another method to achieve schedule robustness is accounting for variations in flight time, as discussed earlier in this section. Jamili (2017) proposes a hybrid particle swarm optimisation - simulated annealing heuristic algorithm for integrated scheduling, fleet assignment, and aircraft routing. Although the author demonstrates that the hybrid algorithm outperforms simulated annealing alone in randomly generated scenario's, no case study is presented.

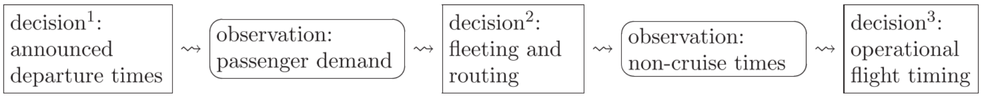


Figure 3.6: Decision logic for a three-stage stochastic optimisation model that accounts for uncertainty in travel demand and delay, Şafak et al. (2018)

Next to the further integration of above mentioned planning stages, crew planning has been subject to integration as well. The crew planning problem itself will not be addressed in detail here, yet its integrated modelling approaches will be briefly discussed. The following work present optimisation methods on the topic, that boast commonly applied solution methods (e.g. row- and column generation) to solve linear programming models. While Salazar-González (2014) adopt an approach that decomposes the problem into smaller sub-problems, suitable for regional airline networks, Shao et al. (2017a) provide a two-phase solution method. In the first phase, the fleet assignment and aircraft routing problem, and the crew planning problem are solved sequentially. This yields cuts in the solution space of the integrated problem in the second phase, reducing computation time for the integrated model by a factor 5.46 for a 676 flight daily network.

Ruther et al. (2017) provide a more operational optimisation approach that incorporates an aircraft's specific maintenance requirements. While this does not fit a strategic or tactical planning scope, the authors furthermore propose a strategy to deal with a large number of pricing problems, generated by the column generation routine. By combining aggregated pricing problems with solving a subset of pricing problems during each iteration, a computation time reduction of 25.6% was achieved compared to a standard approach. The optimality however was compromised, deviating 1.17% from this standard approach.

3.4. Summary

The field of Operations Research has had a longstanding application history in the airline industry. While some literature is available from the 50's, the air traffic that quadrupled in the 60's, ICAO (2013), fuelled the interest in modelling air transport systems. The models developed follow the segregation similar to the different stages in the planning process due the availability of information that evolves over time, and the need to capture operational details.

While in the early 80's, the state of the art was a human-machine interface, the rise of computing power in the 90's allowed for solving much larger and complex optimisation problems. At that time, fundamental models for schedule design, fleet assignment and aircraft routing were developed by Berge (1994), Hane et al. (1995) and Clarke et al. (1997), respectively. These models were capable of providing a near optimal solution for full scale airline networks within reasonable computation time due to advances in solution methods of mixed integer linear problems, such as the column generation algorithm.

The need to better represent reality by integrating different stages of the planning problem became apparent, as solving one stage at a time did not always lead to an optimal, or even feasible, solution of the overall problem. Integrated methods became numerous in the 2000's and mainly involved a combination of schedule design and fleet assignment, and fleet assignment and aircraft routing. While the former are a logical step due to optimise profit trough the simultaneous consideration of supply and demand, the latter ensures a feasible solution for the (maintenance) routing problem.

Later work by Haouari et al. (2011) validates this need by demonstrating that an integrated fleet assignment and aircraft routing approach yields cost savings of 2% compared to a sequential approach.

Simultaneously, the integration of planning stages increased model complexity and therefore the need for improved (near) optimal solution methods. A row- and column generation algorithm applied by Barnhart et al. (1998b) still forms the foundation to a large portion of recent literature. Furthermore, several efforts have been made to improve branching strategies in a branch-and-price algorithm, and to apply a Bender's decomposition. Although dependent of the problem type, the Bender's decomposition provides is able to produce faster near optimal results than the branch-and-price algorithm for an integrated fleet assignment and aircraft routing problem.

In terms of operations, both both point-to-point and hub-and-spoke network structures have been well covered, including the effects of connecting passenger itineraries on different stages of the planning process.

The current state of the art when it comes to deterministic integration involves three planning stages: either from schedule design to aircraft (maintenance) rotation or fleet assignment to crew planning. The integration of schedule design has virtually exclusively been covered by incremental changes, taking a base schedule with proposed time shifts and optional flights as an input, and not by building a schedule from the ground up. Incorporating crew planning has therefore received most attention, for which Shao et al. (2017b) provide a promising two-phase solution techniques which is able to deal with a large number of constraints. A weekly planning horizon is only applied to the latter.

Next to the ongoing effort to integrate three planning stages, the last decade is characterised by the shift in research interest towards providing robust models to deal with uncertainty. While demand has been modelled quite basically due to the degree of uncertainty long before a flight, a recent effort has been made to include demand scenario's in a fleet assignment model, showing an increase in profit of 2%. More work has focused on stochastic (propagated) flight delays, in conjunction with (integrated) aircraft routing. Goals include the reduction of missed passenger connections and allowing for sufficient routings that end a maintenance station. The re-timing of flights plays a major role in developing a corresponding robust model. Finally, a three-stage stochastic model by Şafak et al. (2018) incorporates uncertainty of both demand and flight delay by an integrated scheduling, fleet assignment, and aircraft routing approach with a solution time of 19 hours for a small case study.

Competition is scarcely covered by literature, and when covered it often relies on a basic function of flight frequency extended by weight factors for a particular route. Efforts made to incorporate competition include the timing of flights in a schedule throughout the day, and modelling oligopolic competition as a two-stage game.

Following this summary, area's for research include competition between multiple airlines, modelling uncertainty in demand, further incorporating cruise speed controls, and reduction of computation time for to be developed fully integrated scheduling methods while keeping a high level of detail.

With regard to these gaps, dynamic programming can deal with fully integrated planning schedule planning problems with a high degree of detail in low computation time when formulated cleverly. The next chapter will go into detail on dynamic programming and its use within the airline industry.

4

Dynamic programming

Although its use is far less wide-spread in the airline industry than that of linear programming, dynamic programming has proven to be a powerful optimisation technique. Its application areas are numerous, but predominantly include transportation, energy and finance, or any other areas which involve the management of physical, financial, or informational sources. This Chapter starts with an introduction to dynamic programming in which its working principle and characteristics are briefly presented. Next, dynamic programming models relevant to schedule planning are discussed, with application in the airline industry as well as other domains.

4.1. Introduction to dynamic programming

Opposed to linear programming, dynamic programming does not offer one mathematical formulation and must therefore be viewed as an approach, or framework. It relies on breaking down a problem into smaller sub-problems with the goal of reducing overall complexity, and more importantly computation time. These sub-problems are solved sequentially by making a series of optimal decision based on the information available at each point in time, ultimately providing the optimal combination of decisions. Hence, dynamic programming is a multi-stage optimisation procedure which can furthermore deal with non-linearity and uncertainty.

Characteristics

Due to the lack of a general mathematical solution, each individual problem requires a tailored dynamic programming formulation. However, Powell (2011) describes the elements that each formulation must, at a minimum, include and are therefore listed below with an adaptation in notation for readability. From the initial stage 1, the system advances to the next stage n to the final stage N.

- **State variable** $(S_1,...,S_n,...,S_N)$: For each stage captures all information required to make a decision and tracks how the system evolves over the stages $(1,...,N)$.
- **Decisions variable** $(x_1,...,x_n,...,x_N)$: Tracks what decisions are made to evolve from one state to the next.
- **Exogenous information** (e.g. $p_1,...,p_n,...,p_N$): Information that first becomes known at stage n, e.g. the demand or price for a product.
- **Contribution function** $C_n(S_n,x_n)$: This function may depend on the current state S_n, decision to be made x_n, exogenous information p_n or on what happens at stage $n+1$. It provides the contribution to the objective function.
- **Transition function** $S^T(S_n,x_n)$: This function determines how the system evolves from state S_n to its output S_{n+1}, given decision x_n.
- **Objective function** min or- $\max\limits_{(x_n)_{n=1}^{N}} \sum_{n=1}^{N} C_n(S_n,x_n)$: Specifies the minimisation or maximisation of contributions made for the stages 0 to N.

From this formulation above, Bellman's optimality equation can be written as shown in equation (4.1), where the function $V_{n+1}(S_{n+1)}$ represents the value of being in state S_{n+1}. As this represents a future value, it may be discounted by a factor γ. The value function for the current stage is maximised by making optimal decision x_n from the set of possible decisions X_n. As both the supply of exogenous information and transition function may be stochastic, the expression utilises the expected value of the value function at stage $n+1$, when given S_n.

$$V_n(S_n) = \max_{(x_n \in X_t)} (C_n(S_n, a_n) + \gamma \mathbb{E}[(V_{n+1}(S_{n+1})|S_n]) \tag{4.1}$$

In terms of limitations, Powell (2011) discusses the three so called 'curses of dimensionality', which need to be dealt with cleverly to provide tractable solutions:

- **State space:** If state variable $S_n = (S_{n1}, ..., S_{ni}, ..., S_{nI})$ has I dimensions, and S_{ni} each can take on L possible values, we have L^I states for each stage n.
- **Outcome space:** If the random variable $W_n = (W_{n1}, ..., W_{nj}, ..., W_{nJ})$ has J dimension and W_{nj} each can take on M possible outcomes, we have M^J outcomes for each stage n.
- **Action space:** If the decision vector $x_n = (x_{n1}, ..., x_{nk}, ..., x_{nK})$ has K dimension and c_{nk} each can take on Z possible outcomes, we have Z^K outcomes for each stage n.

To illustrate how fast providing a solution can become intractable, consider the following example for a blood inventory management problem, Powell (2011). As 8 different blood types exist, and both supply R and demand D are considered, for each week (stage n) the state variable is $S_t = (R_t, D_t)$. Each week, both supply and demand are random variables $W_t = (\hat{R}_t, \hat{D}_t)$. The decision vector x_t represents the feasible blood donations and has 27 dimension. Both S_t and W_t have 16 dimensions. With an inventory of 100 of units of blood of any type, the state space has 100^{16} states. When up to 20 units of blood are donated or needed, the outcome space has 20^{16} outcomes. The solution is therefore completely intractable.

Further reference

While Hillier and Lieberman (2015) provide a further introduction to both deterministic and probabilistic dynamic programming by using illustrative examples and exercises, additional literature is recommended. Sniedovich (2010) offers a more in depth break-down of the topics and pays attention to its methodology and mathematical principles, making it great for use as a reference. Finally, work by Lew and Mauch (2007) can be used for consulting a large set of discrete dynamic programming applications written in both mathematical formulation and in pseudo-code.

4.2. Dynamic programming models in the airline industry

4.2.1. Early modelling approaches

Early application of dynamic programming in the airline industry focused on schedule design and vehicle routing. In the schedule construction process, Ward (1966) provides a so called 'aircraft dispatching model' that produced an initial timetable on a route by route basis, without regarding any network considerations. Both non-stop routes as multi-stop routes are considered. In a literature survey, Simpson (1969) distinguishes three different optimisation goals of the dispatching model: (1) minimise passenger delay, (2) minimise 'social cost', the weighted sum of operating a dispatch and passenger waiting time, (3) maximisation of revenue. In all variations, a deterministic time of day dependent demand distribution $P_{pq}(t)$ for the route p to q is used as input. As an illustrative example, the formulation for a multi-stop minimum social cost model is presented here and its usability discussed.

Figure 4.1 shows the 3 'stations' A, B, and C, with different dispatch routes (arcs) between the stations. The stage variable t represents time. Figure 4.2, shows possible decisions to be made at each stage, either 'dispatch' or 'no dispatch', for a simplified network that only considers service AB. The arcs in bold represent the decisions made and show the contribution made towards the next state while not exceeding the aircraft capacity. When returning to the multi-stop problem, Figure 4.3 shows an arbitrary three dimensional state space diagram with some possible dispatch arcs, that can satisfy more than one demand. The collection of state variables $y(y_1, y_2, y_3)$ is a vector that represents the number of passengers waiting for service AC, BC, and AB respectively. The combinations of possible states are denoted in the figure by dots, while the dispatch

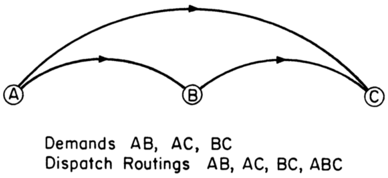


Figure 4.1: Multi-stop routing, Simpson (1969)

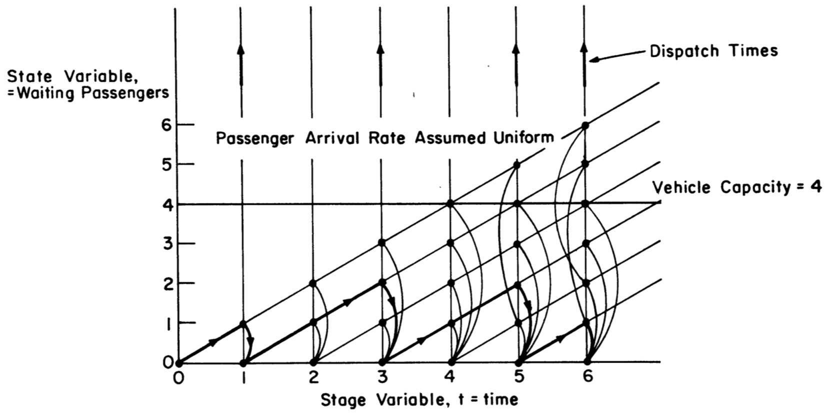


Figure 4.2: Dispatching network, Simpson (1969)

arcs relate the state before a decision to the outcome of that decision. From the figure, one can understand how the dimensionality of the problem grows by including another route, i.e. state variable.

Using Equation (4.2) the number of dispatch routings r for an m stop route can be calculated, which increases exponentially with m, like one would suspect from the figure. Solving an extended problem becomes intractable very rapidly, and even a single stop routing was beyond the computational power available at the time.

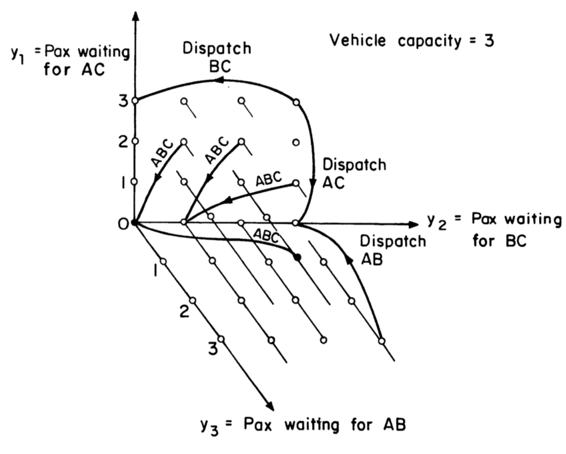


Figure 4.3: Multi-stop state space dispatching network, Simpson (1969)

$$r = \sum_{p=1}^{m} \frac{(p+2)(p+1)}{2} \tag{4.2}$$

While following the same principle for scheduling single, non-stop flights according to the passenger travel demand, Hyman and Gordon (1968) provide a more detailed and practical model. Its objective is to provide a schedule that makes a trade-off between load factor and frequency that maximises earnings, while constrained by competition, regulations, equipment and public image. Starting with the travel demand function, Hyman and Gordon are the first to use data from a passenger time-of-day preference survey to produce a combined route preference function for each route, aircraft type, and day of the week. The curve, of which an example is provided in Figure 4.4, represents a bi-model distribution of the passenger preference. An attraction band around a departure time (here: 9.30 a.m.) determines the amount of passengers that can be captured by that flight, and is shaded in the figure. The authors also provide a small case study, which is not compared to real airline operations.

