Air Cargo Revenue Management

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March 15, 2013
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Preface

Before the summer of 2012 I was trying to find a challenging topic for my master’s thesis. Although I have always enjoyed the theoretical approach of my study Econometrics and Operations Research, I preferred to work on a project in which I could apply many of the things I learned during my study in an important industry, for instance the railway or aviation sector. Before I had even started looking for an interesting research problem, I was told about the e-freight project on which students on the Nyenrode Business University were working. One of the research topics within this project was to evaluate the possible benefits of Revenue Management implementations in the air cargo industry. As this research project was rather technical of nature, it would fit more in the scope of my study Econometrics and OR. The topic caught my interest instantly, and after the summer I started working on the thesis you are holding in your hands right now. Working on this project has not always been easy. It was difficult to derive a simplified but useful model from such a complex industry, and hard to find a balance in keeping the research understandable and useful in the industry and at the same time delivering an interesting thesis for finishing my master’s. With the support of many people in my environment I succeeded in delivering this report, which I hope to be a useful contribution to the research in air cargo revenue management.

Acknowledgements

This thesis has been a tremendous opportunity for me to get a look behind the scenes in the air cargo industry. Without the help of many people, producing this thesis would not have been possible.

I would like to thank my supervisor Joaquim Gromicho, who has always been helpful, interested and very supportive during the project. I would also like to thank my supervisor Ben Radstaak at ACN. He gave me the opportunity to obtain a good view of the industry and introduced me to a lot of people working in the air cargo business at Schiphol. Pieter Klapwijk has been very interested in this research and been very helpful to me, therefore I would like to thank him.

I appreciate that I had the opportunity to work for Rein Nobel as a student assistant for two years. I want to thank him for making me aware of this project, and for his interest and helpful suggestions.

I am very grateful that I had the chance to speak to many people working in the air cargo industry at Schiphol and who helped me a lot by sharing their business knowledge and experience. Therefore I would like to thank Carsten Pellicaan, Bart-Jan Haasbeek, Felix Brückner, Wim Sonneveldt, Ivo Aris and Marianne van Wensen and all the other people from KLM. Their information
has been a major contribution to this thesis. Special thanks go to Marcel Stühmer, who gave me the opportunity to observe the air cargo process in real life. I would like to thank Leo de Haas, who told me a lot about his experience in the industry, introduced me to many people and has always been a lot of fun speaking to at ACN.

My special thanks go to my fellow research interns Steven and Sebastiaan, with whom I always had a good time working at ACN, and who always gave me helpful suggestions.

Last but not least I would like to thank my girlfriend Sanne, my family and friends who always gave me the support I needed.

Thijs Boonekamp
Schiphol, March 15, 2013
Abstract

The practice of Revenue Management (RM) has caused a major revolution in the passenger airline industry and these days sophisticated RM systems are required for airlines to remain viable. After huge successes in passenger airlines other industries like the hotel and car rental business quickly followed in using RM systems. Although the air cargo industry contains many parallels with these industries, cargo RM is still in its infancy.

Due to the weak economic conditions and fierce competition in the air cargo industry it is difficult to make profit. Only focussing on cost reduction might not be sufficient to keep a strong market position, therefore one might consider focussing on revenue increase by efficiently applying RM.

In this thesis we perform a sound analysis of the air cargo industry and develop a practical RM framework. We develop two different models, the first based on the model described by Kevin Pak [30], and the second being our own developed practical model based on information gained from industry experts.

For both models we quantified the theoretical potential of RM implementation by solving the corresponding ILP problems. We tested the performance of easy to implement booking control policies, which are static bid prices in the first model and static booking limits in the second model. For both models we can conclude that compared to a First Come First Serve acceptance policy, a theoretical benefit of more than 20% can be realised.

In our own model various fare classes are constructed in which we included the aspects of an early booking discount and a flexible shipment type which, may be replaced on another flight. This model shows that by using fairly straightforward booking control policies a strong increase in revenue can be realised.
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List of Abbreviations

(C)RM  (Cargo) Revenue Management
BSA   Block Space Agreement
CAO   Cargo Aircraft Only
DG    Dangerous Goods
DP    Dynamic Programming
FCFS  First Come First Served
FTK   Freight Ton Kilometer
GDS   Global Distribution System
MDP   Markov Decision Process
pdf   Probability density function
PP    Poisson Process
r.v.  Random variable
RTK   Revenue Ton Kilometer
ULD   Unit Load Device
1 Introduction

Revenue management (RM) is the art of maximising a firm’s revenue by analytically predicting consumer behaviour and demand. The primary goal in RM is selling the right product to the right customer for the right price at the right time. In order to achieve this goal extensive market knowledge is required to understand customers’ behaviour and valuation of a product. For different customers separate market segments need to be defined corresponding to their specific wishes. As a result, the amount paid by a customer corresponds to his personal valuation of the good.

Since the deregulation of the airline industry in the 1970s and the uprising of the low cost carriers, passenger airlines have developed sophisticated RM techniques. These days, it is hard for an airline to survive without a complex RM system. After successful RM implementation in the airline industry, other industries like hotel and car-rental businesses followed quickly. All industries with a fixed and perishable capacity and varying demand can increase profit by properly applying RM. Although the air cargo industry does have the characteristics for a business where RM is applicable, cargo RM practices are significantly underrepresented in literature and applied in a far less sophisticated way as in passenger airlines. The main reason for this is that the air cargo industry is much more complex than the passenger segment. Products sold for air cargo have multiple dimensions (volume and weight), size restrictions (a piece has to fit through the door), special care (cooled products), coloadability restrictions (live animals cannot be loaded next to radioactive material), weight has to be distributed evenly over the plane, and there are many other practical difficulties which can be thought of.

There is a large variety of air cargo customers and shipments, all with different needs and characteristics. As a result, the price the customer is willing to pay for the required capacity varies for all these different shipments. The main goal of RM is to make sure that enough capacity is reserved to sell to high revenue customers, while still trying to fully utilise the available capacity by offering a low fare product. For each customer the decision has to be taken on whether or not to accept the demand, and for what price. These decisions are currently (mainly) taken manually by industry experts at sales departments, without using any decision support systems.

The introduction of the e-freight concept has been an eye-opener in the generally very conservative air cargo industry, and has stressed the need for better integrated IT systems. Now that digitalized booking is an upcoming trend in the air freight industry, more sophisticated RM systems could be used for efficient cargo pricing in online booking. As digitalization is an upcoming trend, profit margins are low and competition is fierce, this research is of major importance for the air cargo industry.
The objective of this thesis is to analyse the air cargo industry and describe the opportunities for RM in this industry. We will describe possible benefits of RM in the air cargo industry and discuss for what other purposes, other than revenue increase, RM can be useful. Based on this analysis, we try to provide a realistic model to simulate air cargo bookings and test various strategies to determine which shipments to accept and reject to maximise revenue. We use this model to quantify the possible benefits for RM application in air cargo.

The remainder of this paper is organised as follows: Chapter 2 gives a literature review of the published work on cargo RM and RM in general. Chapter 3 provides an overview of the air cargo industry and its main characteristics. Chapter 4 specifies why RM can be implemented in the cargo industry. Chapter 5 proposes a framework to model air cargo bookings. In chapter 6 a single-leg model is analysed and optimized by finding optimal bid-prices, following the model of [30]. Chapter 7 describes a model where we simulate one week of flights where we can replace some shipments on later flights. This model is constructed using information of various industry experts, and is – to our knowledge – a new practical contribution to the existing Cargo RM literature. In the final chapter we conclude.

2 Literature review

While there has been an extensive amount of research on RM, specifically in passenger airlines, the number of applications for air cargo are limited. For an recent and thorough overview of published work on RM, we refer to [8].

In 1996, Kasilingam is the first to highlight major differences between cargo and passenger RM, and discuss the complexities involved in implementing cargo RM [22]. Becker goes deeper into the complexities of cargo RM and suggests various ways to overcome these [3].

Articles proposing a framework for cargo RM include Billings, 2003 [4], who describes the change of cargo business as a result of automation in the industry, and Graff, 2008 [13] who argues that an integrated RM system with both cargo and passenger business is not likely to succeed.

From a more mathematical perspective, several articles are published proposing various optimization algorithms for cargo RM. Overbooking, which is intentionally selling more capacity than available, is a well-known RM practice to prevent losses from late cancellations and no-shows. In Kasilingam, 1997, a cost model for optimal overbooking of air cargo under uncertain capacity is presented [23]. Other articles considering the cargo overbooking problem are [28, 33, 37].

There are several articles on the booking-control problem for air cargo. The problem is to determine whether or not to accept demand for capacity, given
that there are various types of demand. Pak and Pak and Dekker were the
first to develop an algorithm to tackle this problem [30, 31]. They handled
the problem as a multidimensional 0-1 knapsack problem. Han Dong Ling,
2009, considers the same problem and proposes a Markovian model to solve
the acceptance/rejection policy [14]. Huang, 2005, proposes a Dynamic Pro-
gramming (DP) algorithm for the cargo problem where available capacity is
not certain [17]. Amaruchkul, 2007, gives six heuristics for solving the problem
formulated as a Markov Decision Problem (MDP), where each booking has a
random volume and weight [1]. Huang, 2009, develops another DP approxima-
tion algorithm [16]. Levina, 2010, covers capacity management over a network
instead of a single-leg using a Linear Programming (LP) and stochastic simu-
lation approach [27]. Levin, 2011, includes various contract forms in handling
the cargo capacity management problem [26].

3 The Air Cargo Industry

Air freight is the fastest and most expensive way of transporting goods. There-
fore, it is mainly used for high-valued or perishable goods which require fast
delivery. The global amount of world air cargo traffic was 202 billion RTKs
(Revenue Ton Kilometres) in 2011. To compare, containership cargo traffic
was estimated at 10.5 trillion RTKs in the same year [6]. These volumes have
stabilized in 2012 and tend to move evenly with the world economic growth.
Air cargo traffic is strongly related to world GDP and is often seen as a good
indicator for the global economy.

3.1 The Air Cargo Supply Chain

The three main actors in the air cargo supply chain – on the export side –
are shippers, forwarders and carriers. For import, the destination forwarders
and consignees also play an important role. As this thesis considers Revenue
Management for export shipments, we will only consider the left hand (export)
side of the chain, which is displayed in Figure 1.

Shippers are companies or individuals who want to use air freight to transport
their products. Carriers or airlines are the asset holders, who offer cargo capacity
on their planes. Forwarders are intermediaries between the shipper and the
carrier. They negotiate prices with a carrier and provide transportation service
to and from the airport. Added to this, they take care of all the paperwork
and customs involved in shipping goods. Their role in the supply chain can be
compared with the role of a tour-operator in holiday business.
3.1.1 Vertical integration and the role of integrators

In passenger airlines, customers have the choice to book through a tour operator or another intermediary, or book directly at the carrier. The first way of booking allows the customer to compare prices of different airlines, however booking directly at the carrier means that less parties have to make a profit, which implies that the latter might be cheaper. In air cargo industry, all shipments are booked by forwarders. It seldomly occurs that a shipper speaks directly to the carrier. As a result, there is no transparency in air cargo rates. Shippers only know what they have to pay to the forwarder, and forwarders have their rates at the carrier, but do not know what their competitors pay. Because of this intransparency a market equilibrium is hard to achieve.

A special case in the cargo market are the integrators. These are forwarding companies which have their own flight network, which they use for mail and package services. The most famous integrators are DHL Express, FedEx and UPS. Their efficiency is much higher as they own the whole supply chain, so no time and money is lost because of shipment handovers or additional paperwork. The integrators are gaining market share as the size of the shipments they accept increase.

In this thesis we will only consider the traditional air freight services, as the integrator business is considered as a different market than the traditional air cargo industry.

3.2 Types of airplane capacity

Carriers have two different types of capacity available. Both cargo capacity on passenger flights and full freighter services are provided, which both have their own pros and cons. Belly capacity on passenger aircraft is sometimes preferred by customers as these services are subject to the passenger’s schedule, thus these flights are less likely to be cancelled. However not all shipments can be carried on passenger aircraft, due to size or safety restrictions. These cargo aircraft only (CAO) goods have to be carried on full freighter airplanes.

There is a difference in available capacity between wide- and narrow-body
Narrow-body aircraft are smaller aircraft which are mostly used for short flights. In these aircraft cargo is carried in containers or loose. As almost all air freight shipments are intercontinental, wide body aircraft are mostly used. These larger aircraft have more available capacity, divided over a fixed amount of available ULD (Unit Load Device) positions.

Shipments are carried either in lower-deck containers, or on main or lower-deck pallets. An ULD pallet is 244cm × 318cm. A lower deck pallet may not be higher than 160cm, while a main deck pallet can be as tall as 250cm. Main deck ULDs are only available on freighter or ‘combi’ aircraft. The latter aircraft carries passengers in the front on the main deck, and the rear end of the aircraft is available for cargo.

The distribution of the amount of capacity over freighter and passenger aircraft varies between different airlines. Some dedicated cargo carriers do not have a passenger network, so all their capacity is on freighter aircraft. Others mainly use their passenger network for airfreight services. Figure 2 shows the distribution of freight carried on freighters and on passenger aircraft. These values follow the same trend, however the amount of freighter hold cargo is around 9 billion FTKs, and the belly hold capacity around 6 billion FTKs. This difference is due to the fact that a full freighter can carry 100 tonnes of cargo, while capacity on passenger aircraft varies and is usually around 10-20 tonnes.
3.3 Main air cargo markets

The air cargo industry is a worldwide business where shipments are sent all over the world. There are many large trade flows from producing countries to their export destinations. In Figure 3 the market share of the total amount of FTKs by route is shown. Flows from Europe and North-America to Asia and vice versa cover the largest amount of global air cargo traffic. One can also observe the large trade imbalance: for instance the flow from North-America to Asia is 15 billion RTKs, while this is 27 billion RTKs from Asia to North-America.

Most airlines use a certain hub in their home country. Large airlines have their own trucking network within a continent which they use for moving shipments to their main hub, where shipments are loaded on the plane for inter-continental transfers. Trucking is a much cheaper and less polluting way of transportation. This is why the market for air cargo within Europe is very small, only 0.8% of the global FTKs [6]. The domestic US air freight market is somewhat larger, but the main commodity on these flights is mail and express goods, transported by integrators like FedEx or UPS.

3.4 Typical air cargo products

As mentioned above, air freight is the most expensive way of transporting goods, and is therefore used for specific types of products which need fast delivery.
Products which are often transported by air freight are:

- Perishable goods (fruits, vegetables, fresh fish, flowers);
- High-value goods (gold, banknotes);
- High-tech goods;
- Pharmaceuticals;
- Spare parts (to prevent production line stops in factories);
- Live animals;
- Goods with a short economic lifecycle (radioactive material, newspapers).

High-value goods are often transported through air for two reasons. The first reason is safety: fast delivery means less risk of problems with the shipment. When a shipment is on sea for a few weeks, it is a lot more vulnerable to theft or piracy. The second reason is that for high valued goods, the transport costs relative to the product’s value is negligible.

Perishables like vegetables, flowers or fresh fish need to be transported as fast as possible, as well as for instance newspapers. These products have a short economic lifecycle: they lose their value after one or few days.

Some frozen pharmaceuticals need to be cooled during transportation. For these shipments, dry ice is used which is placed in an insulated container.

Spare parts form another common air freight shipment. It is very expensive when factories have line-stops: Not producing means that the staff cannot work and production processes often have a long start-up time. This means that when machinery is broken spare parts need to be delivered as soon as possible. Aircraft engines are another example, it is expensive when a plane is out of service for a long time.

Besides these types there are many more goods which are shipped using air freight. Some of these need extra care, but there is also a large market for general shipments, which are collectively booked as a large consolidation by a forwarding company. This way the forwarder is able to obtain cheap capacity because of scale benefits, and the carrier is ensured of a large amount of capacity utilisation.

3.5 Contracts and booking behaviour

Due to the nature of the goods commonly transported through the air, bookings often come in close to departure. Air cargo is an ad hoc business for products which require fast delivery. Currently, most bookings occur through phone calls.
or e-mails. Advanced systems for online booking are gaining popularity, however many parties still prefer personal contact and negotiations for each booking.

Large forwarders have contracts with carriers in which they reserve a specific amount of capacity on a flight for a favourable rate. Contracts are advantageous for carriers as they have a guaranteed amount of capacity used, and forwarders are able to buy in capacity for a better price. Contract rates are usually specified for a one year period. There are basically two types of contracts:

- **Allotments**: Reserved capacity for a fixed rate per kg. When the forwarder shows up with less or more cargo than specified in the contract, he usually pays the same rate.

- **BSAs (Block Space Agreements)**: Reserved capacity for a fixed rate. The forwarder pays for all the capacity reserved, even when not all this capacity is utilised.

In the allotment contract the risk of not utilising the agreed capacity is for the airline, whereas this is the forwarder’s risk in a BSA. The allotment contract form still is an important point of discussion in the industry. In fact, an allotment contract is a free call option for capacity. This is a system which is very vulnerable to abusement, as customers are not penalised for no-shows or low-shows, and can only survive with a sort of gentlemen’s agreement and mutual respect for bookings (see next paragraph).

Capacity which is not sold in contracts is available on the spot market. This capacity can be used for ad hoc shipments where forwarders and carriers negotiate the price. Airlines have specified standard market rates, however most of the time forwarders try to obtain a better price for their shipments.

Spot market shipments are often more expensive than contract rates. Contract rates are based on a large amount of consolidated general cargo, while capacity acquired on the spot market are mostly back-to-back shipments. This means that the forwarder directly obtains capacity for one shipper’s shipment.

These spot market shipments are most interesting from a RM point of view. Contracts cover a fixed amount of capacity for a fixed rate. The airline’s objective is to utilise the remaining capacity such that revenue is maximised. Reselling contract space by forwarders is also interesting from a RM point of view. When the forwarder has a contract he is in fact the capacity owner, which he needs to resell in an optimal way to his customers.

### 3.5.1 Mutual respect for bookings

A common problem in the air cargo industry is that shipments do not tender as booked, or do not show up at all. Since, unlike in the passenger industry,
payment occurs after the shipment is sent, forwarders (or shippers) are not penalised for not using booked capacity. In essence, this means that a free option on capacity can be obtained. It occurs that much more capacity than needed is booked, either to obtain a better price, or to prevent that capacity is sold to competitors. As a result, carriers usually overbook their flights to increase the load factor.

A part of the discrepancy between capacity booked and tendered is inevitable. For instance spare parts need to be sent when a breakdown has occurred, and needs to be shipped as soon as possible. However, the existence of free capacity options does not stimulate shippers to improve their demand forecasts. This is why overbooking is needed in any fixed capacity industry, although the scale might be reduced when actual demand forecasts are improved.

Due to the lack of motivation to improve demand accuracy, forwarders keep booking more space than actually needed as they want to be sure to have enough space available, which causes carriers to overbook their flights more than necessary. As a result, some shipments cannot be taken on the booked flight when too much freight shows up. This means the industry is in a vicious circle of constantly booking more than needed, and accepting more bookings than available.

Many people have addressed this problem in the industry. Some carriers tried to introduce penalty costs for not showing up. This has not always been successful, as forwarders quit booking capacity from this carrier. This is disastrous in this industry, as carriers are dependent on only a small number of (large) customers. Very recently however, Air France/KLM introduced penalties for low/no-show cargo and realised a 4-5% increase in booking reliability [25]. Hellermann proposes the use of real capacity options instead of allotment contracts [15]. However his results are positive, airlines are very cautious using another penalty or cost structure.

When RM is implemented comparable to the passenger’s system, mutual respect for bookings need to exist. Forwarders should book the amount of capacity which they honestly expect to require – and thus stimulate shippers to improve their forecast – whereas carriers need to make sure they have this capacity available. Flexibility for shipments can be sold: when the size of the shipment is unknown, the prices for those shipments should increase. On the contrary, a cheaper fare class should be available for less time-sensitive shipments, which can be placed on later flights. This is one of the opportunities for RM in the air cargo industry. Successful implementation of RM requires a change in the way of thinking of traditional cargo booking. In the next chapter we propose some of the possibilities for RM in the cargo industry.
4 Air Cargo Revenue Management

Currently, the major problem in the air cargo industry is that customers do not pay for the service or product they actually use. All prices are stated per kg, although nearly all flights are volume constrained. All bookings are scheduled for a specific flight, while most customers only want to have the guarantee that their shipment arrives before a certain day. Furthermore, prices which are established through negotiations are based more on personal relations between the seller and customer and their negotiating skills than they are based on required services or other value added services. Due to the globalisation of the air freight market and competition from other European airports, selling the right product to the right customer is becoming more and more important. Integrators are gaining market share in air freight by accepting larger packages, and in traditional air freight online bookings are an upcoming trend. As the cargo business becomes a more automated business, well-performing RM systems are gaining popularity. This is why currently most airlines are constantly developing their RM practices.