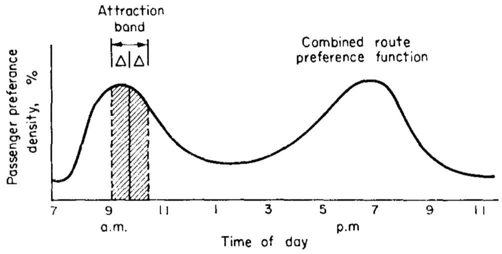


Figure 4.4: Time of day combined route preference function, Hyman and Gordon (1968)

Furthermore, an extension can be made to include competitive services, by incorporating a market share traffic model. However, Simpson is critical towards the usability of dispatching models, despite some real world applications, as it requires accurate analytical traffic- and market share forecasting models that reflect reality.

Follow up research

In the later paper by Hersh (1974), a significant effort is made to deal with the two most important aspects that are neglected by Hyman and Gordon, namely: 1) The interactive effects of multiple flights within an attraction band wherein passengers are confronted with the entire flight schedule (including those of competitor airlines) at once, allowing for choice in routing, and 2) The effects of adding multiple stops whereby each aircraft carries a mix of passengers from various points of departure to a set of various destinations. Hersh proposes a heuristic procedure that allocates both aircraft and passengers, the latter according to their routing preference (e.g. non-stop over single stop), and is distinguished in four major stages:

1. Generation of feasible routes.
2. Sequential assignment of aircraft routings.
3. Passenger assignment and evaluation of the networks.
4. Sequential reassignment of routings to achieve improved performance.

Stage 1 is performed once, and serves as an input to the remainder of the model. Steps 2 and 3 are used to find an initial solution, after which the procedure runs iteratively over these stages, aiming to improve the heuristic solution. While steps 1 and 2 have been covered by Hyman and Gordon, adding an aircraft at the second pass of stage 2 might cause the overall solution to become sub-optimal. This calls for re-optimisation, and potential re-allocation of passengers. For the allocation of passengers, a detailed overview is presented in Figure 4.5.

Finally, after the scheduling of the last aircraft, stage 4 removes the least profitable aircraft, passengers are reallocated, the removed aircraft is reallocated, passengers are again reallocated, etc. This process stops after no significant improvement in profit is made. The subject of periodicity in schedules is briefly touched upon and gives basic methodology on how to link daily route cycles into a weekly schedule. This is required as it guarantees that the number of aircraft at each station is equal for both the beginning and end of the week.

Hersh provides a sample problem in his work that involves the routing of 10 aircraft between 6 stations. The results show a 10 to 20% increase in profit after 7 to 10 iterations. For this sample problem, the run time was limited to a couple of minutes at the time, which will be reduced significant with today's computing

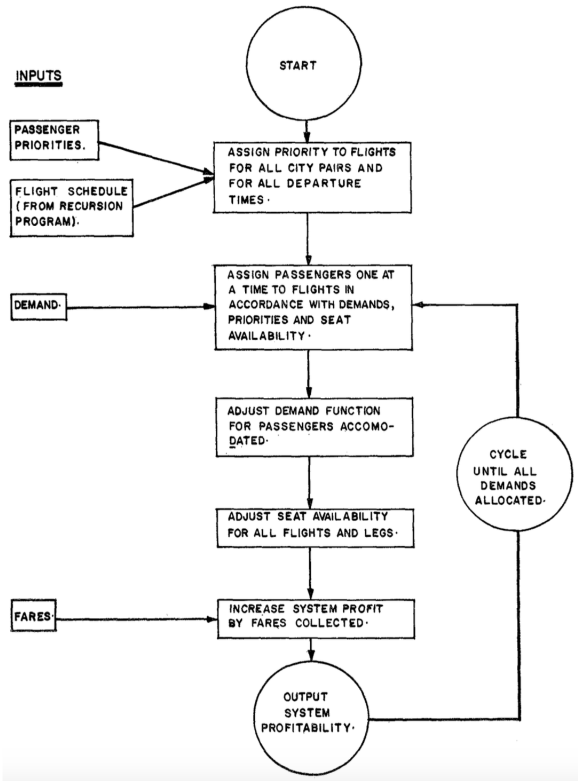


Figure 4.5: Multi-aircraft passenger allocation algorithm, Hersh (1974)

power. Another case study on this model, although more aimed towards revenue management, is shown in more detail in the follow-up work by Ladany and Hersh (1977).

In later work, Magnanti (1981) is critical towards the use of dynamic programming for strategic and tactical decision making. The author deems operational application more useful as this usually features a given, simplified network in which many constraints have already been considered and therefore requires a smaller state space description.

4.2.2. Time-constrained problems

Over the years, dynamic programming has been used in finding a solution to (non-linear) sub-problems that arise by decomposition approaches such as Dantzig-Wolfe and Lagrangian relaxation. These decomposition are generally applied to multi-commodity network flow problems with a time-space network representation, often featured in scheduling problems.

A large number of these sub-problems in literature are formulated as time-constrained shortest path problems and its extensions. While Desrosiers et al. (1995) provide a detailed overview of different variations and corresponding mathematical formulations, Desaulniers et al. (1998) particularly pays attention to the interrelations between the different problems (shown in Figure 4.6). The most used problems are highlighted in the figure by a solid red outline and briefly discussed here, along with applications in the airline industry.

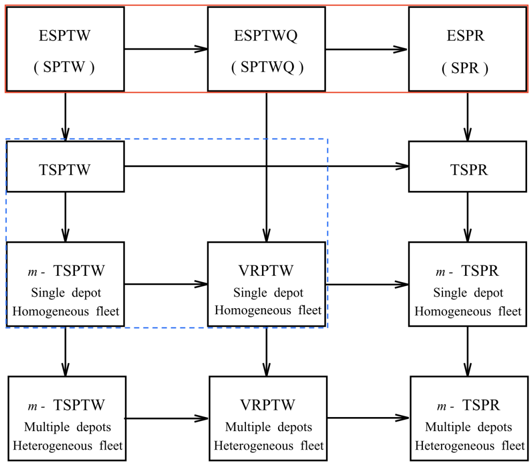


Figure 4.6: Relation between different time-constrained optimisation problems, adapted from Desaulniers et al. (1998)

Shortest path problem with time windows

The shortest path problem with time windows (SPTW) consist of finding a route between two nodes in a network, that can only be visited in a specified time window, at least cost. While most time-constrained problems are very difficult (categorised as NP hard) to solve when they become larger, Desrosiers et al. (1983) propose a pseudo-polynomial time algorithm. Further extensions can be made to include capacity constraints (SPTWQ) and to provide a multi-dimensional generalisation with resource constraints (SPR). Additional time-constrained problem highlighted by a blue dashed line in Figure 4.6 are discussed in the next Chapter. The remaining problem in the figure, which will be not further discussed, is the travelling salesman problem with resource constraints (TSPR).

Ioachim et al. (1998) provide the following application with examples for the airline industry: (1) Schedule synchronisation, where some flights are required to depart in the same time window on different days. (2) Headway constraints, where a minimum time is required between departures with the same origin and destination. (3) Periodic aircraft scheduling. For the latter example, the authors introduce an exact optimisation dynamic programming algorithm that minimises cost for deviating from the weekly mean departure time.

In an extension, Ioachim et al. (1999) provide a fleet assignment and scheduling application with a weekly planning horizon. Their algorithm utilises a Dantzig-Wolfe decomposition and branch-and-bound to produce an integer solution. Solutions for large problems of up to 80.000 arcs are produced in 21 seconds, which is very fast.

For the integration of fleet assignment and aircraft routing, Haouari et al. (2011) provide an exact optimisation method that utilises the constrained SPTW problem in a branch-and-price solution approach, involving Dantzig-Wolfe decomposition. A real case study was performed on a Tunisian carrier, involving 1,050 flight legs, 34 aircraft, and 8 aircraft types and compared its results to a Bender's decomposition approach. While the branch-and-price algorithm provides an optimal solution in just over an hour, the Bender's decomposition did not yield any solution in that same time period for a much smaller case study. However, no quantitative comparison has been made other than stating that the first approach is significantly faster.

El Moudani and Mora-Camino (2000) propose another dynamic programming application to integrated fleet assignment and aircraft routing, yet do not provide any mathematical formulation or detailed computational study.

4.2.3. Integrated fleet planning and scheduling models

Linear programming models for different stages of the airline planning process have become very technical in the 70's and 80's due to the easy of adding (operational) constraints. Dynamic programming has lacked that level of technical detail, despite the efforts by Hersh (1974). This subject was addressed in a master thesis by Rubbrecht (1989) in conjunction with Fokker and includes a breakdown of aircraft characteristics and (in)direct operating cost. A bottom-up fleet planning model is provided that shows some resemblance to the model by Hersh, and addresses both airline schedule design and fleet assignment simultaneously to provide an optimal fleet composition. The method used includes time-space networks and implementation of the Bellman-Ford algorithm for finding a shortest path in a graph Bellman (1958), Ford (1956). In this section, Rubbrechts model architecture shown in Figure 4.7 is discussed, as well as its limitations and how these are addressed by extensions of the model by other authors.

Rubbrecht uses a hub-and-spoke network model that only allows flights from and to the hub. Nevertheless, connections are assumed to be guaranteed and the daily demand between a city pair is an aggregation of the direct demand and transfer demand. This means that each flight can be treated as if it only carriers direct passenger from and to the hub, actually making it an improved point-to-point model, one of its major limitations. The model takes a time-of-day demand density function with attraction band, and daily demand values as an input to produce a demand function by, as shown in Figure 4.4. The aircraft's operating capabilities, and corresponding cost and profit are computed next for each aircraft type per city pair, given the travel demand constrained by aircraft capacity. Finally, by iterating over dynamic programming algorithm, specific aircraft are added as long as it is profitable. After each aircraft, the accommodated passenger from the existing demand. This immediately yields a fleet type and schedule for each aircraft.

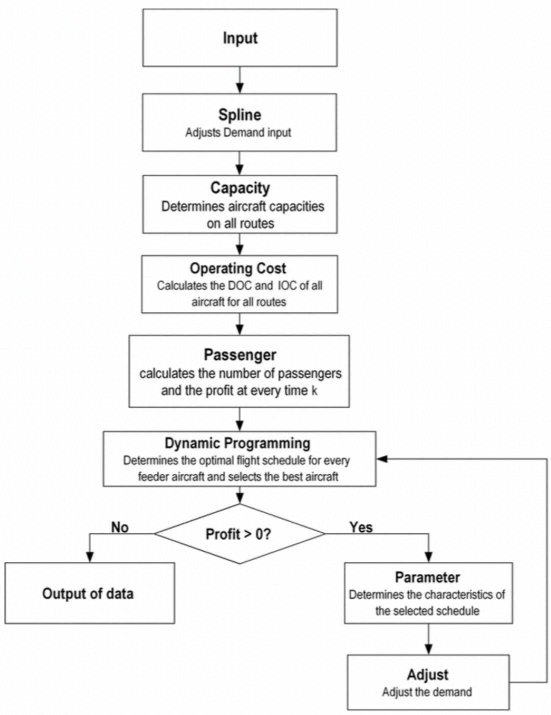


Figure 4.7: 'Airline Systems Simulation Program': model architecture, Pauwels (2014) after Rubbrecht (1989)

An extension is made by Pauwels (2014) as a master thesis and suggests improvements in the two following areas: the realisticity of the demand model, and the network characteristics. The actual demand for a flight can be far less then the market demand that was assumed so far. Therefore, a new demand model is adopted that takes into account many factors. Here, Pauwels combines three existing forecasting models Coldren et al. (2003), Jorge-Calderón (1997), Simpson (1970). The first incorporates other socio-economic parameters such as service, fare price and aircraft size, the second model offers the final daily demand for a specific airline. This model is the S-curve for frequency-market share as introduced in section 3.1, which in this case is a user input and is not found iteratively as in 3.3.2. A basic version of the final model provides a time-of-day share of daily demand for each specific itinerary.

Second, Pauwels expands the network through the introduction of a secondary hub and 'trunk' flights that connect the two hubs. These trunk flights are fixed in terms of daily frequency and time, and are considered an input to the problem. These high demand flights feed both hubs with passengers that either originate from spoke cities or have a spoke city as final destination, while the demand for these flights is condensed at the hubs.

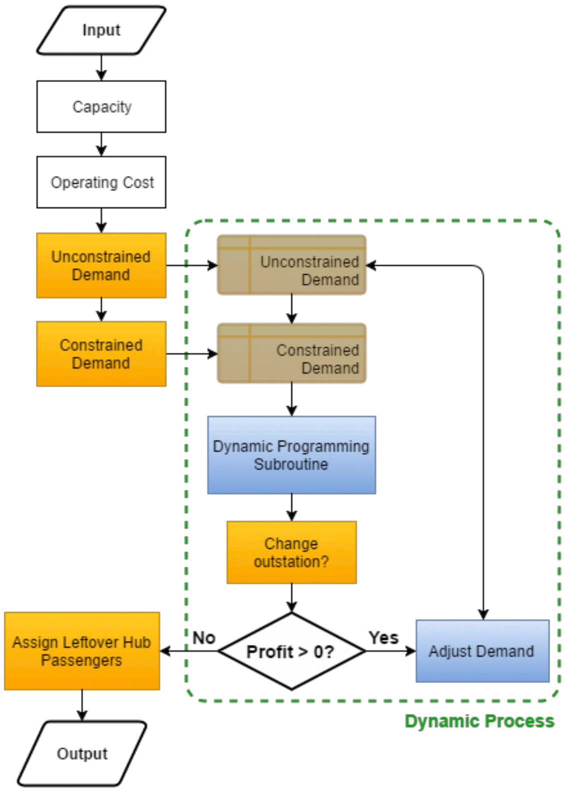


Figure 4.8: 'Airline Systems Simulation Program': model architecture for extended version, Wang (2016)

Another master thesis that provides an extension to Pauwels work, by Wang (2016), introduced a full hub-and-spoke network, in which a more realistic distinction is made between direct and transfer passenger by incorporating OD- demand, itineraries, and hub connectivity. This calls for the division of the 'Spline' routine from Figure 4.7 into both unconstrained and constrained demand, as shown by the new model architecture in Figure 4.8. Other new features are also pictured in yellow. After a schedule is produced for one aircraft with unprofitable first and last flights to position the aircraft at the hub, the new 'Change outstation?' routine checks if there exists any schedule that at least covers the same sequence of flights with any aircraft type, for which it is more profitable to park an aircraft overnight at an outstation. This may form a basis for including multi-day routings as seen in linear programming fleet assignment and aircraft routing models in Chapter 3. The 'Assign Leftover Hub Passengers' routine ensures that no connecting passengers are stranded at the hub after the dynamic process has finished.

Wang has put all new modelling elements to the test using a network that consists of 10 cities, including 1 hub, and 2 aircraft types, although does not compare the solution found to a linear programming optimisation approach. For this small verification case study, the total run time is under a minute. In a practical case study consisting of 1 hub and 8 spoke cities and 6 different aircraft types, the output of the model is compared to real airline operations. The model shows somewhat comparable results in terms of overall network performance indicators, fleet composition and schedule- and fleet assignment. However, Wang notes that adopting a more realistic, multi-day schedule would increase flexibility in planning and relax restrictions on potential transfer passengers.

Overall, the usability of the model for fleet planning can be questioned due to the gap in planning horizon between strategical fleet planning and more tactical schedule design, fleet assignment and aircraft routing, that has been identified in Chapter 2.