4.1 Why is the cargo industry suitable for RM?

Revenue Management can be applied in any industry where tactical demand management is important. Although the cargo industry is much more complex than the traditional RM industries, its characteristics certainly imply that RM is applicable [7].

RM can be applied in an environment where a given amount of capacity is available, and fixed costs are high. For instance a passenger airplane flies at its scheduled time, regardless of how many customers there are on this flight. In order to maximise revenue for a flight, price discrimination gives the airline a possibility to attract high revenue customers, while selling the remaining capacity to lower revenue customers.

A very simple example is given in Figure 4. Suppose every customer is willing to pay a different amount for the capacity. When price discrimination is not possible, we can only set one price to maximise revenue, which is the surface below the price curve. When we can ask different prices to different types of customers, more rectangles can be produced such that the same amount of capacity can generate more revenue.

It is important that the lower price segments are available only under certain conditions. These conditions should be determined such that higher revenue shipments are not willing to use a lower fare class. RM is applicable in an industry with a large variety of customers, all with different preferences for the product. For example, some shipments have high priority and need to be shipped as fast as possible, whereas others might be less urgent. The time of booking or special care for the shipment (safety, cooling) might also influence the price.
4.1.1 Characteristics of RM industries

In [36] characteristics are given of businesses where RM can be used appropriately. These are:

- **Customer heterogeneity:** Various types of customers with a different willingness to pay, variation in preference for different services and different purchase behaviour over time.

- **Demand variability and uncertainty:** When demand varies strongly over time and season, the more important it is to attract high revenue customers during peak demand, and be able to fill up excess capacity with lower-revenue shipments.

- **Production inflexibility:** When the amount of capacity available cannot be adjusted easily to the varying demand, RM becomes more profitable. A fixed amount of capacity has to be allocated optimally over different types of customers.

- **Homogeneous good:** The price of air cargo capacity is – besides value added services – not a signal of quality for the product. This means all customers try to obtain the cheapest capacity available, and do not prefer capacity on another flight because of the higher price. This is for instance the case with brand clothing, where people might buy a pair of expensive shoes, just because of the fact that these are expensive.

- **Data and information systems infrastructure:** Important for implementing RM is that demand can be modelled accurately. This requires a system in which historical booking data is available, and an information system where real-time events can be monitored, such as remaining capacity available after incoming bookings. Industries which use electronic sellings are more suitable for operationalising RM.
The first four characteristics certainly apply to the air freight industry. However, the information system infrastructure is not as good as it is the passenger industry, where electronic sellings have been the standard as of the 1970s. For air cargo, there is no Global Distribution System (GDS). Digital bookings in the airline’s system is an optional service which is available only for some large forwarders who usually have allotment contracts. Online cargo booking platforms (e.g. GF-X [20]) are available, but need further development in order to achieve the opportunity for a RM system comparable to the passenger RM systems.

A large international air freight project is e-freight, which is an initiative to digitalize the cargo supply chain. Recent studies on the implementation of e-freight in The Netherlands pointed out that a centralized IT system is needed to fully implement e-freight [9, 11, 12]. These integrated IT systems could be used to book at all carriers. When all actors in the supply chain increasingly use digitalized bookings, this might lead to an integrated booking system for all carriers, which brings in additional possibilities for RM.

4.2 Complexities of CRM

Revenue Management is much more difficult to implement in the air cargo industry due to its special characteristics. The main difference between the common RM industries – which are the passenger airlines, hotel and car rental industry – is that cargo cannot be defined into units sold. Every booking is different, whereas an airline ticket is specified for one seat, and a hotel room booking is always a room for a certain number of nights. Air cargo capacity cannot be easily divided in such separable units. In many studies on cargo RM its complexities are defined [3, 5, 22, 32]. These are:

- **Multi-dimensional capacity**: Capacity in air cargo has multiple dimensions. It depends on weight and volume, and eventually on ULD positions available (in wide-body aircraft);
- **Uncertain amount of capacity availability**: Capacity for air cargo carried on passenger aircraft depends on the amount of capacity which is occupied by passenger baggage. Capacity varies also for different types of aircraft. This means that available capacity in CRM models might be stochastic;
- **Itinerary control**: More routing options are available as cargo may be shipped along any route as long as it reaches its destination within the time agreed upon;
- **Allotments**: A significant amount of cargo capacity is taken up by allotments, which is space reserved for large customers;
• **Dependence on passenger network:** Cargo capacity on passenger aircraft depends on the network used for passenger services, and the aircraft scheduled for these flights;

• **Flights consisting of more flight legs:** In each flight leg a different amount of capacity is available;

• **Restrictions for certain shipments:** Some shipments are subject to co-loadability restrictions (for instance dangerous goods (DG)), or are extremely heavy which makes it more difficult to distribute weight evenly over the plane;

• **Stowage loss:** Some items are difficult to stack due to the nature of these goods (unusual shape), or due to items not fitting on a single ULD;

• **Trade imbalance:** Cargo traffic is always one-way, which means that there are asymmetric trade flows. There is, for example, more trade from the Far East to Europe than vice versa;

• **Short-term bookings:** Bookings often take place very close to departure, with the peak 1-3 days before take-off;

• **Uncertain size of booked shipments:** There is often a discrepancy between the amount of capacity booked and the size of the cargo tendered at the airport;

• **Business-to-business market:** The air cargo industry is a B2B market, which means there is high dependency on a small amount of customers;

• **Data availability:** As bookings are often made through different channels – by phone or e-mail instead of through digital booking systems – good data is not always available. Further implementation of e-freight might improve this data availability, as mentioned in [11].

All of these complexities need to be considered while developing a suitable RM model for the air cargo industry. Some of these will be taken into account in the model, whereas we leave others out to prevent the model from being unnecessarily complex.

### 4.3 Benefits from implementing RM

Using more sophisticated Revenue Management systems in the air cargo industry can have several benefits. The major benefit is that successful price discrimination leads to the increase of profit and a better utilisation rate. This is not only the case for airlines: Forwarders reselling acquired capacity by allotment contracts can use similar RM methods for selling capacity to their customers.
Next to the possible increase in profit, RM can be used as a tool for other purposes as well. By defining different market segments corresponding to the needs of different types of customers, sellers of cargo capacity can for instance offer lower prices to more flexible customers. These more flexible shipments can be off-loaded without disappointing the customer, so priority shipments, with high profit margins, can be accepted without negative consequences. So the risk of losing customers by overbooking capacity is decreased, as the seller does not violate his mutual agreements with the customer. This may increase customer satisfaction and loyalty. It may also help to break the vicious cycle mentioned before, which has lead to systematic overbooking.

Airlines are observing a large difference between preferences for capacity on certain weekdays. Offering lower price classes can also be used for attracting shipments for off-peak flights. Weekends tend to be more popular than for instance Mondays or Tuesdays. Offering lower prices on these flights might balance the demand over different weekdays.

A problem airlines are coping with is that usually bookings arrive very close to departure (within 3 days). For some shipments this is inevitable, however others might be booked longer in advance. When shippers are motivated – by financial benefits – to place bookings earlier, demand for a flight can be observed earlier in the booking period which is helpful for further booking control decisions. Furthermore, by extending the booking horizon, flight planners have more time to accept shipments for a certain flight, and use last minute planning only for those shipments which really need this priority treatment.

Shipments which do not tender as booked is also a challenge airlines are facing. It often happens that actual shipments deviate from the booked volume or weight. There are no exact numbers for this, but industry experts claim that “35% of the cargo booked at origin does not tender as booked”. Others claim that “60% of the bookings deviate more than 5% from their actual weight”. For some shipments – for instance flowers – this is inevitable, the size is not known until very close to departure. A higher revenue product can be created in which there is a margin within the size may deviate. Lower revenue products may be refused on board or penalized when they show up with less or more than the amount booked. Access to lower rates could also be conditioned to past reliability of the customer.

One core business for forwarders is the consolidation of shipments. Dense and voluminous shipments are packed together to result in the desired 1:6 quantity (see section 4.4). Airlines try to consolidate shipments aswell in order to increase their revenue, as large and light shipments pay according to their chargeable weight. By offering attractive prices when, for instance, dense shipments are needed, the seller can try to acquire these shipments which can provide an optimal consolidation.

Another advantage of using RM systems is that it goes hand in hand with
digitalised systems. Instead of booking through phone calls or e-mails, which is current practice, general cargo can easily be booked online. This saves time for all actors in the chain. The amount of cargo bookings that is done via online systems, is only a fraction of the total amount, and these systems are far less developed than systems used on the passenger’s side.

The implementation of e-freight increases the amount of digital bookings. Better (centralized) IT systems makes the process of digital booking easier. Integrated IT systems are also very valuable for RM practices. Therefore, a centralized IT system has benefits for both e-freight and RM. So next to the cost reduction resulting from e-freight implementation, as mentioned in [12], using these systems might also increase revenues by appropriate RM applications.

In order to realise the benefits mentioned above, a good market segmentation needs to be made. One needs to prevent that customers who are willing to pay more use capacity in lower price segments. This is why these lower price segments need to have strict conditions to which some customers are not willing to commit. The segmentation of the market is called fencing in RM and is described section 4.5.

4.4 Air cargo rates

In order to provide a model where price discrimination is possible, we need to define on which variables air cargo rates depend. According to these variables, we can derive a certain segmentation base to differentiate between certain groups of customers. This practice is known as fencing [38].

As already mentioned, air cargo rates are often obtained through negotiations, and capacity is sold both in contracts or in free sale. Basically, there are three different types of rates, which are:

- Published rates
- Contract rates
- Spot rates

The published rates are available for all general customers. These rates are determined once a year. These rates are usually higher than the price actually paid by most customers, who have contract rates or pay a spot rate.

Contract rates are agreements between forwarders and airlines for a specified amount of space, which can either be allotments or BSAs. Contract rates depend on customer type, destination, commodity, size of contract (volume and amount of shipments) [24]. Contract rates are usually fixed rates for half a year, but can be revised during the year in case of bad performance.
Spot rates are rates for cargo capacity bought on the free sale market. These rates are a result of negotiations between forwarders and carriers and depend on time and space available, density of booked shipments, published rates, customer value and expectation for future demand. When the considered flight departs from a large hub which is fed from the airlines trucking network, rates might also depend on where the booking comes from.

### 4.4.1 Prices per kg and chargeable weight

Air cargo prices are always stated as rate per kg. However, the rate does not only depend on the weight but also on the volume. A kg of lead requires far less space than a kg of pillows. This is why the cargo industry calculates the chargeable weight. The standard volume/weight ratio of a shipment is 1:6. This is equivalent to 166.67 kgs per $m^3$. When a shipment of 1 $m^3$ weighs less, its chargeable weight ($\hat{w}$) is calculated which is the weight based on the 1:6 density. For a shipment with weight $w$ (in kgs) and volume $v$ (in $cm^3$) the chargeable weight is given by:

$$\hat{w} = \max(w, \frac{v}{6})$$

It has been a point of discussion why prices are always stated per kg, while most flights are volume constrained. The most probable reason for this is that this has been regular practice since the beginning of the air cargo industry. In the past, weight was the most restricting factor, but because of modern technology there are newer engines which can carry much more weight. Another reason which is often stated is that volume is more difficult to measure [34]. However, this should not be a reason to refrain from changing the way prices are stated. Volume scanners are available, and most shipments are in fixed packages which have a specified volume.

### 4.5 Fencing in the air cargo industry

In section 3 different products are mentioned which are common air freight shipments. Next to goods mentioned like perishables or other special care products, a significant amount of cargo is general cargo. These are for instance inventory replenishments which need to be delivered within a week, but do not necessarily need to arrive as soon as possible.

In section 4.3 some common industry problems are mentioned which may be handled using RM. Variables which can be used to define various market segments are shown in Table 1.

From these segmentation variables several booking classes can be constructed. Restriction free shipments, which can be delivered just before departure and cancelled without any cost and want to be carried on a direct flight, are the most expensive shipments. Some customers might however consider to allow for certain restrictions to obtain a better price. A large chip factory for
<table>
<thead>
<tr>
<th>Time of booking</th>
<th>Early booking discount</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Priority shipment for short term booking</td>
</tr>
<tr>
<td>Moment of shipping</td>
<td>Off-peak discount</td>
</tr>
<tr>
<td>Delivery conditions</td>
<td>ASAP delivery</td>
</tr>
<tr>
<td></td>
<td>Flexibility (more time)</td>
</tr>
<tr>
<td>Shipment type</td>
<td>Special care shipments</td>
</tr>
<tr>
<td></td>
<td>Cooled, live animals, dangerous goods</td>
</tr>
<tr>
<td>Shipment properties</td>
<td>Large shipment</td>
</tr>
<tr>
<td></td>
<td>Dense/voluminous</td>
</tr>
<tr>
<td>Flight properties</td>
<td>Direct or indirect flight</td>
</tr>
<tr>
<td></td>
<td>Wide- or narrow-body aircraft</td>
</tr>
<tr>
<td>Flexibility</td>
<td>No penalty for deviation from booking</td>
</tr>
<tr>
<td></td>
<td>Free cancellation</td>
</tr>
<tr>
<td>Customer properties</td>
<td>Large customer</td>
</tr>
<tr>
<td></td>
<td>Important customer for additional business</td>
</tr>
<tr>
<td>Channel of booking</td>
<td>Online booking discount</td>
</tr>
<tr>
<td></td>
<td>Extra charge for specialized shipment advice</td>
</tr>
</tbody>
</table>

Table 1: Possible segmentation variables for the air cargo industry
instance might want to replenish its inventory in China within one week. For this flexibility they can get a better price. Shipping a horse to Australia can be planned long in advance. This shipment does require the quickest flight possible and needs special attention, however might get a discount for booking early.

From the variables of Table 1 a very large amount of combinations can be made. Many types can be constructed, all with a price corresponding to the specific needs of this customer. Assigning shipments to a certain type makes price discrimination possible. Some example fare classes are given in Table 2.

<table>
<thead>
<tr>
<th>Fare Class</th>
<th>Class description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Restriction free, priority</td>
</tr>
<tr>
<td>B</td>
<td>Perishable shipment, early booked</td>
</tr>
<tr>
<td>C</td>
<td>Large shipment, size deviation of booking less than 10%</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

Table 2: Example cargo fare classes

The goal of a RM system is to decide how many shipments of a certain type to accept, based on the expectation of future demand. The seller wants to reserve enough capacity to be able to satisfy all high revenue demand. In the next section we use simulation methods to solve these RM problems and calculate the benefits from applying the correct RM system.

5 Modelling air cargo bookings

In order to quantify the possible benefits of implementing a RM system, we need to develop a realistic simulation model for incoming cargo bookings. Therefore, we need to make proper assumptions regarding the distribution of the volume and weight of a shipment and other important characteristics of these bookings.

5.1 Characteristics of air cargo shipments

The first thing needed for a proper simulation model is a way to characterize an incoming shipment. For each shipment, we should at least generate its weight, volume and density. We can randomly generate the weight and density for a shipment, and with the help of this information we can determine the volume. So we assume the weight and density are independent, and the volume depends on these two variables.

Next to the size of a shipment, we could assign more characteristics to each shipment to make price discrimination possible. The revenue that is generated by a shipment certainly needs to be generated. There are different ways to do this. Pak and Dekker (2005) assign a randomly generated revenue per kg to
each shipment [31], whereas Amaruchkul et al. (2007) use $m$ different types of shipments [1].

For RM practices it is interesting to observe how long before the flight takes off a booking takes place. Bookings arriving very close to departure should imply that these are unexpected emergency shipments, which tend to generate higher revenues than regular shipments booked earlier in the booking period. On the other hand, lower revenue shipments may be accepted very close to departure when not all capacity is used. Although it is difficult to decide how the revenue for a shipment depends on the arrival time, this certainly is interesting information for a shipment.

Another possible characteristic for a shipment is that, when we look at a sequence of flights for the same destination, we can assign a demanded departure/arrival moment for the flight instead of booking for a desired flight. The latter is common practice in the current industry, however for most customers the most important thing is to have a guaranteed arrival moment. When we can implement this, we can show the possible benefits of accounting for the flexibility of shipments.

5.2 Modelling weight and volume

The size of the shipment is the first and most important thing we have to consider for an incoming booking. As mentioned earlier in this thesis, the size of a shipment can differ very strongly. Air cargo shipments can differ from a small package to very large and heavy machinery. Density of shipments may also vary enormously: compare for instance fashion items to gold.

Given these characteristics, we chose the lognormal distribution to model the shipment’s weight and density. The characteristics of this distribution are that values are always positive, and the density function has “fat tails”. This means that there is a reasonable probability for values much higher than the mean. These properties are recognized in the cargo industry by experts, and are also widely used in cargo RM literature [14, 26, 31]. In Figure 5 an example of the probability distribution function (pdf) of a lognormal distribution is given. In Appendix A we describe how to simulate from a lognormal distribution.

5.2.1 Weight and volume calculation

Let the random variables $W$ and $V$ be respectively the weight and volume of a shipment, with $W \sim \log N(\mu_W, \sigma_W^2)$, and $V \sim \log N(\mu_V, \sigma_V^2)$. Obviously these variables are not independent, as a heavier shipment is more likely to have a higher volume. Therefore we introduce a r.v. $D$ representing the inverse density of a shipment ($\frac{m^3}{w(kgs)}$). We assume $D \sim \log N(\mu_D, \sigma_D^2)$, and $W$ and $D$ are
independent, which is a reasonable assumption as the density of shipments can vary, regardless its weight. Now we can derive the volume:

\[ V = W \cdot D \]

The product of two lognormal r.v.s is also lognormally distributed. Hence \( V \sim \logN(\mu_W + \mu_D, \sigma^2_W + \sigma^2_D) \), so the volume also follows a lognormal distribution.

### 5.2.2 Chargeable weight

Now we have realisations \( w \) and \( v \) for the weight and volume of the shipment, respectively, we can determine its chargeable weight. Chargeable weight is commonly used in the air cargo industry to account for discrepancy in weight and volume. Ideally, a shipment should have a weight/volume ratio of 1:6. When a shipment has a lower inverse density, its chargeable weight is used for revenue calculation rather than its actual weight. The chargeable weight \( \tilde{w} \) is given by:

\[ \tilde{w} = \max(w, \frac{v}{6}) \]

### 5.3 Modelling revenue

For each booking its revenue needs to be determined. As already mentioned in section 4.4, the cargo rates are dependent on many variables. In our model we only consider spot market shipments. These rates depend on the size of the shipment, expected demand for the flight, the commodity and eventually the customer value. We generate revenues per kg of chargeable weight, which is common practice in the industry, this way we account for dependency of the rates on the shipment’s size.

The variability in revenues can be simulated in 2 different ways. We can
either follow the model of [31], which randomly generates the revenue per kg from a certain distributions. Other CRM models use a fixed amount of fare classes, which indicates the revenue per kg for each shipments [1].

5.3.1 Random revenues

Let \( R \) be the r.v. indicating the revenue per kg for each shipment. \( R \) is a continuous r.v. with pdf \( g(r) \). The total revenue of a shipment, \( \rho \) with revenue per kg \( r \) and chargeable weight \( \hat{w} \) is given by \( \rho = r \cdot \hat{w} \).

This way of modelling revenue represents the real world practice of requesting a booking for a shipment for a certain price. As it is not the case in the cargo industry that one can book capacity for a certain fare class, but poses a price for the desired capacity, this is a realistic way of modelling. In this thesis, we use this way of modelling revenues for the single leg booking problem as described in section 6.

5.3.2 Fare classes

A common practice in passenger airline industry is the existence of certain fare classes, which can be booked by customers [36, 38]. These fare classes are constructed using various differentiators, like time of booking or flexibility for adjustments or cancellations. Most of the passenger RM models use the existence of various fare classes [10, 35].

Different types or fare classes can also be used for CRM models, as in [1], among others. In section 4.5 we proposed various possible differentiators for the air cargo industry. Using these differentiators we can set certain fences, such that people from a higher fare class are not willing to accept the conditions to which lower fare classes are subject. In Table 3 we proposed a framework of values which we can assign to the different segmentation variables. Now we are able to construct numerous fare classes by combining all possible outcomes. In this case, one can create \( 3 \cdot 2 \cdot 3 \cdot 2 \cdot 2 \cdot 4 \cdot 2 \cdot 3 \cdot 2 \cdot 2 = 41472 \) combinations. Not all of these combinations make sense – for instance a perishable shipment which may be shipped within 5 days – but this number indicates the large variety of shipments encountered in the air cargo industry.