4.3. Summary

Dynamic programming has proven to be a powerful multi-stage optimisation technique for managing physical, financial or informational resources. By breaking down a problem into sub-problems, complexity can be reduced and a higher degree of detail can be captured. However, the number of sub-problems also plays a vital role in the performance of a dynamic programming algorithm, which suffers from the three curses of dimensionality in state-, outcome-, and action space. As dynamic programming is a modelling approach, it requires a formulation tailored to the specific problem, while aiming for a low dimensionality.

The application of dynamic programming within airline schedule planning has been longstanding, yet less widespread than linear programming. In the majority of application, a time-constrained shortest path problem is solved as part of a larger decomposition approach such as Dantzig-Wolfe.

Where Magnanti (1981) were still sceptical about the use of dynamic programming for strategic and tactical decision making, work by Rubbrecht (1989) launched a research stream that focuses on integrated schedule using dynamic programming. Although the model provides a solution for the stages from fleet planning to aircraft routing, the usability of the fleet plan can be questioned due to the gap in planning horizon between said decisions.

While latest work on the topic incorporates origin-destination demand for a hub-and-spoke network over a one day planning horizon, a point-to-point network structure that allows flight between cannot be evaluated. In general, the model lacks realism despite the fact that a high level of operational detail is captured.

As dynamic programming is a tailored approach, a challenge lies in incorporating additional constraints to increase realism.

5
Cargo

Literature on schedule planning for air cargo is significantly less widespread than on passengers, yet faces many similar challenges. This Chapter elaborates on the inherent characteristics of air cargo operations. First, an overview is presented on the different business models for cargo airlines and how these affect the operation. Hereafter, the modelling of air cargo flights is discussed by first describing more generic models for pickup and delivery, then describing cargo characteristics, and ultimately presenting model features covered in literature. For further reading on theory and models of air cargo operations, the reader is directed to a literature survey by Feng et al. (2015).

5.1. Cargo airline business models

There is a significant different between the transportation between transporting passengers and cargo. While the first usually book a specific origin-destination (usually round-trip) itinerary, the latter needs to be transported one-way from an origin to a destination under a time constraint. This potentially causes even greater demand inequality for origin-destination pairs but simultaneously allows an airline to choose the itinerary and include one or more stopovers. How cargo airlines are able to deal with these factors depends on their business model, which in turn affects the size and complexity of their operation. Figure 5.1 shows a fictitious overview of typical cargo airlines and their characteristics, which will be discussed in more detail in the remainder of this section, following Derigs and Friederichs (2013), The World Bank (2006). The external 'flights' described in the figure are provided by either a road feeder service (RFS) or passenger flights (PAX).

All-cargo airlines
All-cargo airlines such as Cargolux restrict themselves to transporting various forms of cargo and provide a scheduled service. This service is mainly used by forwarders that that pick-up and drop-off cargo at the the final customer, see Figure 5.2 for a simplified supply chain. They tend to operate with one hub and in markets with limited competition by integrators. All-cargo airlines can be subdivided by scope: regional and international. While regional airlines offer short delivery times as most cargo is transported over a few short flight legs, international airlines include many stops as its international flight legs are long. They can also include a road feeder network to collect cargo from a smaller destinations to an airport with more frequent air traffic and are characterised by delivery times up to a week. In some special cases, an aircraft will behave more like a charter flight and waits on the ground for a complete load, without a predetermined scheduled departure time.

Mixed carriers
Mixed carrier such as KLM are airlines that use belly capacity on passenger flights to transport cargo. This passenger network is likely operated in combination with the airline's dedicated air cargo subsidiary, such as KLM Cargo. These carriers are often major international airlines that rely on their extensive passenger network and account for the majority of the top 10 airlines in tonnes of freight carried, IATA Cargo (2018).

Integrators
Two out of the top three airlines in tonnes of freight carried are so-called integrators, or international express carriers such as FedEx. They offer door-to-door service as they also take on the forwarder role, depicted in

Airline		RC	IC	MI	EX
Characteristics					
Type		Cargo only	Cargo only	Mixed	Cargo only
Scope		Regional	Intl.	Intl.	Intl.
Main freight		Cargo	Cargo	Cargo	Express
Delivery time (days)		1–3	2–7	2–7	1–3
En-route stops		1–2	2–5	2–5	1–2
External flights		–	RFS	PAX	–
Network					
Destinations	Cargo	23	69	42	142
	External	–	77 (RFS)	81 (PAX)	–
	Total	23	134	93	142
Hubs		1	1	2	4
Freighter	*Total*	9	16	23	84
Typical schedule					
Cargo flights (avg.)		90	80	120	800
Revenue TKM		13,788,512	90,962,599	111,849,662	119,806,624
Offered TKM		20,749,359	136,775,422	173,540,852	191,806,624

Figure 5.1: Typical, yet fictitious, cargo airline characteristics for a weekly schedule for regional all-cargo (RC), international all-cargo (IC), mixed (MI) and integrator airlines (EX), Derigs and Friederichs (2013)

Figure 5.1. This enables cutting down the delivery time for the airline part of the operation while creating more flexibility. Due to their size and international character, an integrator network uses multiple hubs that are distributed around the world, and served by a much greater number of flights than other cargo carriers.

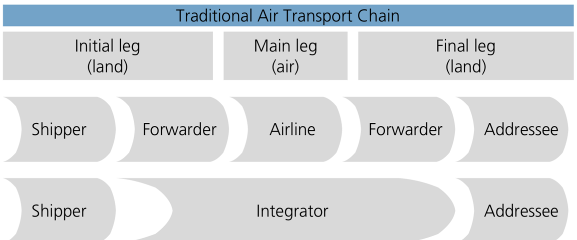


Figure 5.2: Cargo transport value chain, Reichmuth (2008)

5.2. Modelling cargo flights

Having a profitable schedule plan is just as important to the majority of cargo airlines as it is to passenger carriers and therefore calls for a similar optimisation approach. The core of both passenger and cargo operations relies on the scheduling of flights to transport commodities from one location to another. Nevertheless, there are significant distances. This section will first list the characteristics of transporting air cargo, after which modelling efforts found in literature are discussed.

5.2.1. Characteristics of transporting air cargo

The following list provides aspects that differ from passenger operations and could potentially affect the way a schedule plan is modelled.

- **Aircraft capacity:** Constrained by either volume and weight, while weight also influences the operating capabilities of the aircraft. Cargo is predominantly transported in unit load devices (ULD's): aluminium alloy pallets and containers up to sixteen cubic meters in size Verwijmeren and Tilanus (1993). For express carriers that typically transport packages, volume is usually the constraining factor, while for all-cargo airlines the load is typically heavier and therefore constrained by weight.
- **Network:** All-cargo airlines usually operate flights that feature up to three stops, before returning to the hub. Mixed-carriers and integrators employ a hub-and-spoke network where the total frequency of

flights between spoke cities is larger than for a similar passenger airline. While all-cargo airlines generally use one hub, the number of hubs for other carrier types depends on its (inter)national character and size.

- **Schedule:** All-cargo and combination carriers usually publish a schedule a fixed time period in advance, e.g. a month, which can change from one time period to another while integrators are even more flexible. Potential arrival and departure times depend on demand and airport operating hours, possibly allowing for operation during the night.

- **Demand:** Origin-destination demand is depends on the route, just as for passenger operations. On low demand routes, cargo is condensed at a hub by mixed-carriers and integrators. Direct flights then take the cargo to either the final destination, or first to another hub. Cargo is only transferred at the hub, and should ultimately be delivered within a time window that ranges from 1 to 7 days. For all-cargo airlines, demand is can be erratic and aircraft could therefore fly at very low load factor on one leg, while being at maximum capacity at the next.

- **Fleet composition:** The fleet mix depends on the operating capabilities required. While most carriers opt for a single aircraft type for fleet commonality benefits, the larger integrators operate their own mixed fleet next to a large number of chartered aircraft. The mix in fleet is required to best serve a hub-and-spoke network model with low-demand spoke, equal to passenger operations.

- **Revenue:** An airline receives revenue according to the 'chargeable weight', the maximum value of the actual weight and the volumetric weight as both dimensions are scarce. The latter is the volume of a piece of cargo multiplied by a density constant of 166.67. Although a concave tariff structure is used to charge forwarders or shippers, Tang et al. (2008) poses that for schedule planning models an average fare per unit weight per kilometre can be taken.

5.2.2. Generic cargo models and applications

The most dominant aspect of transporting air cargo is the lack of preference for any itinerary as long as the destination is reached within the time window. In literature, the temporal aspect of scheduling and routing problems has been widely studied in industrial and logistics application due to the rising importance of cost cutting and increase in service levels in the 80's, as shown by literature surveys by e.g. Bodin et al. (1983), Magnanti (1981), Solomon and Desrosiers (1988).

In an extensive literature survey on modelling schedule and routing problems, Desrosiers et al. (1995) discusses the 'dial-a-ride' problem, the core of research on pick-up and delivery, originally developed by Wilson et al. (1971). This problem considers the routing and scheduling of a single vehicle to pick-up single passengers and dropping them off before a set time. Psaraftis et al. (1985) proposes an application in which the pick-up and delivery of sea cargo in case of military emergencies is optimised heuristically, as well as another maritime application to bulk cargo by Fischer and Rosenwein (1989). Extensions to this problem have been made to include multiple vehicles with application to goods transportation by Dumas et al. (1991) and is solved exactly using a Dantzig-Wolfe decomposition in conjunction with a branch-and-bound method. The model architecture is described as follows by Desrosiers et al. (1995):

"The master problem results in the linear relaxation of a set partitioning type model, while feasible routes or columns are generated by a sub-problem modelled as a shortest path problem with coupling, precedence, time window and capacity constraints."

Although the algorithm provided solutions within a reasonable computation time for up to 5 pick-up requests per vehicle, for larger, realistic problems of up to 3,000 requests it could not. Dumas et al. (1991) concludes that heuristics should be used instead.

However, as the pick-up and delivery model introduced above can capture cargo routing characteristics, it is described in the remainder of this section. Furthermore, the relation to other time-constrained problems is discussed.

Vehicle routing problem with pick-up and delivery: theory

Starting from the shortest path problem with time windows (SPTW) problem discussed in section 4.2.2, the relation to the vehicle routing problem is described first (see Figure 4.6). The travelling salesman problem with time windows (TSPTW) is a more confined version of the SPTW problem where each node in a network must be visited exactly once, within the specified time window and at least cost. Gélinas and Soumis (1997) provide a polynomial time dynamic programming algorithm for this problem.

Next, this TSPTW can be extended to a multiple travelling salesman problem with time windows (m-TSPTW) allowing at most m minimum cost itineraries to cover all nodes in the network. A further extension is made to incorporate capacity constraints for both arcs and nodes, resulting in the single-depot heterogeneous fleet vehicle routing problem with time windows (VRPTW). A multi-commodity flow representation is adopted to allow for multiple depots and multiple vehicles types, where a vehicle represents a commodity.

This vehicle routing problem is finally extended to include pick-ups and deliveries (VRPTWPD). Desaulniers et al. (1998) describe a formulation for simultaneous pick-ups and deliveries, pioneered by Halse (1992).

Vehicle routing problem with pick-up and delivery: application
Applications of this problem are widespread through literature, especially in the last decade and, besides the work by Mingyong and Erbao (2010),are predominantly solved by dynamic programming algorithms, for which an introduction is presented in Chapter 4.

Literature on simultaneous pick-up and delivery that best represents the cargo flight scheduling problem is scarce, Mingyong and Erbao (2010) makes a very significant recent contribution. Their model covers a set of customers where each customer requires both a delivery and a pickup of a certain amount of goods and must be visited once for both operations. The model formulation is generic and a small road logistics case study is provided concerning only 8 customers.

Pang et al. (2011) makes another simultaneous pick-up and delivery application on ship routing, where vessels are routed from an initial location to a final location, while delivering and picking-up batched cargo along the way. A dynamic programming based heuristic is suggested to provide a solution. The authors note that it is possible to adapt a regular VRPTWPD to cope with simultaneous pick-up and delivery.

In that light, other work by Cramia et al. (2001) and later Fabri and Recht (2006), Mahmoudi and Zhou (2016) present algorithms for passenger pick-up. The latter provides a very elaborate breakdown of modelled elements and formulation. Xu et al. (2003) addresses practical consideration for parcel delivery where dynamic programming is used to provide a lower bound for a developed heuristic. Finally, Psaraftis (2011) proposes an exact dynamic programming algorithm for both single-vehicle and two-vehicle cases, for delivery only, and both pick-up and delivery respectively.

In more recent work, Bertsimas et al. (2016) provide an application which is closer related to cargo airline operations: the military airlift planning problem. The VRPTWPD is extended to include elements such as "hard and soft time windows, variable wait times, constraints on maximum active time, and a combination of delay and up-time as an objective. As this model proves to become intractable to solve for large instances, the fleet assignment and scheduling decisions are decoupled. An initialisation heuristic, which is used to provide an initial solution, is combined with a column generation algorithm to solve the mixed integer linear programming model. For a case study consisting of 100 potential aircraft and 111 transport requests, a 10% reduction of aircraft flight time is achieved. However, the model does not consider any (operating) cost.

5.2.3. Air cargo models

In this section, literature on air cargo scheduling models is categorised by characteristic modelling elements.

Cargo routing problem
Air cargo carriers generally follow the sequential schedule planning process presented in Chapter 2, according to Antes et al. (1998), Friederichs (2010). However, in the schedule evaluation phase an additional step is required to find optimal cargo itineraries, the cargo routing problem. During the preceding schedule construction phase, operating costs for a schedule are minimised in a similar fashion as presented in Chapter 3. Derigs and Friederichs (2013) make an application to cargo operation, by adopting a time-space network representation for scheduling of flights, which does not differ from models developed for passenger operations and is therefore not discussed in further detail.

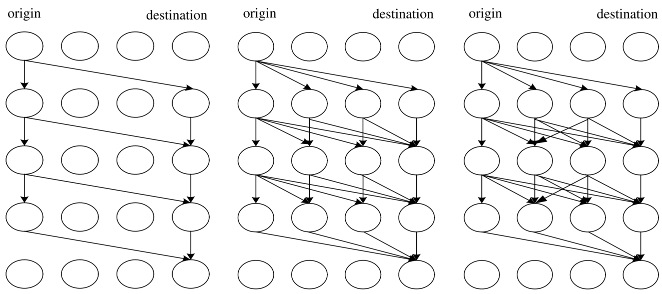
When considering the cargo routing problem, Jones et al. (1993) represent it as a multi-commodity network flow problem, for which the authors conclude that a node-arc formulation yields the best solutions and is frequently used in literature.

The purpose of cargo routing, is to maximise revenue for the given schedule subject to the following constraints: (1,2) OD cargo flow over the network must not exceed the demand and capacity. (3) Cargo must be routed on connecting flight legs. (4,5) Cargo can be picked up only after the earliest pick-up time and delivered before the latest delivery time. (6,7) Cargo can only be transferred at the hub and when the minimal transfer time between two flights is realised. Derigs and Friederichs provide a column generation based solution method to this problem, which is integrated with other planning steps as discussed in the next section.

In recent work, Wang et al. (2018) present a basic optimisation model that depicts a shipper's view on the cargo routing problem. From different shipping options (i.e. express flight, belly of passenger flight, and dedicated general cargo flight) with corresponding cost and transit time, the least cost option is selected. Timely delivery is ensured through a large penalty cost if an option exceeds the delivery deadline.