Given certain characteristics of the shipment or the customer, a booking is assigned to a certain fare class which is either available or not available for this customer. So the acceptance/rejection policy is dependent on the availability of a fare class. In section 7 we use a model with a small set of five fare classes. This way we can keep the model clear and tractable.
| **Time of booking** | <1 day to departure  
1-3 days to departure  
4-7 days to departure |
|---------------------|-------------------|
| **Moment of shipping** | Weekend  
Weekday |
| **Delivery conditions** | ASAP delivery within 3 days within 5 days |
| **Special shipment (CAO/DG)** | Yes  
No |
| **Perishable** | Yes  
No |
| **Size properties** | Large shipment  
Small shipment  
Main deck shipments  
Long shipment (not on single ULD) |
| **Density** | Dense  
Volume |
| **Cancellation** | Free  
Paid |
| **Flexibility** | <10% deviation  
<25% deviation  
>25% deviation |
| **Customer valuation** | Very important (level 1)  
Important (level 2)  
Normal (level 3) |
| **Channel of booking** | Online booking  
Phone or e-mail |
| **Payment** | Prepaid  
CASS (after shipping) |

Table 3: Proposed segmentation variables for the air cargo industry
6 Single Leg Booking Problem

The first CRM problem we analyse is the single-leg case. We consider a single flight to a popular destination which has constrained capacity. We make this assumption, because when capacity exceeds demand, there are no accept/reject decisions to be taken as all demand can be served. Bookings arrive according to a Poisson Process (PP). Each arrival (booking) is assigned a random weight, volume and revenue.

In this model we derive a minimum acceptance price for a shipment. These prices are known as bid-prices in the RM industry and are widely used in passenger airline applications [36].

6.1 The model

We follow the model given in [31]. Weight and volume are lognormally distributed, for reasons given in section 5. The revenue per kg for each shipment is a r.v. $R$ with pdf $g(r)$. We assume that $R$ is also lognormally distributed.

We use the following variables:

- $\lambda$ Arrival rate of the PP
- $C_w$, $C_v$ Weight and volume capacity, respectively
- $W_i$, $V_i$ Weight and volume (respectively) of shipment $i$
- $w_i$, $v_i$ Realisation of $W_i$, $V_i$
- $R_i$ Revenue per kg of shipment $i$, with realisation $r_i$
- $\rho_i$ Total revenue of shipment $i$
- $T$ Time horizon
- $h_w$, $h_v$ Minimum acceptance price (bid price) for weight and volume, respectively

6.1.1 Arrivals and the Poisson Process

We simulate booking arrivals in a booking period. The booking period starts at the time horizon $T$, and ends at the moment that $t = 0$. In the air cargo case, this is usually within a week before departure. In the passenger case, this could be one year. During this period, bookings come in randomly over time. Each time a booking occurs, the RM system has to decide whether or not to accept this shipment.
We use a Poisson Process to model this arrival pattern. Bookings arrive according to a PP with arrival rate $\lambda$. A PP is a useful model for arrivals in various simulation models. An example of the booking pattern by using a PP is given in Figure 6. In Appendix B we describe the simulation of a Poisson Process.

### 6.1.2 The booking control problem

Using the PP, we now generate a sequence of bookings. For each booking we generate a random realisation for the weight, volume and revenue. We do this according to the method described in section 5. Now we have to develop some strategy which determines for each booking whether or not to accept it, in order to maximise the total revenue of the flight leg. In order to test the performance of the strategy, we compare its generated revenue to the ex-post optimal solution.

### 6.2 The ex-post optimal solution

In order to quantify the theoretical benefits of RM, and to observe the performance of the booking control policies compared to the theoretical optimum, we want to compute the ex-post optimal solution. By ex-post optimal solution, we mean the solution under the condition that perfect information is available. This means the ex-post optimal solution determines which shipments should have been accepted when all other incoming bookings are observed.

The ex-post optimal solution can be found by formulating an Integer Linear Programming (ILP) model. The decision variables are binary in this case, as each booking is either accepted or not accepted. The ILP problem is given by:
\[
\begin{align*}
\max_x & \quad \sum_{i=1}^{n} r_i x_i \\
\text{s.t.} & \quad \sum_{i=1}^{n} w_i x_i \leq C_w, \\
& \quad \sum_{i=1}^{n} v_i x_i \leq C_v, \\
& \quad x_i \in \{0, 1\}, \ i = 1, \ldots, n.
\end{align*}
\] (1)

Where: \( x_i = \begin{cases} 
1 & \text{if booking } i \text{ is accepted} \\
0 & \text{otherwise}
\end{cases} \)

And \( n \) is the number of bookings arrived.

This is a two-dimensional 0-1 knapsack problem. The 0-1 knapsack problem is a very well-known operations research problem. In this problem one has to choose a subset from \( n \) items, with profit \( r_i \), such that the overall profit is maximized, while the capacity constraint is not violated. In the standard knapsack problem there is only one capacity constrained, but as cargo capacity consists of both weight and volume this is a two-dimensional knapsack problem.

The multidimensional knapsack problem is NP-hard. Rinnooy Kan et al. propose a method to approximately solve this problem [21]. Their method uses a greedy algorithm while changing the ordering of the items based on their relative profit to the restrictions. For instances of the size in our model, which are representative for real world instances, the problem is tractable and can be optimally solved using an ILP solver.

### 6.3 Strategies/heuristics

As, in real life, not all information on incoming bookings is available in advance, we need to design certain decision policies to determine which bookings to accept, and which to reject. The most straightforward decision policy, which will be used as the policy representing the situation in which no RM is applied, is the FCFS decision policy. This strategy accepts a booking if there is space available for this booking, and does not accept otherwise.

Other common decision strategies try to prevent rejecting higher revenue demand, by reserving capacity for high demand customers or limiting the capacity available for low revenue customers. These capacity restrictions are useful when a fixed number of fare classes are available. In this case, where all shipments bring a different revenue, we use a decision strategy based on bid-prices.
6.3.1 Bid price policy

A bid-price is a minimum revenue a shipment should generate in order to be accepted. A booking is accepted if its revenue exceeds this hurdle price, and rejected otherwise. In the cargo model there should be two bid-prices, one for revenue per kg and one for revenue per $m^3$, as capacity may be constrained in these two dimensions. A shipment is accepted if its revenue exceeds both hurdle prices.

We need to find a method to generate optimal bid prices, such that enough capacity is reserved for high revenue custumers while keeping load factors sufficiently high. Optimal bid prices can be used through both static and dynamic policies.

6.3.2 Static and dynamic policies

One may distinguish static and dynamic policies. In static policies there is a fixed hurdle over the booking period which decides whether or not to accept a shipment. Dynamic policies use real-time information of the bookings already accepted. In a dynamic environment the bid-prices can be adjusted, so bid prices may decrease when there is a lot of free capacity just before the flight takes off, or increase when demand is high.

Static models are more consistent and may perform well on average. In the air cargo industry demand is very hard to forecast and a significant amount of bookings arrive just before take-off. Therefore an easy to implement, static model might be more suitable for usage in air cargo practice.

On the other hand, dynamic models are more challenging RM models, which use all information currently available to optimize booking controls. This could be useful in maximising revenues and simultaneously utilize capacity as well as possible.

We use two different static models to determine the fixed bid-prices.

6.4 Simulation experiments

In Tables 4, 5 and 6 the values chosen for the variables in our simulation experiments are depicted. These values are the mostly the same as in [31], which are claimed to be based on real airline data. We only decreased the volume to $60m^3$, where this is $75m^3$ in [31]. The reason for this is that currently almost all flights are volume constrained. Another reason is that the inverse density is 1:6 by IATA standards, which agrees with our choice of values.
<table>
<thead>
<tr>
<th>$C_w$</th>
<th>10000 kg</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C_v$</td>
<td>60 m$^3$</td>
</tr>
</tbody>
</table>

Table 4: Weight and volume capacity

| $T$ | 10000 |
| $\lambda$ | 0.00225 |

Table 5: PP parameters

### 6.4.1 Static model performance

We use two methods to determine the best performing static bid-prices. The first model tries to find the best hurdle prices, relative to the weight and volume prices, by simulation. The other model solves 1000 samples optimally and calculates the mean of the minimum acceptance prices. We expect these models to result in the same bid-prices.

#### Bid-prices by simulation

We tried to find the optimal minimum acceptance price for shipments by executing several simulation runs with different values for bid-prices, based on weight and volume. In Figure 7 a three-dimensional plot with the resulting revenues against weight and volume bid-prices is shown. One can observe this graph is not very smooth. Increasing the number of simulations does not improve this significantly.

A possible explanation for this bumpiness is that using different combinations of bid prices, high bid-prices in one dimension give such a strong restriction that the other bid-price is irrelevant. In essence, only one hurdle price is important, depending on the flight being weight or volume constraint. Let $h_w$ and $h_v$ be the hurdle prices for weight and volume, respectively. Using the brute force search method we found an optimum in $h_w = 1.75$ and $h_v = 300$.

#### Calculating bid-prices using ex-post optimum

Using simulation to optimize over 2 bid prices is not very efficient. Another approach is to solve a large number booking sequences optimally using model (1), and return the minimal accepted revenue per weight and volume as the bid prices. We take the mean

<table>
<thead>
<tr>
<th>$w$</th>
<th>$\mu$</th>
<th>$\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d$</td>
<td>793.474</td>
<td>942.370</td>
</tr>
<tr>
<td>$v (= w \cdot d)$</td>
<td>0.00581</td>
<td>0.00338</td>
</tr>
<tr>
<td>$r$</td>
<td>4.610</td>
<td>6.879</td>
</tr>
</tbody>
</table>

Table 6: Size and revenue distribution parameters

<table>
<thead>
<tr>
<th>$w$</th>
<th>$d$</th>
<th>$v (= w \cdot d)$</th>
<th>$r$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.559</td>
<td>1.946</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6: Size and revenue distribution parameters
of a large number of these generated bid-price, and use these values for the
booking control problem. Resulting values are $h_w = 1.77$ and $h_v = 318.97$, with
 corresponding 95% confidence intervals: (1.757, 1.795) for $h_w$ and (315.272,
322.671) for $h_v$.