Integrated scheduling
As stated in Chapter 3, integrated two or more steps in the schedule planning process may yield a better solution. In a paper by Yan et al. (2006), a method is proposed to integrate flight scheduling, aircraft rotation, and cargo routing for homogeneous fleets. Maintenance requirements are not taken into account and a specified cargo flow must be met. Next to a traditional time-space network for aircraft flow, another time-space network is used for cargo flow to deal with cargo routing. The two networks are then combined to allow for simultaneous flow of all aircraft and cargo. The model is formulated as a mixed integer program, characterised as NP-hard, Yan et al. (2006) recognises that solving even a small problem with 6 nodes can become intractable for the adopted realistic planning horizon of one week.

Therefore, a heuristic solution method is proposed and described in detail in their paper. It is developed around the number of stops a flight can include in the network, which is either non-stop (a), one-stop (b), all-stops (c), as shown in Figure 5.3. For the entire model, it can even be a combination of the three: a mixed-stop heuristic.



(a) Non-stop network **(b)** One-stop network **(c)** All-stop network

Figure 5.3: Heuristic networks for integrated scheduling, fleet assignment and cargo routing, Yan et al. (2006)

Through a small real word case study on a small Taiwanese cargo airline involving 8 stations and 4 aircraft, initial results were obtained showing that the mixed-heuristics outperforms the rest, although the one-stop heuristic approaches the mixed-stop heuristics' objective value to within 0.7% in less than one fifth of the computation time for this network. An extensive sensitivity analysis shows effects of change in available fleet size, cargo demand, station's fixed cost, and problem size on the performance. The latter is interesting as a larger problem consisting of 24 stations, 60 origin-destination pairs, and 30 aircraft only takes 33 minutes to produce a solution with an optimality gap of 2.97% using the mixed-stop heuristic.

Another effort to model multiple stages of the schedule planning process has been made by Derigs and Friederichs (2013). In contrast to Yan et al. (2006), they do not plan on the level of single flight legs but plan on the level of flights: here, a predefined sequences of flight legs. Furthermore the goal is not to generate a schedule from the ground up, but to optimise an existing schedule by means of listing mandatory and optional flights in a master flight list. Both features drastically reduce total problem size and therefore allows exact optimisation for large networks, even with a mixed integer linear programming formulation chosen by the authors. However, these features severely limit the solution space and may therefore not lead to the optimal solution.

The model integrates scheduling, fleet assignment, aircraft (maintenance)routing with the cargo routing problem described earlier in this section. This approach has the objective to maximise profit and also yields an extensive set of constraints, that have all been covered in the respective sub-problems for passenger flights in Chapter 3 and for cargo routing. The authors opt for a time-space network representation for the fleet assignment and rotation problem, and 'flight string' introduced by Barnhart et al. (1998a) for meeting maintenance requirements, and a planning horizon of one week.

Furthermore, four extensions are mentioned in a Ph.D. thesis by Friederichs (2010) to increase realisticity of the model: (1) Fixed costs for external flights, operated by a partner airline or road-feeder service and to be booked in advance at a fixed price (see Express shipment later in this section). (2) Cargo handling cost and constraints. (3) Frequency constraints, for setting a minimal frequency for airlines to stay competitive. (4) Equal aircraft utilisation, trying to ensure equal wear and tear for the entire fleet.

By using a branch and price and cut algorithm, the model is able to produce an exact, integer solution to large real world problems (e.g. a carrier with 6,000 origin-destination pairs, 2,500 flight legs served with a fleet of 84 aircraft) without maintenance constraints in a reasonable 4 hours. Unfortunately, no comparison is drawn to the schedule and financial performance of an actual airline.

Express shipment

The subject of express shipments is considerably different from other cargo airline operations as will become clear in this paragraph. Early literature on express networks includes work by Chan and Ponder (1979), Chestler (1985), Emery et al. (1986), Feldman (1985), Finnegan and Andrade (1984).

Hall (1989) was the first author to address the impact of hub-location and time-zone differences on the design of a carriers air service network for express shipment. This topic is further studied quantitatively by Zhang et al. (2017) and described in later in this section. However, Barnhart and Schneur (1996) were the first to provide a computational model for the entire network design. This model can be used to:

- *Design air stops*, location designated for pick-up and delivery of shipments.
- *Design ground feeder routes*, to serve locations where no air stop is present.
- *Schedule air stops and provide a fleet assignment*, meeting service and technical requirements posed by the shipment, aircraft network.
- *Determine the number of shipments to be serviced by commercial air*, for shipments that cannot pass through the hub due to time or capacity restrictions.

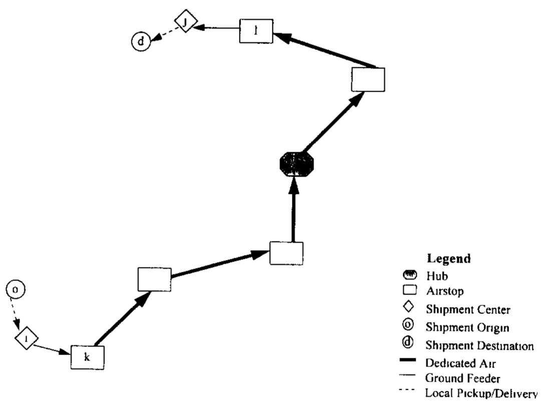


Figure 5.4: Dedicated air and ground service value chain for a single shipment Barnhart and Schneur (1996)

A typical transport route for a shipment is found in Figure 5.4. An (integer) linear programming formulation is used with the following objective: *to minimise cost while satisfying the posed service requirements by determining the air stops, ground feeder routes, aircraft routes and schedules, fleet composition and size, and the quantity of shipments serviced by commercial air simultaneously.* Constraints that are required specifically for this problem, compared to passenger operation, are: (1) pairing of pick-up and delivery routes through the hub for each aircraft, (2) ensuring the spacing of arrivals and departures at the hub for equipment balance. The solution method used is column generation and provides optimal results within a reasonable computation time of 1 hour. A real world case study is presented in which an express carriers operating costs have been reduced by 7%. Nevertheless, application to other types of carriers is limited due to the segregation of pick-up and delivery flights and feeder routes, required for express service but far from optimal for other service models.

In later work on the same subject, Yan et al. (2005) confine the model by Barnhart and Schneur (1996) to short-term aircraft routing and flight scheduling with a draft timetable, and includes another, considerably smaller case study which is solved within a few seconds.

Zhang et al. (2017) propose a network development model that integrates the strategic decision for hub location with frequency planning and aircraft assignment. The rationale behind this approach is that cargo airline hub selection is more variable than for a passenger airline in terms of time horizon and that total time from origin to destination is less strict (apart from a fixed deadline). For the aircraft assignment, both self owned aircraft and (optional) chartered aircraft are used. The model employs a two-stage polynomial time greedy algorithm. In the first stage, some flight legs are selected and have aircraft assigned to them based on the least cost. In the second stage, the problem is optimised with the previously fixed flight legs to reduce computation time. Through a practical case study, the authors demonstrate the ability to select multiple hubs based on the cargo demand. However, any other network and operational constraints are not considered.

Mixed carriers

While Derigs and Friederichs (2013) accounts for transporting cargo on a passenger flight at fixed cost as it were an external service, better results may be reached by an approach that optimises a schedule plan for both passengers and cargo. Tang et al. (2008) proposes an extension to the work by Yan et al. (2006) by means of adding more time-space networks and corresponding constraints. The model incorporates additional networks for the flow of the passenger fleet, mixed fleet and passengers. A Lagrangian based heuristic is used to provides a solution to this fleet assignment and scheduling problem, again using demonstrated by a case study on a Taiwanese airline.

Li et al. (2007) take a different approach where their contribution is confined to integrating the passenger- and cargo fleet assignment problem, to maximise profit. The former two are based on the work by Hane et al. (1995) while the latter is described earlier in this section. A two-stage Bender's decomposition is adopted to provide an exact solution to the problem. Even for a large case study (involving 1404 passenger flight legs, 201 cargo flight legs, 6 passenger fleets and 1 cargo fleet) conducted by the authors, an optimal solution is found in several minutes, which is very fast for planning problems.

Alliances and competition

To cope with increasing competition, air cargo carriers have entered into alliances -just like passenger airlines- to increase their (global) network and improving operational efficiency, according to Yan and Chen (2008). In their paper, the authors offer an extension to an integrated scheduling model by Yan et al. (2006) that has been discussed earlier in this section. Three types of alliances are modelled in regular aircraft flow time-space networks: (1) Swap space alliance, a collaboration on individual routes which are chosen by negotiation. (2) Complementary alliance, a collaboration for extending each others network that feeds traffic to one-another. (3) mixed-alliance, which is a combination of the two depending on the route.

Furthermore, three resource sharing strategies are presented to extend the model: (1) Cargo handling, (2) flight quota per station, (3) flight quota per two connected stations.

A small verification case study shows that operating under an alliance could not only reduce operating cost but also increase profit. Due to formulation as a mixed integer multi-commodity network flow problem, solving large problems becomes intractable. Later work by Chen et al. (2010) introduces a Lagrangian based heuristic that was successful in providing numerical results to a large numerical case study on two Taiwanese carriers within reasonable time.

Competition between air cargo carriers has, to the best of the author's knowledge, only been modelled through two methods: an agent-based approach and a game theory approach. The latter, presented by Feng-Yeu Shyr and Lee (2012), pricing and scheduling strategies are modelled as non-cooperative games between airlines for oligopolic competition. As it mainly focuses on pricing and forwarding and lacks detail on the scheduling part, it is not further discussed here. The agent-based approach is employed to define an equilibrium between the cargo demand and its supply in a competitive market. Based on the total historic market supply of capacity over different days of the week, an airline forms an independent strategy for the amount of capacity offered. Although the authors state that the simulated demand approaches the actual demand with reasonably high accuracy, no direct computational results are provided.

Network assessment

A substantial research stream has focused on assessing air cargo networks on a variety of metrics. Two notable contributions are presented here. Boonekamp and Burghouwt (2017) provide a model to assess the magnitude and connectivity of a cargo network, based on indicators such as frequency, transport time and connection time. For an airport, the authors make an application to the European market. In other work, Janić (2019) presents a methodology for estimating the resilience to an external disruptive event, such as a snowstorm.

5.3. Summary

Compared to passenger operations described in Chapter 3, the most significant differences for air cargo operations are as follows: The lack of preference for a specific itinerary, and the increased flexibility for departure- and arrival time, while adhering to a time constraint.

The variability in time sensitivity is the main driver behind different cargo airline business models, together with the market demand, network structure and other cargo characteristics such as weight and revenue per tonne per kilometre. In general, three types of cargo airlines can be distinguished: all-cargo carriers, mixed carriers (utilising belly capacity of a passenger network), and integrators.

Throughout history, modelling air cargo operations has received only a fraction of the attention that passenger operations have gotten in terms of research. In recent work, Bertsimas et al. (2016) demonstrate the application of the widely researched vehicle routing problem with time windows and pick-up and delivery to related military air lift operations. As important cost aspects have been neglected, the use within the air cargo industry is therefore limited at this point in time.

The cargo flight schedule planning process bears resemblance to that for passenger operations. Therefore, models for the different planning stages can be adjusted and applied to cargo operations. The cargo routing problem however, that flows cargo over a network, is unique to the cargo domain is generally solved after an aircraft routing is provided. The two most notable contributions to knowledge provide methods that integrate schedule design, fleet assignment, aircraft routing, and cargo routing at different levels of detail. Yan et al. (2006) are capable of solving a small case study, involving a homogeneous fleet and fixed cargo flow, with a heuristic in reasonable computation time. Derigs and Illing (2013) make different simplification by assuming a base schedule and predefined sequences of flights. As this drastically reduces the solution space, large real world problems can be solved in reasonable computation time, while compromising the optimality of the solution. A combination of the two approaches, that fully integrates the planning process while including multiple fleets, detailed operational constraints, and can be solved for a large case study within reasonable computation time has not been covered by literature.

Equal to passenger operations, competition in the air cargo market has been covered sparsely in literature. However, modelling alliances has received more attention and shows potential in increasing profit. To the best of the author's knowledge, uncertainty in relation to modelling air cargo flights has not been covered by any literature.

Since the research efforts by Derigs and Illing (2013), no significant contribution to schedule planning models have been made. This provided opportunities to apply faster linear programming solution techniques and other optimisation methods. Recent work on air cargo in general has primarily taken the forwarders perspective to select the optimal flight for transporting a set of goods.

6
Summary

In this Chapter, the state of the art of modelling schedule planning in the airline industry is discussed. This is the result of literature survey presented in the previous Chapters, where a selection has been made to include the most valuable contributions form the abundance in literature. Evaluation of the state of the art identifies knowledge gaps in literature; opportunities for future work on this subject. The framework presented in Figure 6.1 provides a methodology for this evaluation and distinguishes four areas: modelling elements, application area, modelling perspective and optimisation method. The extend to which the topics within these areas are covered is reforested by colours. This methodology is used to cover the four areas in the remainder of this Chapter.

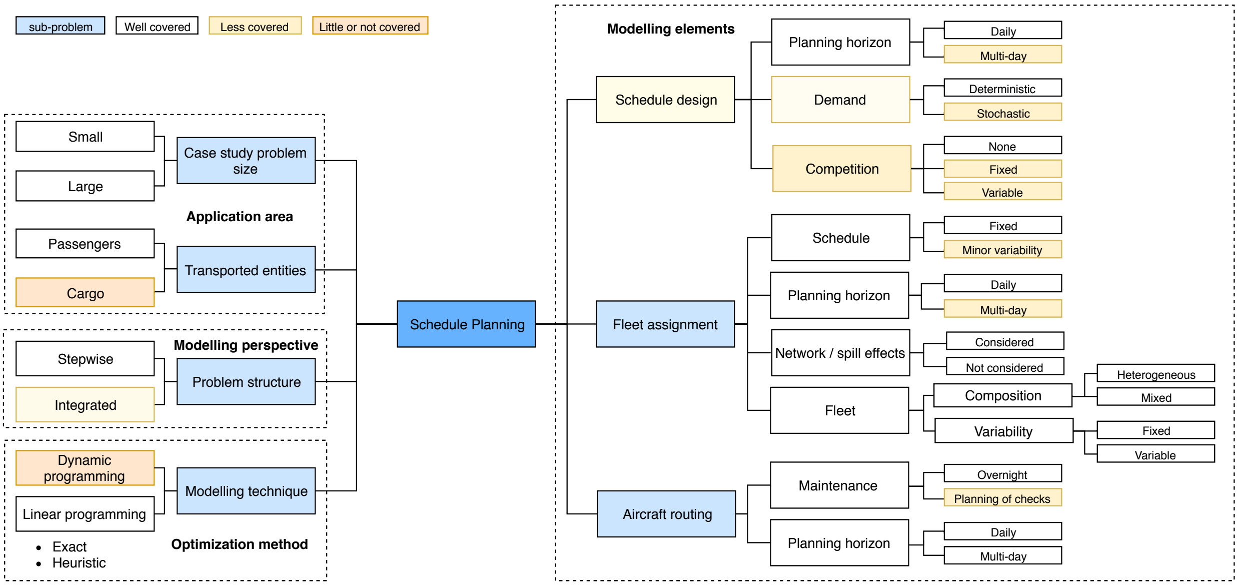


Figure 6.1: State of the art evaluation framework

Modelling elements

Over the years, modelling different stages of the airline schedule planning process has received very substantial attention in literature. In general, the level of detail and therefore complexity has increased over the years. While models have first been primarily deterministic of nature, work in especially the last decade has focused on better representing reality by stochastics. The planning horizon has also increased for all stages in schedule planning to 4 days or a week.

Current schedule design in practice involves relatively minor changes due to operational impracticality and consistency of service opposed to designing schedules from scratch earlier. Competition is generally modelled quite basically, if modelled at all, due to its long-term uncertainty and difficulty to capture all elements accurately, especially for highly competitive markets. This approach determines the route market share based on flight frequency, while a more advanced approach uses game theory.