**Static model heuristic** For reasons given above, we used the bid-prices de-
rivered for solving the ex-post optimization problem for 100 times. Resulting val-
ues are those given above. We compare the results from this heuristic, named
H1, to the FCFS policy and the ex-post optimal policy. Results are shown in
Table 7.

One can observe that the revenue for the static model heuristic is a more
than 10% increase from the FCFS policy, which is currently mainly used in
Figure 8: Results for three different acceptance policies using the same arrivals. The top row of figures depicts a set of arrivals for which H1 gives a good result, whereas the bottom row shows a case where H1 performs worse than FCFS practice. The static policy results in an average of 85% of the theoretical optimum. On the other hand, the load factor of H1 is lower than the optimal and the LF obtained using the FCFS policy. This is not very surprising as we introduce a more constraining entry condition in order to reserve more space for higher revenue shipments. On average, this will lead to higher revenues, although in some cases H1 will generate a much lower revenue compared to the FCFS policy. In Figure 8 six scatter plots are shown. The most plots display the accepted (blue) and rejected (red) shipments. The position of the shipments depend on their revenue per $m^3$ ($x$-axis) and revenue per kg ($y$-axis). The left figure depicts the FCFS acceptance policy, the middle the H1 policy and the one on the right hand side the optimal solution.

We could try to increase the revenue by improving the capacity utilization of the static model by adjusting the entry conditions throughout the booking period. When there is a lot of free capacity the entry condition should decrease. Using a dynamic model we try to overcome this problem.
7 Revenue Management using flexible shipment types

A shortcoming of the single leg model is that it is not possible to make a distinction between urgent and less urgent shipments, which is one of the key factors indicating the rates. In this model we simulate the booking process for more flights – with the same (popular) destination – simultaneously.

A common problem in the air cargo industry is that airlines overbook their flights. There are several solutions proposed how to optimally solve the overbooking problem [23, 28]. However, due to overbooking, airlines cannot always provide the service level they would like to. We propose a model where airlines offer a low-fare product, which is not booked for a specific flight but needs to be shipped before a certain moment. The advantage of this system is that customers are not disappointed if their shipment cannot be placed on a flight, and airlines are able to accept high revenue demand which is booked very close to departure. In this section we model a system with flexible shipments and propose both static and dynamic booking control policies.

7.1 The model

We simulate a week in which each day a flight departs. Shipments arrive during the booking period, which starts one week in advance and ends just before the final flight departs.

7.1.1 Variable definition

In the model we use the following variables:

- $L$: Number of flights
- $m$: Number of fare classes
- $C_w$: Weight capacity for each flight
- $C_v$: Volume capacity for each flight
- $W_i, w_i$: R.v. and realization of the weight of a booking of type $i$
- $D_i, d_i$: R.v. and realization of the inverse density of a booking of type $i$
- $V_i, v_i$: R.v. and realization of the volume of a booking of type $i$. $V_i = W_i \cdot V_i$
- $\hat{w}_i$: Chargeable weight of a booking of type $i$. $\hat{w}_i = \max\{w_i, \frac{v_i}{1000}\}$
- $r_i$: Revenue per kg for booking of type $i$
- $\rho_i$: Total revenue for booking of type $i$. $\rho_i = \hat{w}_i r_i$
$T$ Time horizon of the discretized booking period

$P_{,p_{it}}$ Probability matrix for booking arrivals, with entries $p_{it}$ probability of type $i$ arrival in time period $t$. $p_{0t}$ denotes the probability of no arrival in time period $t$.

Given is a schedule where $L$ flights are scheduled, and for each flight bookings may come in over a period of length $T$. At time $t$, the probability of an arrival of type $i$ is given by $p_{it}$. The booking horizon is discretized such that for each flight at most one booking arrives. For each arrived booking, the problem is to decide whether or not to accept the incoming request, in order to maximize revenue.

### 7.1.2 Shipment types

As well as in section 6, we use lognormally distributed weight and volume. However, the parameters for the variables depend on the cargo types we analyze. We use 5 fare classes, which all refer to a certain cargo type. As seen in section 4.5 many more types of cargo can be thought of, but to make the model tractable we distinguish only 5 types. The 5 types we use are, ordered from most to least expensive:

1. Express items, need ASAP delivery;
2. Special care products;
3. General cargo;
4. General cargo with early booking discount;
5. Flexible shipments.

The last category contains flexible shipments which are scheduled on the first flight, but can also be placed on the next flight when higher revenue bookings arrive.

Each type has its own revenue per chargeable weight. For greater shipments an additional quantity discount is given, which is common practice in the industry.

### 7.1.3 Booking period

For this model we do not use a Poisson Process to model arrivals, as probabilities for the type or flight of the bookings change during the period. Therefore, we use another approach. The planning horizon for each flight is discretized into
70 periods (10 periods divided over 7 days), in which at most one booking request arrives. Each day the probability for a booking of type $i$ changes. The probabilities are given in matrix $P$ with entries $p_{it}$, which denote the probability of a booking of type $i$ in time period $t$. $p_0t$ is the probability for the event that no booking occurs.

As we have 7 flights in the planning period we simulate, with 70 booking periods for each flight, we need a full length booking period of $T = 130$, where from $t = 130, \ldots, t = 121$ only bookings for flight 1 can arrive, for $t = 120, \ldots, t = 111$ bookings for flight 1 and 2 can arrive, until period $t = 10, \ldots, t = 1$ where only bookings for flight 7 arrive.

7.1.4 Size and revenue

An incoming booking of a type $i$ is assigned a random weight ($W_i$) and inverse density ($D_i$) ($\frac{w}{d}$), following a log-normal distribution with respective means $\mu^w_i$ and $\mu^d_i$ and standard deviation $\sigma^w_i$ and $\sigma^d_i$. The random variable for the volume of shipment is determined by $V_i = W_i \cdot D_i$. This is similar to section 6, however the mean and variance of the r.v.s change over the different fare classes.

An incoming booking can be of type $i = 1, \ldots, 5$, with probability $p_{it}$. The corresponding revenue of the shipment per kg is given in revenue matrix $R$. The rates per kg also depend on the weight of the shipments, large bookings are cheaper. The total revenue for booking $j$ is denoted by $\rho_j = r_j \cdot \hat{w}_j$.

7.1.5 Airplane capacity

In our model we determine the capacity on the plane, $C_w$ and $C_v$, as a fraction of the expected demand. We do this to be able to test our models for various levels of constraintness. We define $\xi_w$ as the fraction of weight capacity, and $\xi_v$ the fraction of volume capacity. Let $E[W]$ be the expected total weight booked for one flight, and $E[V]$ the expected total volume booked. Hence the following relation:

$$C_w = \xi_w \cdot E[W]$$
$$C_v = \xi_v \cdot E[V].$$

This way of modelling capacity is realistic, as cargo capacity is variable, especially when belly hold capacity is considered.

7.2 Simulation

We simulate the booking period by first creating a vector of incoming bookings. We start at time period $t = 130$, and for each flight a booking of type $i$ arrives with probability $p_{it}$, and no booking arrives with $p_{0it}$. As the length of the
booking period is 70 for each flight, the no-arrival probability $p_{0t}$ is 1 in some cases.

Each entry in the booking vector contains the following fields:

- Type
- Flight
- Weight
- Volume
- Chargeable weight
- Revenue

An arrival of type $i$ at time period $t$ is $p_{it}$ for each flight. We simulate these arrivals by drawing a random number $u \sim U(0, 1)$. Then an arrival is of type $i$ generated by:

Arrival of type $i$ if $p_{i-1,t} < u \leq p_{i,t}$ for $i \in \{1, \ldots, 5\}$

The weight, volume and chargeable weight are determined the same way as described in section 5. Now the parameters of the lognormal weight and density distribution depend on the type of the booking. The weight of a booking of type $i$, $W_i$, is lognormally distributed with parameters $\mu_{w_i}, \sigma_{w_i}$.

The total revenue of a booking $j$, $\rho_j$, is determined by $\hat{w}_j \cdot r_i$. $r_i$ is the revenue per kg, specified for each type.

For each entry in the booking vector, we have to decide consecutively which bookings to accept and which to reject. First we provide a solution to the optimal solution when perfect information is available. Next we propose several static and dynamic booking control policies.

**Flexible shipments.** In this model we also assume there are no cancellations and low- or no-shows. The shipments of types 1-4 have to be shipped on the flight they are booked for. Shipments of type 5 can be shipped on the flight booked of the next day. Therefore we can accept a shipment for a flight by replacing one or more type 5 shipments to the next flight. We assume that all incoming bookings for this week have to be taken on this week’s flights. Therefore type 5 shipments booked for flight 7 are in fact not flexible, as this is the last possible flight they can be taken on.

### 7.3 Ex-post optimal solution

To be able to measure the performance of the used heuristics we need to derive the ex-post optimal solution. This is the optimal solution which can be derived
when all information of the bookings is available.

The ex-post optimization problem is the following: Given a sequence of bookings of length $n$, make a selection of bookings to accept such that the total revenue is maximized. For each flight not more than available volume and weight capacity may be accepted. All shipments of type 1-4 need to be taken on the flight which they booked, whereas type 5 shipments can be replaced to the flight on the next day. A shipment cannot be partially accepted or rescheduled to another flight.

To formulate this as an ILP problem we need to modify the problem. The constraint that a shipment booked for a certain flight can only be flown on that flight cannot be formulated as a linear constraint. In order to force the ILP model to satisfy this constraint, we define revenue matrix $R$, with entries $\rho_{ij}$, which is the total revenue if booking $i$ is accepted on flight $j$. Now $R$ is given by:

$$R = \begin{bmatrix}
\rho_{11} & \cdots & \rho_{1j} & \cdots & \rho_{1L} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
\rho_{i1} & \cdots & \rho_{ij} & \cdots & \rho_{iL} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
\rho_{n1} & \cdots & \rho_{nj} & \cdots & \rho_{nL}
\end{bmatrix}$$

With entries

$$\rho_{ij} = \begin{cases} 
-M, & \text{if } j \notin F_i \\
\rho_i, & \text{if } j \in F_i
\end{cases}$$

Where $F_i$ is the set of available flights for booking $i$, and $M$ is a sufficiently large number. $F_i$ is only the flight for which the shipment is booked in case the type is 1-4, and includes also the next flight if the type of the booking is 5.