Similar to competition, demand modelling has received little attention in literature and is generally assumed given. The last decade, more efforts have been made to include stochastic demand into schedule design and fleet assignment.

Fleet assignment is widely covered in literature and in some fundamental work network effects and spill effects are taken into account to fully capture the characteristics of a hub-and-spoke network. Some fleet assignment models allow for minor variability in the predefined schedule to increase connectivity and reduce cost.

Aircraft routing on itself in general is less covered than the two stages above, yet models are present than can accurately create predominantly feasible routings that distribute mostly weekly maintenance activities equally. More work is spent on the integration of aircraft routing and crew scheduling.

Modelling perspective

Some models described in early literature have considered frequency planning and fleet assignment simultaneously. This was possible due to the small scale of operations. Since, due to the dramatic increase in fleet and network size and former limitations in computing power, a more strict segregation of different planning stages was required to be able to provide meaningful results in acceptable time. When computation power increased, first the level of detail and therefore realisticity in models was enhanced. At the same time, many authors opted for the integration of schedule planning stages. This is explained by the fact that solving one sub-problem at the time may not lead to an optimal solution of overall problem and due to the strong interdependence between the different stages, and has been demonstrated quantitatively.

Depending on the modelling approach, the schedule planning stages that have been successfully integrated differ. While fleet planning to aircraft routing have been considered within dynamic programming, linear programming features the integration of both schedule design to aircraft routing, and fleet assignment to crew routing. No fully integrated approach has been observed, and furthermore, the level of detail of presented approaches differs significantly.

Optimisation method

Although in early modelling approaches in the airline industry dynamic programming was often regarded, linear programming was favoured throughout history.

Linear programming formulations for different planning stages share a great number of (decision) variables and constraints, and can easily be expanded to include more constraints. First applications of linear programming within the airline industry were trivial. There always existed a trade-off between the level of detail captured by the model, the solution time and accuracy of the solution. There have been, and are still, heuristics developed that claim to come close to the optimal solution while capturing more detail in a shorter time. Over the years, researchers have paid a great deal of attention to developing efficient solution methods that can provide exact (integer) solutions to very large and complex problems within hours. A reasonable computation time for tactical planning models.

Dynamic programming offers an approach that seems more intuitive as decisions are made one at a time and depend on previous decisions. In contrast, linear programming makes all decisions at the same time. While linear programming features polynomial time complexity, dynamic programming suffers from the curses of dimensionality. This generally makes it less suitable for large scale tactical problems and is deemed to be better suited for operational problems with small state space description. Finally, a dynamic programming formulation needs to be tailored to a specific problem.

These reasons have resulted in an abundance of linear programming approaches and only a small number of dynamic programming approaches throughout literature. However, when a dynamic programming algorithm is designed in such a way that its time complexity is pseudo-polynomial, it allows for very fast solutions to detailed problems.

While agent-based modelling has been applied to airline schedule planning as well, it is not further regarded in this review due to the small number of literature present.

Application area

Compared to passenger operations, the most significant differences for air cargo operations are as follows: The lack of preference for a specific itinerary, and the increased flexibility for departure-and arrival time, while adhering to a time constraint. The variability in time sensitivity is the main driver behind different cargo airline business models, together with the market demand, network structure and other cargo characteristics such as weight and revenue per tonne per kilometre. In general, three types of cargo airlines can be distinguished: all-cargo carriers,mixed carriers (utilising belly capacity of a passenger network), and integrators.

The vast majority of literature focuses on passenger operation, and besides some literature on express shipments form the 80's, the last two decades produced a new interest in schedule planning for cargo. Air cargo carriers generally follow the sequential schedule planning as passenger carriers, however, in the schedule evaluation phase an additional step is required to find optimal cargo itineraries, the cargo routing problem.

In terms of modelling, making use of the high flexibility in transporting cargo can potentially dramatically increase the objective value while it simultaneously allows for a far grater solution space when trying to integrate planning stages.

While highly integrated models have been presented in literature, a model that fully integrates the planning process while including multiple fleets, detailed operational constraints, and can be solved for a large case study within reasonable computation time has not been covered by literature.

Since research efforts on integrated scheduling in 2013, no significant contribution to schedule planning models has been made. This provided opportunities to apply faster linear programming solution techniques and other optimisation methods. Recent work on air cargo in general has primarily taken the forwarders perspective to select the optimal flight for transporting a set of goods.

III

Research Methodologies

previously graded under AE4010

1. Abstract

This report provides a project proposal and plan for a research project on modelling integrated schedule planning of cargo airline operations. The work will offer an improvement and extension to an existing research stream on dynamic programming, making a novel application to air cargo operations, in collaboration with Airbus. The project aims to provide a decision-support tool for optimised schedule planning that represents real-life air cargo operations with detailed constraints within a reasonable computation time. Results could be an improvement to those obtained from current (often Excel based) network planning models used by many airlines in both content and computation time. This work provides the foundation for future research on integrated airline schedule planning through dynamic programming both on air cargo- and passenger operations.

2. Introduction

The airline industry is characterised by highly complex and costly operations, where planning decisions have a large impact on an airline's profitability. These decisions reflect an optimisation problem that, even for a very small airline, can hardly be solved by hand. Many airlines have used Excel based tools to aid in making (part of) their planning decisions, and some still do today Belobaba et al. (2009). However, history has proven that dedicated optimisation models for simulating real airline operations have a major impact on an airline's financial performance, both reducing cost and improving revenue Eltoukhy et al. (2017). This is especially the case for cargo airlines as their operations can be more complex Feng et al. (2015) and have received far less attention from research compared to passenger operations.

One of the key challenges in modelling these operation is to balance the degree of realism captured by the model and the computation time required to provide an accurate solution in order to function as a decision-support tool. The latter is especially important with decreasing profit margins in the industry IATA (2018). Modelling the interrelation between different schedule planning stages by making these decisions simultaneously, has proven to increase profits by 2% Haouari et al. (2011). Although the integration of more planning steps can provide better results, it adds computation time.

This research projects focuses on addressing the challenges posed above specifically for air cargo operation and has the following goal: Providing a decision-support tool for optimised schedule planning that represents real-life air cargo operations with detailed constraints within a short computation time.

The remainder of this project proposal is structured as follows. In section 3, the state-of-the-art of the research field is presented and main research areas are highlighted. Together with Airbus' requirements, section 4 provides the resulting project objectives and research question. Next, sections 5 and 6 respectively go into detail on the methodology for the project and the experimental set-up. In section 7, the outcome of the research and the relevance is discussed. Consecutively, in section 8, the project planning is displayed. Finally, section 9 presents the conclusions of this project proposal.

3. Literature review

This section provides an overview of relevant research streams to the project together with a corresponding state-of-the-art evaluation. Focus lies on mathematical modelling methods and their performance, which will come forward in the remainder of this section. Literature is grouped by the following key topics: the integration of different schedule planning stages, the optimisation method used, and how air cargo operations is modelled specifically. Finally, a synthesis is provides that links the research project with literature.

3.1. Integration of schedule planning stages

The project scope is limited to medium-term strategic and tactical planning stages involved in schedule planning. These sequential steps as described in order, as follows Belobaba et al. (2009):

- **Frequency planning:** The frequency of flights per route per time period (e.g. day or week).
- **Timetable development:** Providing departure and arrival times for each flight.
- **Fleet assignment:** Assigning an aircraft type to each flight.
- **Aircraft routing:** Also known as tail number assignment, it involves flowing an individual aircraft over the network by assigning it to (a series of) flights, often while meeting maintenance requirements.

Solving one sub-problem of the scheduling process at the time may not lead to an optimal solution to the overall problem. In fact, a solution to a sub-problem may not even yield a feasible solution to the consecutive sub-problem. Integration was therefore a logical step Barnhart et al. (1998b). Considering the deterministic integration of two planning stages, research from mostly the 2000's (and still the state-of-the-art) has yielded combined timetable design and fleet assignment Barnhart et al. (2002), Jiang and Barnhart (2009), and combined fleet assignment and aircraft routing Liang et al. (2011), Sarac et al. (2006). The main limitation of the former integration is that an existing schedule with corresponding frequency planning is required and a schedule cannot be created from scratch. The latter also takes maintenance considerations into account.

When it comes to the integration of multiple planning stages, conducted mostly in the 2010's, the current state-of-the-art in literature integrates the last three steps that are described above Gürkan et al. (2016). Simultaneously, the research focus has shifted from developing deterministic- to stochastic planning models that provide robust solutions. The stochastic variables demand and flight delay are either considered individually Ben Ahmed et al. (2017b), Boudia et al. (2018), or simultaneously Şafak et al. (2018). However, all stages described above have been integrated by an unpublished research stream at Delft University of technology, geared towards fleet planning Wang (2016).

The integration of planning stages increases model complexity and therefore the need for improved (near) optimal solution methods.

3.2. Optimisation methods

Virtually all optimisation methods used to provide solutions to the problems posed in this section rely on linear programming. It is widely used due to its ease of defining a objectives and imposing constraints. Due to the high combinatorial nature of, especially integrated, optimisation problems in airline schedule planning, methods have been devised to speed up computation time. A row- and column generation algorithm that has been introduced in 1998 Barnhart et al. (1998b) still forms the foundation for a large portion of modern work.

Modern day methods, that integrate multiple planning stages, often rely on more tailored algorithms to not only limit the number of decision variables, but also cut down the solution space. While two-stage integration for a small airline can near optimal results within an hour Haouari et al. (2011), three-stage integration (with stochastic variables) can take significantly longer. For a similar small airline network, the run-time exceeds 19 hours to come to solution which is 7% from the optimum Şafak et al. (2018).

As becomes apparent, finding a balance between computation time, solution quality and level of detail is important. The research stream at Delft University of Technology, described earlier in this sections takes a different approach which is centred around a dynamic programming technique. It provides a potentially very detailed integration of the different steps and can provide results to a small network within several minutes. Doing so requires dividing the entire problem in smaller, manageable parts, which lead to potential and unknown sub-optimality in the solution found.

3.3. Modelling air cargo operations

Having a profitable schedule plan is just as important to the majority of cargo airlines as it is to passenger carriers and therefore calls for a similar optimisation approach. The core of both passenger and cargo operations relies on the scheduling of flights to transport commodities from one location to another. Nevertheless, there are significant distances in aircraft characteristics, network structure, schedule operated, demand profile, fleet composition, and revenue generationTang et al. (2008), Verwijmeren and Tilanus (1993).

Air cargo carriers generally follow the sequential schedule planning process as described in this section Antes et al. (1998), Friederichs (2010). However, when evaluating the schedule plan, an additional step is required to find optimal cargo itineraries, the cargo routing problem. This problem is commonly formulated as a multi-commodity network flow problem. As stated before, integrated two or more steps in the schedule planning process may yield a better solution. Flight scheduling, aircraft rotation, and cargo routing can be successfully integrated for homogeneous fleets Yan et al. (2006). Another approach additionally allows for a heterogeneous fleet and takes some maintenance constraints into account Derigs and Friederichs (2013). However, this approach requires both an existing schedule as input and predefined sequences of a small number of flights. Both approaches do not provide solutions for different cargo airline business models.

3.4. Synthesis

Following the dynamic programming research stream, the contribution to the body of literature is three-fold. First, additional level of detail is introduced to make the model up to par with the features as used by existing linear programming models that are more geared towards aircraft rotations. Second, by using dynamic programming effectively, computation time of fully integrated modelling can be reduced significantly without requiring an existing schedule as an input. Finally, the model will provide solutions that take into account operational aspects of different cargo airline business models.

4. Research question and objective

This section states the main research question and objective for the thesis project that have been drafted by using the state-of-the-art in literature, and Airbus' and Delft University of Technology's requirements. First, the research question is stated and subsequently split into sub-questions.

4.1. Research question

"How can the existing dynamic programming based integrated airline schedule planning optimisation model be extended to cargo operations and capture reality sufficiently so that it can be used as a decision-support tool?"

1. Can additional planning stages be integrated within the dynamic programming framework?
   (a) Which planning stages allow to be further integrated from a operational perspective?
   (b) Which planning stages can be further integrated from an airline's decision making time line?
   (c) How is dynamic programming currently implemented within the optimisation algorithm?
   (d) For which planning stages do the characteristics of dynamic programming and its existing implementation allow integration?
2. How can the existing model be extended for air cargo operations?
   (a) Which cargo business models can the model be made suitable for?
   (b) What are characteristics of freighter aircraft (e.g. payload-range curve, capacity, and economics)?
   (c) What are typical operational characteristic of flowing cargo over the network (i.e. using air-stops and transfers) for different business models?
   (d) What are transport time constraints for air cargo and how is demand spread over the week?
   (e) How can air cargo characteristics in terms of weight, volume and divisibility be incorporated into the model?
3. How can the existing model be adapted to better represent reality?
   (a) What assumptions exist in the current model that, what require to be adapted and what new assumptions need to be introduced?
   (b) What other drivers for flying can sensibly be introduced besides origin-destination demand?
   (c) To how many days should the planning horizon be extended and how?
   (d) How can schedule start moments for individual aircraft be spread over the planning horizon?
   (e) How can the model be made suitable for long-haul operations?
   (f) What operational constraints, vital to real-life operations, need to be added and how?
4. To what extent can the model contribute to making better informed schedule planning decisions?
   (a) Is the computation time reasonable, compared to current tools, for a decision-support tool that is used iteratively?
   (b) Is the effort required to change the input parameters sufficiently low to be able to use it as a decision-support tool?
   (c) Are the required inputs available to airlines?

(d) Can the outputs from the model directly be used to make decisions?

(e) How far are the optimised results away from the exact optimum?

(f) To what extent do the results from the model represent real airline operations?

(g) Does the model feature an architecture that can be easily adapted for future research and implemented within an existing tool-set?

From these research questions, a research objective with corresponding sub-objectives is formulated below. These objectives are used to finally provide an answer to the research questions. In the next section, the research methodology is discussed and a research framework provided that will lead to the completion of the objectives posed below.

4.2. Research objective

"To apply the existing dynamic programming based airline scheduling model to cargo operations, and increase the degree of realism and applicability by incorporating a novel set of objectives, operational constraints, and modelling elements into the optimisation framework."

A. Adapt the model to cope with two main air cargo business models (general cargo and express cargo) by allowing for both point-to-point and hub-and-spoke operations and differentiating between potential connection possibilities.

B. Include alternative objectives by adopting a market supply-demand model and assessing the number of origin-destination itineraries a flight offers.

C. Incorporate additional constraints by accepting an existing fleet as an input, considering airport slot availability and prices, having a minimum route frequency, and preferable flight operating window.

D. Add additional modelling elements by allowing for a multi-day planning horizon, spreading the schedule starting points over the planning horizon and allowing for operations between different time zones.

E. Validate the applicability of the model by conducting 4 real-life case studies, in the form of real airline requests and simulating actual airline operations, for airlines networks that vary in size, complexity, and business model.

F. Improve the existing model architecture by using a database-style input and modular approach to allow for future research efforts and ease of implementation in existing tool-sets.

The motivation for the objectives is three-fold. First, a historic lack of (academic) interest in modelling air cargo operations compared to passenger operations has resulted in potential benefits to airlines, especially with a forecasted average annual market growth rate of 4.2 % IATA (2019). Second, dynamic programming optimisation method has been little studied within in airline operations context compared to linear optimisation. The consequence is that the level of detail captured by the first method is not up to par and therefore requires extension to provide meaningful results. Third, the real-world applicability and scalability of this modelling method has not been proven, which is a barrier for future applications.

Regarding the feasibility of the objectives, it is vital to keep a balance between the level of detail captured for cargo operations, degree of realism of the model, and demonstrating the capabilities of the tool for real-life operations. Keeping this balance is further complicated by having both the university and Airbus as a client since their requirements do not fully coincide. However, with the well-structured project planning as discussed in section 8, these objectives should be ambitious, yet feasible.

5. Methodology

As stated in the introduction, this research involves simulating real-life airline operations. The approach taken involves mathematical optimisation and, more specifically, relies on the principle of dynamic programming. An advantage is that this approach does not require an expensive commercial solver such as CPLEX. As the model will build on top of existing work, continuing a line of research at the Delft University of Technology, using dynamic programming is required. However, the previous work, together with the literature review, do provide promising results.

The research objectives, as presented in the previous section, can be completed by undertaking five consecutive steps. These are visualised by using a research framework, which is shown in Figure 6.2. The steps are marked by the letters A to E, starting with the literature survey that precedes the actual thesis work. Phase B provided the first model extension, the extension to air cargo, and some early verification. Phase C is the enhancement in model realism. In phase D, (combinations of) different model features are further verified and validated after which the final conclusions and recommendations are drafted in phase E.

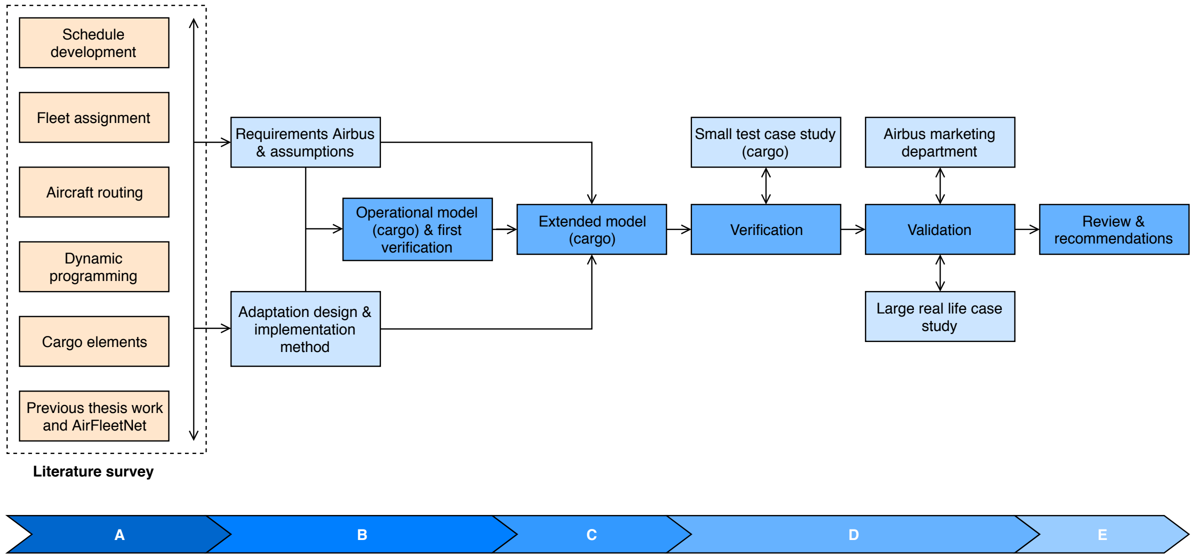


Figure 6.2: Thesis research framework

6. Experimental Set-up

The programming language used to implement the model is kept the same as the latest work conducted in this research stream: Python. This language is wide-spread throughout most industries and open-source. However, the new code is mostly written from scratch in order to follow modern Python style conventions, which will benefit both readability and modularity of the code. In order to manage both input and output data effectively, these are Excel based and consist of tabs formatted as databases. This allows for both easy adaptation when considering different case studies and future integration with actual databases used in existing schedule planning tool-sets.

Collecting the majority of appropriate assumptions, required modelling elements, operational characteristics and input data is performed through the literature review. These findings can be complemented and verified with industry experts from both aircraft manufacturer and airlines due to the collaboration with Airbus. Therefore, frequent feedback session take place to make sure that the model solves planning problems that an airline actually faces, the model relies on the input parameters that would be available to an airline, and that the solution found represents real-life operations.

To be able to extend and run the model, a very simple imaginary airline network is used first. However, the existing model utilises detailed technical aircraft parameters that feed into a module that computes (operating) cost. These parameters are also used in the extend model, at this early stage. Keeping this approach is important as hourly average (operating) cost vary significantly per airline, and using these would reduce the model's ability to easily adapt to different case studies.

Validation of the model is performed through three types of case studies. The first type considers 3 actual airline request on how to conduct future operations. The second involves a historically operated schedule, which the model should match. The third case study type is taken from literature to be able benchmark the solution.

The next section goes more into detail on the (anticipated) results and their relevance both in terms of research and real-life application.

7. Results, Outcome and Relevance

In order to validate the results that the optimisation model provides, the existing inputs are changed to Airbus' data for the aircraft and public IATA[1] data for airport tariffs. With these realistic inputs, two types of case studies can be conducted.

The results of the optimisation model are foremost schedules with an aircraft assigned to each flight (aircraft rotation), with a corresponding capacity offered. To assess these results, KPI's[2] that are widely used in the industry are provided at a flight, aircraft, and network level, and compared to real-life operations. These are either economic of nature ((direct) operating cost, potential revenue, potential profit, break-even yield, and break-even load factor) and technical of nature (available tonne kilometre, revenue tonne kilometre, average daily aircraft utilisation, average daily flight cycles, number of aircraft swapping opportunities, and number of connecting itineraries offered).

Next to evaluating KPI's, the results are assessed qualitatively for all types of case studies: "Do the obtained results represent real airline operations?" For the airline requests which cannot be compared to historic operations, this is performed together with industry experts from both aircraft manufacturer (Airbus' marketing intelligence department) and from airlines. Furthermore, a workshop is conducted with user to assess the usability as a decision-support tool.

From an academic perspective, the output of case study that uses an existing schedule as an input should provide a highly similar result to the input itself. For the additional small test case study from literature, the results are compared along the parameters described in literature. This will give an indication of the optimally of the solution obtained.

As all results can be traced back to making each decision in the dynamic programming algorithm, following all logic introduced into the model the results that are obtained are well motivated. However, some consideration made by airlines, e.g. to have a minor preference for operating one departure time over the other, can only be captured by specifying very detailed input parameters.

Providing an optimised schedule planning that represent real-life operation within a short computation time is the ultimate goal. If the model is able provide this, with as little fixed input requirements as possible, it will be a very powerful decision-support tool. Simultaneously, if the solution obtained is close to the solution provided by traditional linear programming model, the dynamic programming in airline operation research stream will receive more attention.

8. Project Planning

The project planning is drafted by following the thesis research framework as presented in section 5. The phases in this framework relate to work packages with tasks that are oriented towards completing the objectives. The overall research planning is represented visually by the Gantt chart shwon in Figure 6.3. A milestone (e.g. providing a proof of concept, handing in a deliverable or presenting to the client) should be achieved at a minimum at the end of each project phase.

The work will not only be conducted in cooperation with Airbus, but will also in part be conducted at Airbus in Hamburg. Therefore, some elements of the research planning, such as getting feedback and holding meetings, might require more effort to schedule and increased flexibility in the planning in order to find suitable dates. These are important points that need to be taken into account when managing the project.

9. Conclusions

In a growing air cargo industry, with decreasing profit margins, accurately modelling operations is more important than ever. A decision-support tool that provides an optimised schedule planning in reasonable computation time, while taking into account detailed operational constraints can greatly benefit operational efficiency. Despite significant differences with passenger operations, modelling air cargo operations has only received interest from academia. The project described in this proposal aims to improve and extend an existing model for passengers that integrates different stages in the airline schedule planning process. The existing model uses a dynamic programming optimisation approach, that has been very little explored within this context, yet displays promising results. A mathematical model is extensively validated with different case studies that are used to replicate historic airline operations, benchmark results to those found in literature,

[1] International Air Transport Association
[2] Key Performance Indices

and provide an answer to real-life airline requests. Furthermore, industry experts from both aircraft manufacturer and airlines are consulted to further validate if the results obtained could represent actual operations. Upon successful validation, the model that results from the research project is able to provide support in making schedule planning decisions that any cargo airline faces within a short computation time. This furthermore provides the foundation for future research on integrated airline schedule planning through dynamic programming both on air cargo- and passenger operations.

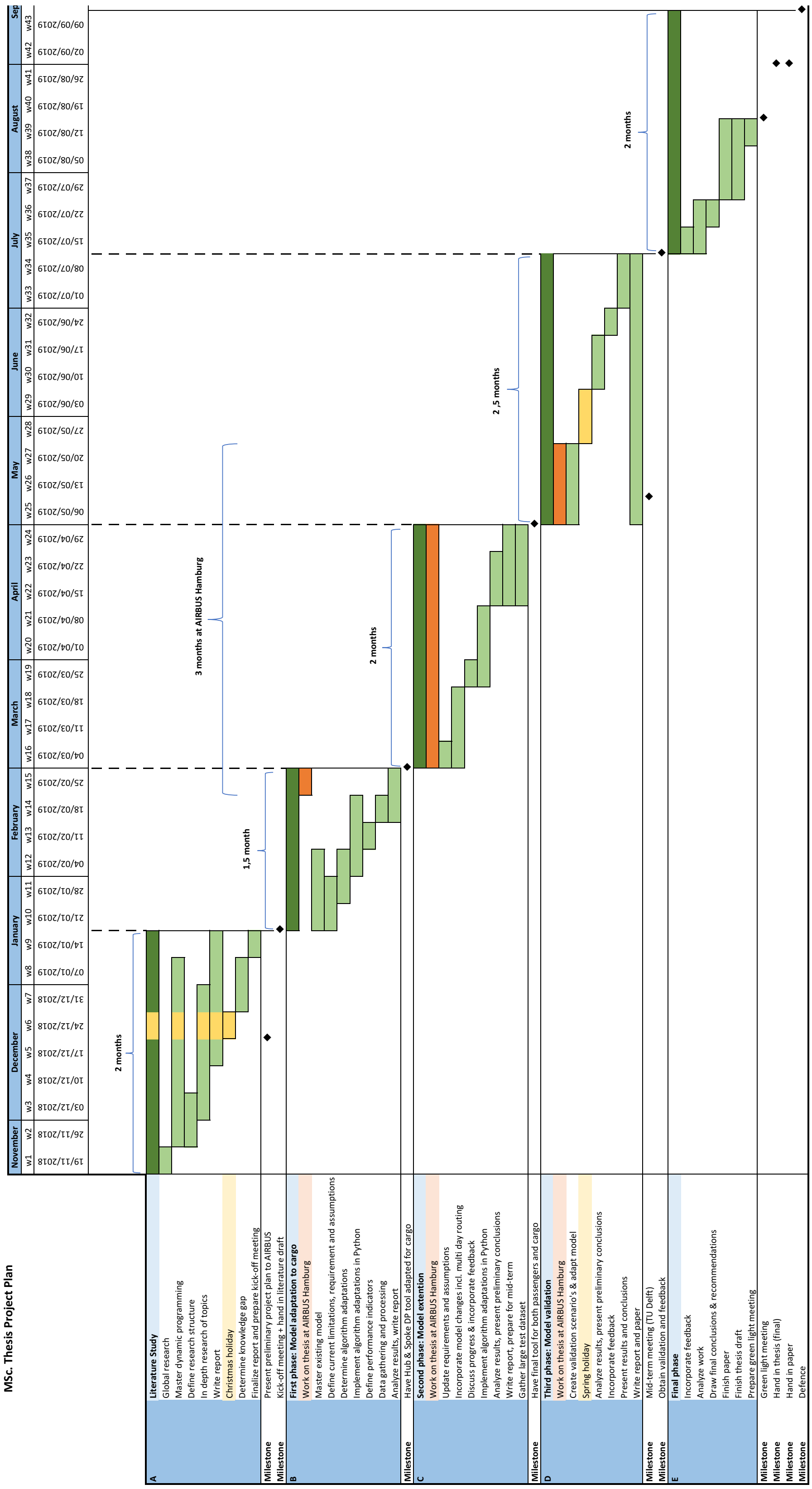


Figure 6.3: Thesis research planning

IV

Appendices

A

Cost Computation

This appendix describes the computation of cost incurred by operating a flight. These cost are split in direct operating cost, and airport dependent servicing cost, following the functional cost breakdown by ICAO (ICAO, 2017). The computation methods are to a great extent equal to the methods proposed by Rubbrecht (1989), Wang (2016). First, the methodology for computing other operating parameters that serve as an input for cost computation is presented.

1. Operating Parameters

1.1. Operating Time

The time an aircraft is in operation is split into two parts: 1) block time, 2) turnaround time. The block time is further subdivided following a typical flight profile as seen in Figure A.1. and for modelling purposes is split into two parts: 1) flight time, 2) taxi time. The flight time is computed using an aircraft's average speed over the flight profile and great circle distance between the two airports. In reality, both flight time and distance flown may significantly differ per individual flight due to ATM constraints, weather, and airline preference to control speed in order to maintain a certain arrival time.

$$time_{flight} = distance * speed_{average}$$

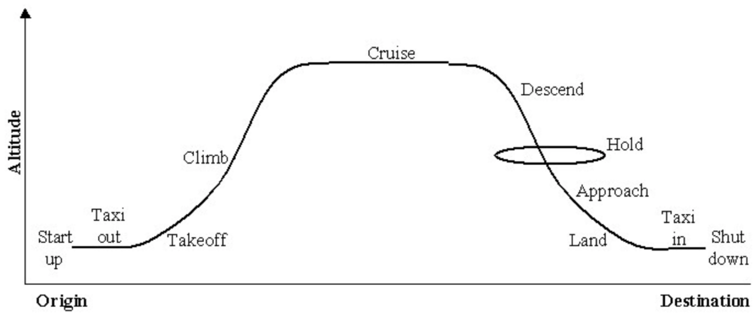


Figure A.1: Typical flight profile used by Rubbrecht (1989), Wang (2016).

1.2. Aircraft Payload Capacity and Range

Although an aircraft has structural payload limits, payload-range performance may limit the amount of payload an aircraft can carry on a specific route, as additional fuel must be carried. Using a chart such as shown in Figure A.2, the maximum payload capacity for a route can be computed. In reality, this characteristic also depends on the hourly fuel burn.

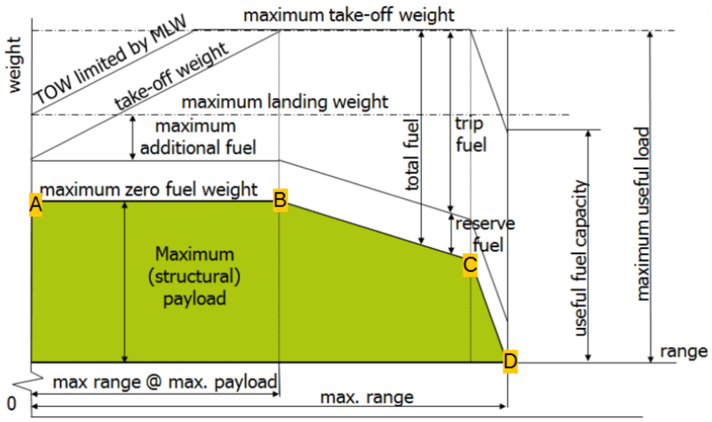


Figure A.2: Typical aircraft payload-range characteristics.