The corresponding ILP problem is given by:

$$\max_x \sum_{j=1}^L \sum_{i=1}^n \rho_{ij} x_{ij}$$

s.t. $\sum_{i=1}^n w_i x_{ij} \leq C_w, j = 1, \ldots, L$

$\sum_{i=1}^n v_i x_{ij} \leq C_v, j = 1, \ldots, L$

$\sum_{j=1}^L x_{ij} \leq 1, i = 1, \ldots, n$

$x_{i,j} \in \{0, 1\}, \forall i, j$
with decision variable

\[ x_{ij} = \begin{cases} 
1 & \text{if booking } i \text{ is taken on flight } j \\
0 & \text{otherwise} 
\end{cases} \]

The first two constraints are the weight and volume capacity constraints, respectively. The third constraint makes sure a shipment is not carried on more than one flight.

We tried to solve instances of this problem with glpk. For instances of \( L = 7 \) and \( n = 140 \), this took very long. Therefore we used another MIP-solver, Gurobi, which performed better than glpk.

7.4 Strategies/heuristics

7.4.1 FCFS policy

We choose the FCFS policy as a benchmarking policy, to compare our derived strategies to the revenue generated when no RM is implemented. We use two different FCFS policies, one where we do not use the flexibility of the shipments of type 5, and the other where we do replace shipments to the next flight.

**FCFS without replacing shipments.** The FCFS policy where the flexibility of type 5 shipments is not used, is a very straightforward policy. An incoming booking is accepted when there is enough weight and volume capacity available on the flight booked, and rejected otherwise.

**FCFS with replacing shipments.** This strategy accepts type 5 shipments using the same policy as above. A reason for this is that it is not useful to replace a shipment on a flight to create capacity for a shipment which generates the same revenue. When a shipment of type 1-4 arrives, we need to check if there is enough capacity available when some shipments of type 5 are being moved. We developed an algorithm which tries to move the minimum amount of shipments (in terms of weight and volume) such that there is just enough room for the incoming shipment, see algorithm 1. Before the algorithm is executed we check if there is enough space on the next flight to carry the incoming shipment, for which room needs to be created on the flight booked for.
while Volume or weight capacity not sufficient do
    if weight constrained then
        Sort available type 5 items in decreasing order of weight;
    else
        Sort available type 5 items in decreasing order of volume;
    end
    if Sufficiently sized available then
        Move the smallest item creating enough capacity;
    else
        Move the largest item;
    end
end

Algorithm 1: Moving shipments

7.4.2 Static booking limits

A common RM practice is the use of booking limits for certain low-revenue classes. This means there is a maximum amount of capacity available for low fare classes. In our model, type 5 shipments are the lower revenue shipments, and are used to fill up excess capacity. We assume that capacity is hardly fully utilized without type 5 shipments. Therefore, we expect that revenue may be increased when we set a booking limit for the type 5 shipments, to reduce the amount of rejections of higher revenue shipments.

We tried to find an optimal fixed booking limit. Let $\alpha$ be the fraction of the total capacity (in terms of both volume and weight) available for type 5 shipments. A type 5 shipment is only accepted if the total amount of capacity used for this type does not exceed the booking limit.

We used two ways to determine the optimal booking limit. The first method uses a brute force approach, which calculated the mean revenue for different values of $\alpha$. The second method solved a large number of problem instances optimally, and returns the fraction of accepted type 5 shipments as $\alpha$.

7.5 Numerical experiment

For our simulations, the values chosen for matrix $P$ are given in Table 8. The parameters for the weight and density distribution are given in Table 9, these are the same as in section 6. Given these values, the expected total weight of the bookings for each flight is 22500 kg, and the expected booked volume is 135 $m^3$. We set the volume and weight capacity of the plane according to fraction $\xi_v = 0.9$ and $\xi_w = 0.9$ multiplied with the expected values, which results in a weight capacity of 20250 kgs and a volume capacity of 121.5 $m^3$.

For revenue matrix $R$ we chose the values depicted in Table 10.
Table 8: Probability matrix $P$. $p_{0t}$ denotes the probability of no arrival at time $t$.

<table>
<thead>
<tr>
<th>Type</th>
<th>$p_{0t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.72</td>
</tr>
<tr>
<td>2</td>
<td>0.68</td>
</tr>
<tr>
<td>3</td>
<td>0.75</td>
</tr>
<tr>
<td>4</td>
<td>0.69</td>
</tr>
<tr>
<td>5</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 9: Parameters for the Log-normal r.v.s $W$ and $D$, for different types.

<table>
<thead>
<tr>
<th>Type</th>
<th>$\mu^{w}$</th>
<th>$\sigma^{w}$</th>
<th>$\mu^{d}$</th>
<th>$\sigma^{d}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>500</td>
<td>1000</td>
<td>0.006</td>
<td>0.00338</td>
</tr>
<tr>
<td>2</td>
<td>500</td>
<td>1000</td>
<td>0.006</td>
<td>0.00338</td>
</tr>
<tr>
<td>3</td>
<td>1500</td>
<td>1000</td>
<td>0.006</td>
<td>0.00338</td>
</tr>
<tr>
<td>4</td>
<td>1500</td>
<td>1000</td>
<td>0.006</td>
<td>0.00338</td>
</tr>
<tr>
<td>5</td>
<td>1000</td>
<td>800</td>
<td>0.006</td>
<td>0.00338</td>
</tr>
</tbody>
</table>

Table 10: Revenue matrix $R$. $\hat{w}$ denotes the chargeable weight.
All chosen values are based on the practical experience of air cargo experts. Due to the unavailability of data we derived these values by interviewing various market experts. They validated that generated values are very comparable to the real air freight booking process.

The differences in parameters for the different types can be motivated by the characteristics of these types. The expected weight of the expensive shipment types is lower. These shipments are mostly back-to-back shipments, which are mostly unique shipments from a shipper. On the contrary, general cargo shipments are mostly consolidated by forwarders. These consist of separate shipments from different customers. The mean weight of such a “consol” is therefore larger. The flexible shipments are smaller as these are not the large consolidations. Furthermore the variance for type 5 shipments is lower, as extremely large shipments are more likely to be special cargo which is in type 2, or consolidations.

In Figure 9 the pdf of the lognormal distributions for the different types are shown. Figure 10 denotes the expected distribution of the total weight arrived over various types. One can see that there are a lot of type 5 arrivals. This is because we assume that there is a lot of demand for the low revenue fare class, however using efficient RM practices only a part of this demand can be satisfied.

7.5.1 Static model performance

We use two different methods to determine a static booking limit for the type 5 fare class.

**Brute force booking limit** We use 1000 simulation runs, where a run contains bookings for one week. We calculate the mean revenue generated when a booking limit of $\alpha$ is used. In Figure 11 the revenue for various booking limits is shown. One can observe that the optimum is somewhere between $\alpha = 0$ and $\alpha = 0.3$. Now we execute another 1000 simulation runs with more values between 0 and 0.3, which is shown in 11. Now we see that the optimum can be found at $\alpha = 0.075$. This means that only a very small fraction of type 5 shipments should be accepted. This might be due to the fact that the revenues corresponding to higher revenue types are relatively very high. Turning away these customers might be more costly than the profit of these type 5 shipments might generate.

**Booking limit by using ex-post optimum** Our next approach is solving a large number of instances for the ex-post problem as defined in section 7.3. We calculate the fraction of type 5 bookings accepted when the optimal problem is
Figure 9: Pdfs of the lognormal distributions with parameters specified in Table 9
Figure 10: Distribution of the types of the shipments booked

Figure 11: Revenue generated for different values of $\alpha$
Table 11: Results for the two static models and the FCFS policies, compared to the optimal result

<table>
<thead>
<tr>
<th></th>
<th>FCFS NF</th>
<th>FCFS</th>
<th>BL opt</th>
<th>BL bf</th>
<th>OPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rev</td>
<td>166 607</td>
<td>175 675</td>
<td>185 114</td>
<td>188 397</td>
<td>220 113</td>
</tr>
<tr>
<td>95% c.i.</td>
<td>163 691</td>
<td>172 816</td>
<td>181 903</td>
<td>184 016</td>
<td>215 135</td>
</tr>
<tr>
<td></td>
<td>169 525</td>
<td>178 532</td>
<td>188 325</td>
<td>192 778</td>
<td>225 090</td>
</tr>
<tr>
<td># rej</td>
<td>27.38</td>
<td>24.88</td>
<td>27.09</td>
<td>40.28</td>
<td>17.60</td>
</tr>
<tr>
<td>LF_w</td>
<td>0.89</td>
<td>0.91</td>
<td>0.87</td>
<td>0.76</td>
<td>0.93</td>
</tr>
<tr>
<td>LF_v</td>
<td>0.87</td>
<td>0.89</td>
<td>0.84</td>
<td>0.75</td>
<td>0.91</td>
</tr>
<tr>
<td>% of OPT</td>
<td>76%</td>
<td>80%</td>
<td>84%</td>
<td>85%</td>
<td>100%</td>
</tr>
</tbody>
</table>

7.5.2 Results

The results of the numerical experiments, after 100 simulations, are given in Table 11. One can observe that the static booking limit determined by the brute force method performs slightly better, however results in low load factors. As airlines try to obtain a load factor as high as possible, we prefer the larger booking limit obtained by the second method.

In Figure 12 the performance of different policies is shown graphically. The bar on the left hand side shows the total amount of arrived bookings during the week, and 4 bars on the right hand side show the amount of accepted shipments for each type for the total amount of flights during the week. The size of the bar shows the fraction of capacity used for the corresponding type, in terms of weight. The height of the four bars on the right hand side is lower as they cannot be higher than the total capacity available, which is $7 \cdot 20250 \text{kg} = 141750 \text{kg}$ in this case. One can see that in the FCFS case, a lot of type 5 shipments are accepted and therefore higher revenue shipments needed to be rejected. The policy using the static booking limit performs much better.

7.6 Reaching the optimum

As we have seen, the theoretical optimum offers approximately a 25% increase from applying the FCFS policy. Using a static booking limit during the entire period a gain of 7.5% relative to the FCFS policy can be realised. Using booking limits which are determined using information about the shipments already accepted, this gain could possibly increase. The use of dynamic booking limits are described in [1, 26, 27].