2. Direct Operating Cost

2.1. Fuel

Fuel cost depend on the fuel price and fuel required for a flight (block fuel), which is the fuel required for the entire flight profile shown in Figure A.1. The block fuel is computed by using the Breguet range equation as given below. While contingency fuel is not consumed and therefore not included in the fuel cost, it does add to the aircraft's weight. The parameters used are assumed constant over the flight profile and include engine specific fuel consumption sfc, the mach number $mach = 0.866$, lift-to-drag ratio ldr, the number of engines $n_{engines}$, and the aircraft's landing weight w_{land}. The latter consists of the operating empty weight (OEW), contingency fuel (a percentage of the OEW) and a payload at an assumed average load factor (LF).

$$w_{land} = (1 + contingency_{\%}) * OEW + LF_{average} * payload_{max}$$

$$fuel_{block} = [e^{(\frac{distance*sfc}{mach*speed_{average}*ldr})} - 1] * w_{land} * n_{engines}$$

$$cost_{fuel} = fuel_{block} * fuel_{price}$$

2.2. Ownership

Owner ship cost depend on the aircraft's financing structure: purchase or different types of lease. Here, the aircraft are considered as a purchase, and the three main costs are interest, depreciation, and insurance. An average daily utilisation as well as a number of yearly operating days are assumed to express the average ownership cost per block hour. The aircraft is subject to a straight line depreciation with a residual value that is a percentage of the initial purchase price. For maintenance, spare parts costs are taken into account as a percentage of the initial purchase price. Insurance is assumed to be a fixed percentage of the aircraft purchase price during the entire depreciation period.

$$utilisation_{year} = utilisation_{year} * days_{operating}$$

$$cost_{depreciation} = \frac{(1 + spareparts_{\%} - residualvalue_{\%}) * price_{purchase}}{time_{depreciation} * utilisation_{year}}$$

$$cost_{interest} = \frac{(1 + spareparts_{\%}) * price_{purchase}}{2} * \frac{time_{depreciation} + 1}{time_{depreciation}} * \frac{interest_{rate}}{utilisation_{year}}$$

$$cost_{insurance} = \frac{insurance_{rate} * price_{purchase}}{utilisation_{year}}$$

2.3. Crew

The crew cost are assumed to primarily consist of cockpit crew salaries, which depends on the airline. Freighters are assumed to be operated by a pilot and first officer at an average salary. For each aircraft, multiple crews are required to meet the aircraft's utilisation goals and crew duty time and rest time restrictions. Crew cost are again expressed per block hour.

$$cost_{crew} = \frac{salary_{average} * n_{crewmembers} * n_{crews}}{utilisation_{year}}$$

2.4. Maintenance

The amount of maintenance to be conducted on an aircraft is set by requirements that are expressed in flight hours, flight cycles and calendar days. The maintenance tasks are divided into air frame tasks and engine tasks. The cost to complete each task depend on the amount of labour required in hours, the hourly labour costs, and material cost. However, as these parameters can vary significantly depending on the specific aircraft and its use over time, an average maintenance cost per block hour is assumed.

3. Aircraft Servicing and Traffic Service Cost

These cost are incurred by the flight and ground operations at an airport. Other cost, such as a fuel volatility surcharge and customs cost, are directly passed on to the customer.

3.1. Navigation

Air navigation charges consist of two parts: 1) en-route charges, 2) terminal-navigation charges. Both are computed following the methods prescribed by Eurocontrol (Eurocontrol, 2018). The first are incurred while flying in airspace of a country. The overflight distance $distance^{country}_{overflight}$ and country specific unit rate $unitrate^{country}_{overflight}$ are used to compute the total en-route charges for a flight operated by a specific aircraft type with a maximum takeoff weight $MTOW$. Here, an average unit rate is assumed for the entire flight path.

$$charge_{en-route} = \sum_{country \in countries} \sqrt{\frac{MTOW}{50}} \frac{distance^{country}_{overflight}}{100} * unitrate^{country}_{overflight}$$

The second type of charges are related to approach and departure at an airport and comprise control, traffic services, and flight information. These charges depend on the aircraft's maximum takeoff weight and the unit rate charged by the departure airport only.

$$charge_{terminal} = unitrate_{terminal} * (\frac{MTOW}{50})^{0.7}$$

3.2. Ground handling charges and landing fees

A great variety of tariff structures exists for ground handling and landing charges among airports around the world. Here, a separate ground handling charge, landing charge and environmental charge is assumed. All are assumed to depend on the aircraft's maximum takeoff weight, although categorical and non-linear tariff structures exist. The environmental charge depends is a surcharge based on noise levels produced over the time of day. The surcharge is assumed to be active, or inactive, depending on the time of day.

$$charge_{groundhandling} = handling_{rate} * MTOW$$

$$fee_{landing} = (landing_{rate} + environmental_{rate}(time)) * MTOW$$

3.3. Cargo handling fees

A cargo handling fee is paid for every weight unit of cargo that is loaded on- and unloaded from the aircraft. The cargo is assumed to be divisible in tonnes. Furthermore, an average fee per tonne is assumed whereas in practise, distinction is made between different commodity types.

B
Case Study Description

This appendix describes the different case studies used to verify and validate the developed model as a whole and its composing individual elements.

1. Airline requests

The following case studies have been provided by Airbus and reflect actual airline requests on how to conduct future operations with both dedicated freighter and freighter converted Airbus aircraft.

1.1. Japanese Airline

Network symmetry: All bi-directional routes.

Goal: Provide a schedule that achieves a high utilisation.

Route frequency requirement: Operate all routes at least once, with an evenly distributed frequency.

Aircraft requirements: Narrow body aircraft. Fixed number of aircraft: 3.

Cargo routing requirements: None.

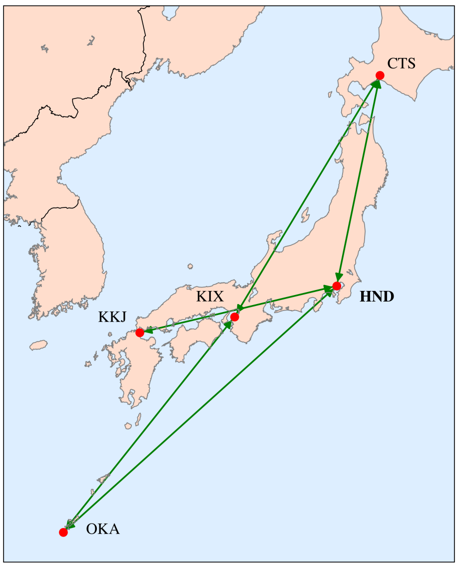


Figure B.1: Japanese airline.

1.2. African Airline

Network symmetry: Both uni- and bi-directional routes.

Goal: Provide a schedule that meets cargo route requirements.

Route frequency requirement: Operate all routes with a specified frequency.

Aircraft requirements: Wide body aircraft type. Minimum number of aircraft.

Cargo routing requirements: Offer a given origin destination capacity.

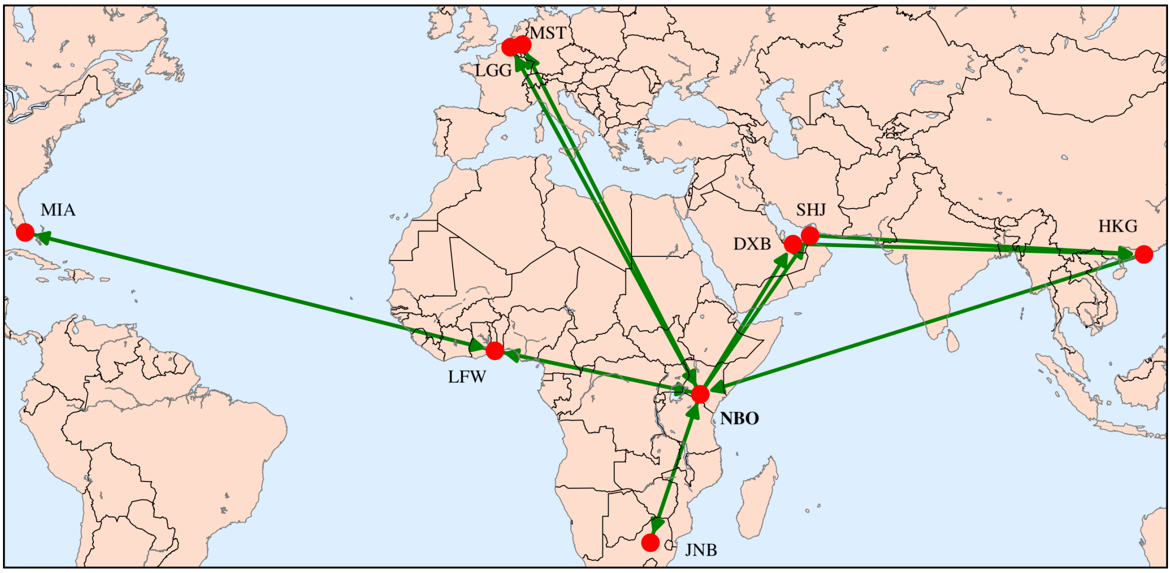


Figure B.2: African Airline network map.

1.3. South American Airline

Network symmetry: Both uni- and bi-directional routes.

Goal: Provide a least cost schedule.

Route frequency requirement: Operate all routes at least once.

Aircraft requirements: Wide body aircraft for routes with $distance \geq 2000nm$, narrow body aircraft for other routes. Minimum number of aircraft.

Cargo routing requirements: None.

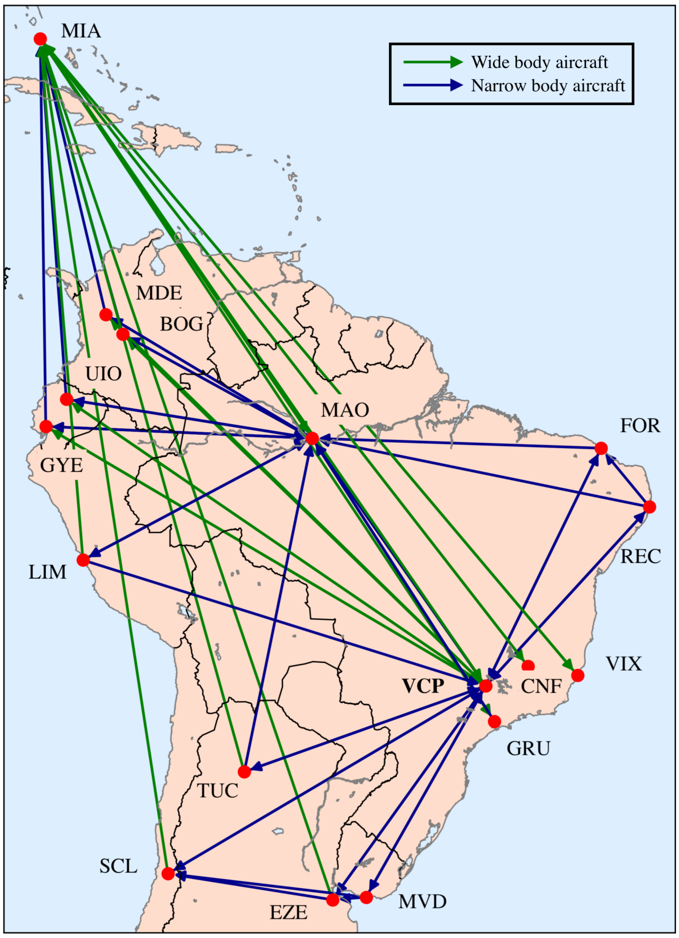


Figure B.3: South American Airline network map.

C
Verification

In this appendix, different verification experiments are presented along with the corresponding results. These experiments involve testing individual or a collection of novel model features, and are conducted on the Yamato case study. This small network is selected to be able to present the resulting flight schedules. Some modification are made to the case study to test the model feature at hand. For some features, intermediate results are presented.

1. Minimum frequency

Two methods of introducing a minimum frequency constraint are tested. The first involves an artificial reward that is granted when a flight contributes toward achieving the minimum frequency. The second involves adhering to all constraints only when no more profit can be made. For the first method, two moments are used to update the route frequency: after each aircraft and after each flight.

While the first directly maximises the number of frequency constrained routes operated, only then allowing for additional flights, the second involves prioritising making profit. For the first method, two moments are used to update the route frequency: after each aircraft and after each flight. The results of the experiments on the first method are presented in Table C.1. These two schedules clearly indicate that the minimum frequency must be evaluated after each flight within the dynamic routing optimisation process. Table C.1 (b) fits all mandatory flights within a single day with a single aircraft.

Setup Cost minimisation with minimum frequency of 1 for all routes, 2 aircraft, 1 day planning horizon

Table C.1: Minimum frequency verification schedules for cost minimisation.

(a) Minimum frequency evaluated after each aircraft.

Aircraft 1			Aircraft 2		
Dep.	Route	Arr.	Dep.	Route	Arr.
04:05	HND-CTS	05:10	04:05	HND-KKJ	05:10
06:10	CTS-HND	07:15	06:10	KKJ-HND	07:15
08:15	HND-CTS	09:20	02:15	HND-KKJ	09:20
10:20	CTS-HND	11:25	10:20	KKJ-HND	11:25
12:25	HND-CTS	13:30	12:25	HND-KKJ	13:30
14:30	CTS-HND	15:35	14:30	KKJ-HND	15:35
16:35	HND-CTS	17:40	16:35	HND-KKJ	17:40
18:40	CTS-HND	19:45	18:40	KKJ-HND	19:45
20:50	HND-CTS	21:50	20:50	HND-KKJ	21:50
18:40	CTS-HND	23:55	18:40	KKJ-HND	23:55

(b) Minimum frequency evaluated after each flight.

Aircraft 1			Aircraft 2		
Dep.	Route	Arr.	Dep.	Route	Arr.
00:15	HND-OKA	02:20			
03:20	OKA-KIX	04:55			
05:55	KIX-HND	07:30			
08:30	OKA-KKJ	10:35			
11:35	HND-HND	12:40			
13:40	KKJ-CTS	14:45			
15:45	HND-CTS	16:50			
17:50	CTS-KIX	19:20			
20:20	KIX-CST	21:50			
22:50	CTS-HND	23:55			

The second method produces equal results when minimising cost, the results however differ when revenue is introduced through a decreasing market yield curve. In Table C.2 the results for both methods are displayed. As expected, the artificial reward method in Table C.2 (a) operates the minimum frequency routes (in bold) when routing the first aircraft, while the other method (b) does so after all maximising profit. While the second method provides a much higher profit for the first aircraft, the overall profit is 4.34% lower due to some profitable routes require higher loss making routes to be operated first. Both methods should be considered based on whether or not the number of aircraft is fixed and airline requirements.

Setup Profit maximisation with minimum frequency of 1 for routes CTS-KIX and OKA-HND (both with revenue of $0), 2 aircraft, 1 day planning horizon, decreasing market yield curve for revenue.

Table C.2: Minimum frequency verification schedules for profit maximisation.

(a) Minimum frequency with artificial reward method.

Aircraft 1				Aircraft 2			
Dep.	Route	Arr.	Profit [$]	Dep.	Route	Arr.	Profit US [$]
00:15	HND - CTS	01:20	3.762				
02:20	**CTS - KIX**	**03:50**	**-7.059**				
04:50	KIX - OKA	06:25	6.478				
07:25	**OKA - HND**	**09:30**	**-9.386**				
10:30	HND - OKA	12:35	8.858				
13:35	OKA - KIX	15:10	6.278				
16:10	KIX - CTS	17:40	5.881	14:40	HND - OKA	16:45	1.149
18:40	CTS - HND	19:45	4.232	17:45	OKA - KIX	19:20	478
20:45	HND - KKJ	21:50	3.772	20:20	KIX - CTS	21:50	508
22:50	KKJ - HND	23:55	4.242	22:50	CTS - HND	23:55	165
			27.058				2.299

(b) Minimum frequency evaluated after profitable flights.

Aircraft 1				Aircraft 2			
Dep.	Route	Arr.	Profit [$]	Dep.	Route	Arr.	Profit US [$]
01:10	HND - CTS	02:15	3.762				
03:15	CTS - HND	04:20	165				
05:20	HND - OKA	07:25	8.858				
08:25	OKA - KIX	10:00	478				
11:00	KIX - OKA	12:35	6.478				
13:35	OKA - KIX	15:10	6.278				
16:10	KIX - CTS	17:40	5.881	08:40	HND - CTS	09:45	-304
18:40	CTS - HND	19:45	4.232	**16:45**	**CTS - KIX**	**18:15**	**-7.059**
20:45	HND - KKJ	21:50	3.772	19:15	KIX - OKA	20:50	678
22:50	KKJ - HND	23:55	4.242	**21:50**	**OKA - HND**	**23:55**	**-9.386**
			44.145				-16.071

2. Flight timing

Constraints have a major impact on the timing of flights throughout the planning horizon. To verify the route operating window, slot unavailability, and curfew a test is conducted where these are given. Furthermore, the timezone conversion is tested to ensure constraints are adhered to in local time. In Table C.3, the resulting flight schedule is presented. Besides adhering to all constraints in the correct timezone, one can again observe that the dynamic programming aims to schedule all flights as late in the planning horizon as possible.

Setup Cost minimisation with minimum frequency of 1 for routes CTS-HND (15:00-24:00) and HND-OKA (00:00-08:00), 1 aircraft, 1 day planning horizon. Curfew at HND 05:00-23:00, slot availability at CTS 14:00-17:00 (local time), timezone for CTS UTC+10 and for other airports UTC+9.

Table C.3: Flight timing verification schedule with the local departure- and arrival times in bold.

Aircraft 1				
Dep. UTC+9	Dep. UTC+10	Route	Arr. UTC+9	Arr. UTC+10
05:55	06:55	HND-OKA	**08:00**	09:00
10:50	11:50	OKA-KIX	**12:25**	13:25
13:25	14:25	KIX-CTS	14:55	**15:55**
15:55	**16:55**	CTS-HND	**17:00**	18:00

Although a decreasing market yield curve stimulates the spreading of flights with the same origin and destination over the planning horizon, a hard constraint is tested that guarantees a minimum time separation between these flights. With the following setup, the schedule in Table C.4 shows for the flights in bold that the minimum time separation is adhered to. Without this constraint, the schedule would look similar to that of aircraft 1 in Table C.1 (a).

Setup Cost minimisation with minimum frequency of 6 for all routes, 1 aircraft, 1 day planning horizon. 12 hours minimum separation between departure times of flights with same origin and destination.

Table C.4: Verification schedule for flight departure time separation.

Aircraft 1		
Dep.	Route	Arr.
00:35	**HND-KKJ**	01:40
02:40	KKJ-HND	03:45
04:45	HND-CTS	05:50
06:50	CTS-KIX	08:20
09:20	KIX-CTS	10:50
11:50	CTS-HND	12:55
13:55	**HND-KKJ**	15:00
16:00	KKJ-HND	17:05
…	…	…

3. Yield

When computing profit using a fixed yield, the model will choose to operate the most profitable back and forward routes only when no static demand is present to limit the amount of revenue that can be captured. This behaviour results in schedules similar to the first column of Table C.1 (a). An experiment is performed with a decreasing market yield curve of which the resulting schedule is presented in Table C.5. We observe that profit of each route is decreasing with the frequency flown. This has two effects: flight of the same routes are spread over the planning horizon of a single aircraft and the number of aircraft is limited as total profit per aircraft is decreasing.

Setup Profit maximisation with decreasing yield curve for revenue (maximum market yield of 1.00 US$, minimum market yield of 0.06 US$, market size parameter of $1+\frac{1}{48}$), unlimited number of aircraft, 1 day planning horizon.

Table C.5: Verification schedule for decreasing market yield curve.

Aircraft 1				Aircraft 2				Aircraft 3			
Dep.	Route	Arr.	Profit [US $]	Dep.	Route	Arr.	Profit [US $]	Dep.	Route	Arr.	Profit [US $]
				01:05	HND - CTS	02:10	1,323				
				03:10	CTS - HND	04:15	1,793				
04:25	HND - OKA	06:30	10,067	05:15	HND - OKA	07:20	4,234				
07:30	OKA - KIX	09:05	7,188	08:20	OKA - KIX	09:55	2,799				
10:05	KIX - CTS	11:35	6,724	10:55	KIX - OKA	12:30	2,999	08:35	HND - OKA	10:40	74
12:35	CTS - KIX	14:05	6,703	13:30	OKA - HND	15:35	4,524	11:40	OKA - KIX	13:15	-331
15:05	KIX - OKA	16:40	7,388	16:35	HND - KKJ	17:40	1,329	14:15	KIX - CTS	15:45	2,658
17:40	OKA - HND	19:45	10,357	18:40	KKJ - HND	19:45	1,799	16:45	CTS - KIX	18:15	2,637
20:45	HND - KKJ	21:50	4,411	20:45	HND - CTS	21:50	4,399	19:15	KIX - OKA	20:50	-131
22:50	KKJ - HND	23:55	4,881	22:50	CTS - HND	23:55	4,869	21:50	OKA - HND	23:55	365
			57,719				30,067				5,272

4. Schedule start moments

The schedule start times are staggered over the planning horizon to prevent all aircraft starting having to start and end the planning horizon at the base. Table C.6 shows the results of an experiment conducted. It becomes clear that the schedules of aircraft 1 and 3 start at the beginning of the planning horizon while the schedule of aircraft 2 starts at day one (all highlighted in bold).

Setup Cost minimisation with minimum frequency of 6 for all routes, 3 aircraft, 2 day planning horizon. Schedules start times are separated by 1 day.

5. Schedule continuity and maintenance

From the end to the start of the schedule (without schedule star time separation this coincides with the start of the planning horizon), continuity is guaranteed. The turnaround- and maintenance time requirements are adhered to dynamically. From Table C.7 it becomes clear that during the schedule, a maintenance opportunity of 4 full consecutive hours exists. This results in a 3 hour requirement for the start of the planning

Table C.6: Simplified verification schedule for staggered schedule start moments.

Aircraft 1			Aircraft 2			Aircraft 3		
Dep.	Route	Arr.	Dep.	Route	Arr.	Dep.	Route	Arr.
00:03:05	**HND - KKJ**	00:04:10	00:00:05	KIX - CTS	00:01:35	**00:04:35**	**HND-OKA**	00:06:40
…	…	…	…	…	…	…	…	…
00:23:55	HND - CTS	01:01:00	00:22:50	KKJ - HND	00:23:55	00:22:35	KIX-OKA	01:00:10
01:02:00	CTS - HND	01:03:05	**01:03:25**	**HND - OKA**	01:05:35	01:01:10	OKA-KIX	01:02:45
…	…	…	…	…	…	…	…	…
01:22:50	CTS - HND	01:23:55	01:21:35	CTS - KIX	01:23:05	01:21:50	OKA-HND	01:23:55

horizon, which is met. Note that while the first flight could have been scheduled at 03:00, this does not provide an increase in profit.

Setup Profit maximisation with decreasing market yield curve, 1 aircraft, 7 day planning horizon. On day 3, slots at HND are unavailable 09:00-13:00, 7 hours of weekly maintenance required at base HND.

Table C.7: Simplified continuity verification schedule with maintenance and turnaround time constraints.

Aircraft 1		
Dep.	Route	Arr.
00:04:05	HND-OKA	00:06:10
…	…	…
03:06:50	OKA-HND	03:08:55
03:13:00	HND-KKJ	03:14:05
…	…	…
06:21:50	OKA-HND	06:23:55

6. Itinerary generation

Feasible itineraries to transport OD cargo are generated for each flight. The cargo is either transported on a sequence of connected flights with the same aircraft, or through transfer at the base, HND. Constraints must be met that guarantee cargo is transported at a maximum transit time, by a maximum number of connected flights, and with sufficient transfer time. Furthermore, all flights must be contained within the planning horizon. For the schedule presented in Table C.2 (a), the itineraries that use these flights are found for both types of transport. The results are presented in Table C.8.

Setup Profit maximisation with minimum frequency of 1 for routes CTS-KIX and OKA-HND (both with revenue of $0), 2 aircraft, 1 day planning horizon, decreasing market yield curve for revenue. Maximum transit time of 24 hours, minimum transfer time of 2 hours, maximum 3 sequential flights.

Table C.8: Itineraries generated for transporting OD cargo on sequential flights and with a transfer a the base.

Aircraft 1					Aircraft 2				
Dep.	Route	Arr.	Sequential	Transfer	Dep.	Route	Arr.	Sequential	Transfer
00:15	HND - CTS	01:20	HND-KIX, HND-OKA						
02:20	CTS - KIX	03:50	CTA-OKA, CTS-HND						
04:50	KIX - OKA	06:25	KIX-HND						
07:25	OKA - HND	09:30		OKA-KKJ (AC1: 20:45)					
10:30	HND - OKA	12:35	HND-KIX, HND-CTS						
13:35	OKA - KIX	15:10	OKA-CTS, OKA-HND	OKA-KKJ (AC1: 20:45)					
16:10	KIX - CTS	17:40	KIX-HND, KIX-KKJ		14:40	HND - OKA	16:45	HND-KIX, HDN-CTS	
18:40	CTS - HND	19:45	CTS-KKJ		17:45	OKA - KIX	19:20	OKA-CTS, OKA-HND	
20:45	HND - KKJ	21:50			20:20	KIX - CTS	21:50	KIX-HND	
22:50	KKJ - HND	23:55			22:50	CTS - HND	23:55		

Using the same definition for feasible paths, an alternate objective function that maximises the number of itineraries is tested. Table C.9 presents the results of these experiments. For each flight, the number of additional itineraries that this flight creates is counted. For paths that use a sequence of flights with the same aircraft (a), the schedules for both aircraft are exactly the same. The schedule shows that the model aims to show the longest chain of flights. While for the paths that allow for a connection at the base (b) the schedules are the same, the number of additional itineraries is not only higher but increases for the second aircraft.

Additionally, the model tries to fly as many times back and forward forward from the hub as possible to maximise the number of connections, as expected. Of same OD itineraries, each occurrence is counted. While this is unrealistic for a small network with a single day planning horizon, after applying other constraints having multiple itineraries is indeed realistic.

Setup Itinerary maximisation, 2 aircraft, 1 day planning horizon, maximum transit time of 24 hours, minimum transfer time of 2 hours, maximum 3 sequential flights.

Table C.9: Verification schedules for itinerary maximisation.

(a) Sequential flights.

Aircraft 1				Aircraft 2
Dep.	Route	Arr.	Itineraries	Itineraries
01:20	HND - KKJ	02:25	1	1
03:25	KKJ - HND	04:30	3	3
05:30	HND - CTS	06:35	2	2
07:35	CTS - KIX	09:05	1	1
10:05	KIX - CTS	11:35	3	3
12:35	CTS - HND	13:40	3	3
14:40	HND - OKA	16:45	3	3
17:45	OKA - KIX	19:20	3	3
20:20	KIX - CTS	21:50	2	2
22:50	CTS - HND	23:55	1	1
			22	22

(b) Transfer at the base.

Aircraft 1				Aircraft 2
Dep.	Route	Arr.	Itineraries	Itineraries
01:05	HND - OKA	03:10	1	1
04:10	OKA - HND	06:15	5	9
08:15	HND - KKJ	09:20	1	2
10:20	KKJ - HND	11:25	3	5
12:25	HND - KKJ	13:30	1	2
14:30	KKJ - HND	15:35	2	3
16:35	HND - CTS	17:40	1	3
18:40	CTS - HND	19:45	1	1
20:45	HND - CTS	21:50	1	4
22:50	CTS - HND	23:55	1	1
			17	31

D

Sensitivity Analysis

In this appendix, an initial sensitivity analysis is performed.

1. Slot availability

Using the African Airline case study, the impact of limiting the available slots for each hour of the day based on the number of flight movements of passenger aircraft was examined. The multiplier α of the standard deviation σ is varied by the values shown in Figure D.1, such that for all airports a new limit of flight movements is computed. The results of these experiments are presented in Figure D.2. Both the flight cycles (a) and block hours (b) generally drop for the first aircraft while rising for the second aircraft, when the number of available slots is decreased, besides a swap in flights at $\alpha = 0$ for feasibility. Furthermore, an additional aircraft is required from $\alpha = 0.4$. For this network and the imposed requirements, a value for α should be chosen in the range $[0.6, 0.4]$ to ensure even wear and tear on the two aircraft in terms of both flight cycles and flight hours.

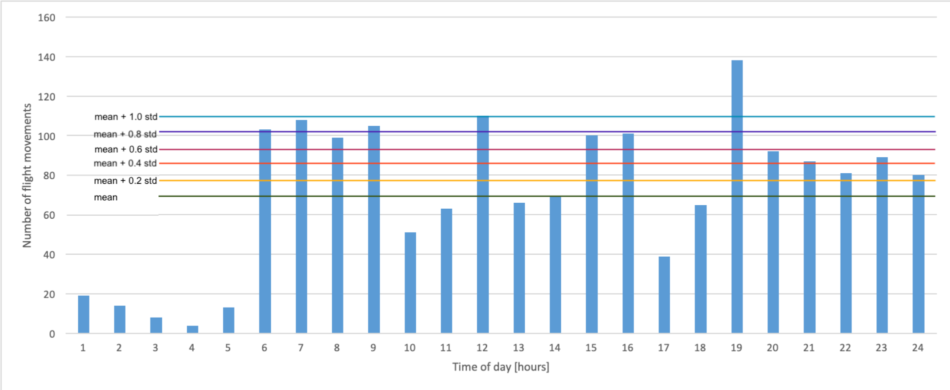
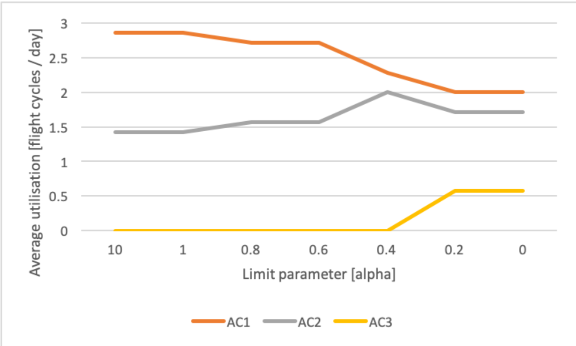
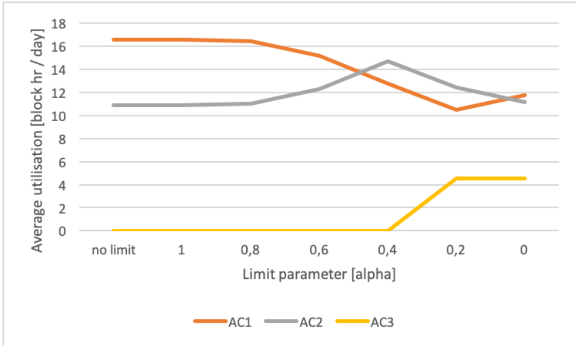


Figure D.1: Scheduled flight movements per hour at the base airport for the African Airline case study (OAG, 2019).



(a) Utilisation in flight cycles.



(b) Utilisation in block hours.

Figure D.2: Average utilisation per aircraft when varying the available slots for the Kenya Airways case study.

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