To quantify the possible benefits of the availability of perfect booking limits,
Figure 12: Distribution of accepted flight using different strategies
we define the optimal booking limit for type $i$ as the fraction of accepted type $i$ shipments in the optimally solved booking control problem. We determine this booking limit for each flight separately. This corresponds with the case where the amount of bookings for each type can be forecasted perfectly. Only the order in which they arrive and the lumpiness of the demand forms an obstacle in reaching the optimum.

We ran 5 different simulation sets, in which we used 1, 2, 3, 4 or 5 booking limits. One booking limit means only a booking limit for type 5, two booking limits include type 4 and 5, until we use a booking limit for all classes. Results for 1, 3 and 5 booking limits are displayed in Table 12. One can observe that the results are very close to each other. This is not very surprising as these booking limits correspond to the fractions of the optimal result. One can see that using one booking limit performs worst. This is because it might not be optimal to accept all the (early booked) type 4 shipments. Including a booking limit for type 4 increases the revenue generated, and revenue increases even more using a booking limit for type 3 as well.

Including more booking limits, however, results in a decrease in revenue. This is due to the fact that one might accept one shipment which causes other shipments, which ideally should have been accepted, are not accepted as they do not fit in the exact booking limit any more. This can also be observed from the decreasing load factors, when the number of booking limits increase.

The availability of the perfect booking limit leads to a 17% increase compared to the FCFS decision policy, and an almost 10% increase from the static booking limit. Being able to set a perfect booking limit provides the opportunity to reach a revenue of 93% from the theoretical optimum.

### 7.7 Application of the model

The model described in this section can easily be applied in the air cargo industry. One may use the proposed segmentation of the classes, or may distinguish other fare classes which comply better to the company’s business model. When a proper fare class structure is implemented, one has to derive booking limits for

<table>
<thead>
<tr>
<th></th>
<th>BL5</th>
<th>BL345</th>
<th>BLall</th>
<th>OPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rev</td>
<td>195 888</td>
<td>205 366</td>
<td>202 387</td>
<td>219 250</td>
</tr>
<tr>
<td>95% c.i.</td>
<td>192 595</td>
<td>201 262</td>
<td>198 278</td>
<td>214 886</td>
</tr>
<tr>
<td></td>
<td>199 181</td>
<td>209 470</td>
<td>206 496</td>
<td>223 613</td>
</tr>
<tr>
<td>LF$_w$</td>
<td>0.86</td>
<td>0.85</td>
<td>0.84</td>
<td>0.92</td>
</tr>
<tr>
<td>LF$_v$</td>
<td>0.85</td>
<td>0.84</td>
<td>0.83</td>
<td>0.91</td>
</tr>
<tr>
<td>% of OPT</td>
<td>89%</td>
<td>94%</td>
<td>92%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 12: Results using optimal booking limits
the lower fare classes. Based on historical booking information one can derive the ex-post optimal booking limit, as described in this section. Combining this booking limit with expectations based on the market knowledge of the user, one can find a very accurate booking limit. In section 7.6 we found that using a perfect booking limit for the 3 lowest fare classes could lead to results very close to the theoretical optimum. During the booking period the user may stick to the static booking limit, or may adjust the booking limit whenever a strong deviation from the forecast occurs.

8 Conclusion

In this thesis we analyzed the air cargo market and underscribed the possibilities of RM in the air freight industry. We discovered that the state of the art in cargo RM is far less sophisticated as it is in passenger business, mainly due to its complexity. The cargo industry is very conservative, therefore new methods of working are very difficult to implement: most actors all over the supply chain prefer to stick to their usual way of working.

Due to the bad economic conditions, the air cargo markets have not observed any growth since 2010 [18]. Profit margins are very small and competition is fierce, therefore it is very difficult for companies to remain viable. Reducing costs is not the only way to prevent from a default, as market share can easily be taken over by competitors. By focussing on maximizing revenues instead of minimizing costs air freight companies will stay healthy without losing their market share. Better revenue management is an excellent tool for both carriers and forwarders to stay, or even grow, in their business.

Further digitalization of the air cargo industry, initiated by projects such as e-freight, stresses the need for centralized IT systems. These systems bring in additional possibilities for RM, as they provide opportunities for online booking, which is common practice in passenger business. The increase of data availabilty by using these systems could also provide extra information for accurate booking forecasts.

Next to revenue increase, RM might also be useful to solve industry problems regarding the cargo booking pattern. Bookings often deviate from the amount of cargo actually tendered. By rewarding shippers (or forwarders, eventually) for their reliability they can be motivated to book the amount of capacity which they actually need. Another problem is that the larger part of air freight shipments are booked for weekends. Therefore carriers face low load factors during weekdays and have constrained capacity in weekend. By offering lower fares during off-peak demand, demand might be shifted from the weekends to cheaper shipping moments.
8.1 Segmentation of air cargo shipments

An important aspect for RM is fencing, which is the technique of creating separable market segments to distinguish high and low revenue customers. In this thesis we derived the most important characteristics to determine the price of a shipment, and to what extent we can use these characteristics to define market segments to create different fare classes. Segmentation variables which are useful in the air freight industry are:

- Time of booking
- Shipping moment (Monday is cheaper than Saturday)
- Delivery condition (ASAP or more time)
- Properties of shipment (perishable/special care/main deck)
- Flexibility
- Customer importance
- Booking channel (online booking discount)

Each shipment has certain values for all these variables. Using a combination of various properties numerous fare classes might be constructed, which are subject to certain conditions. These fare classes can be used in RM models compared to those commonly used in passenger airline, hotel and car rental business. In these models, some fare classes are available depending on the expected demand, given the capacity already sold.

8.2 Cargo RM models

In this thesis we developed two different simulation models for the cargo industry. The first model considers a single flight leg, where all incoming bookings have a random revenue, instead of using different fare classes. The second model simulates 7 flights in one week to the same destination, and quantifies the possible benefits for using a flexible shipment type.

8.2.1 Model 1

This is the model proposed by Pak [30]. Using this model we show the shortcomings of a FCFS decision policy, which is currently the main practice used to accept bookings. We develop a static model using two bid prices, specifying a minimum revenue per kg and a minimum revenue per m$^3$ required to accept the shipment. This model, which does not require booking forecasts or real-time
adjustments, already leads to a 11% increase in revenue, and realised a revenue 85% from the optimum. This is an easy to implement model and does not require complex modifications in the current booking process.

8.2.2 Model 2

In this model we analyze a series of 7 flights over one week, which depicts the situation of one daily flight during the week. In this model we use various types of shipments, based on some segmentation variables derived in this thesis. The cheapest type of shipment is a flexible type, which can be placed either on the flight booked or the next flight. These flexible shipment types can be useful to prevent that high revenue shipments are rejected. When a high revenue shipment booking arrives, one can replace a flexible shipment to the next flight to regain capacity.

Using simulation we quantified the benefits for using these flexible shipments. Following a FCFS acceptance method with using this flexibility already led to a 5% in revenue increase. Besides this, we used booking limits for the lowest fare class to prevent to much capacity being used for these low revenue shipments. By setting a static booking limit, revenue gains up to 7% were realized in our numerical experiment. Using static booking limits, results 86% from the theoretical optimum can be realized. When optimal booking limits for individual demand sequences can be used, a much larger increase revenue can be realized.

8.3 Static vs. dynamic models

A disadvantage of static booking limits is that these are not adjusted in case of extremely low or high demand. Therefore, the higher the booking limit – or bid price as in model 1 – is, the lower the load factor. Lower load factors mean a loss of revenue, as this capacity could have been sold to gain additional revenue and is now lost. Dynamic models, using real time information, might be able to account for these problems. On the contrary, these are more difficult to implement.

As extensive market knowledge is required to be able to forecast demand, a first step to efficient cargo RM is to carefully set the static bid-prices or booking limits, and manually adjust these hurdles throughout the booking period.

8.4 Suggestions for further research

Cargo RM is an interesting field of research, with many opportunities for future work in various fields of interest. A very interesting research topic would be how the air cargo industry needs to be developed such that efficient and effective RM
can be implemented compared to the way RM is practiced in passenger airlines. There might even be a possibility to integrate the passenger’s and cargo RM systems.

As mentioned in this thesis, RM can be used to take care of problems commonly encountered in the air cargo industry, for instance deviating from the amount booked, last minute bookings and peak demands at the end of the week. One could investigate to what extent shippers are willing or able to provide better weight forecasts, book earlier or ship at off-peak moments, when they are rewarded with a substantial financial benefit.

From an operations research perspective, air cargo RM has also numerous possibilities for the optimization of different decision support systems. Interesting research fields are optimization regarding different contract forms, or network optimization considering various routing options. Another interesting problem is optimizing a model using a large number of fare classes constructed by assigning values to the different segmentation variables defined in this thesis.

The digitalization of the air freight market leads to an extensive amount of data availability. Data analysis could be very interesting from a RM perspective, to find solutions to solve the complexity of air cargo RM. Interesting research topics using this data could be:

- Estimation of show-up rates
- Analysis of booking reliability
- Analysis of cargo booking patterns
- Customer analysis
- Controlling e-freight reliability
- Airline, airport and ground handling benchmarking
- Potential of horizontal and/or vertical collaboration in the air cargo supply chain
References


[18] IATA. Air transport market analysis, December 2012.


A Simulating from a lognormal distribution

The lognormal distribution is generated by taking the natural logarithm from a Gaussian distribution. So if $Y$ is a r.v. with a lognormal distribution, $X = \log(Y)$ has a normal distribution. If $X \sim N(\mu, \sigma^2)$, the mean of $X = \mu$ and the variance equals $\sigma^2$. For a lognormal distribution this is not the case.

The pdf of a lognormally distributed r.v. $X \sim \logN(\mu, \sigma)$ is given by:

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\log(x) - \mu)^2}{2\sigma^2}}, x > 0$$

And the mean and variance are given by:

$$\text{E}[X] = e^{\mu + \frac{1}{2}\sigma^2}$$

$$\text{Var}[X] = (e^{\sigma^2} - 1)e^{2\mu + \sigma^2} = (e^{\sigma^2} - 1)(\text{E}[X])^2$$

We want to generate realizations from a lognormal distribution $Y$ with expectation $\text{E}[Y]$ and variance $\text{Var}[Y]$. Hence we can determine $\sigma$ and $\mu$ from above equations by:

$$\sigma^2 = \log \left(1 + \frac{\text{Var}[X]}{\text{E}[X]^2}\right),$$

$$\mu = \log(\text{E}[X]) - \frac{1}{2} \log \left(1 + \frac{\text{Var}[X]}{\text{E}[X]^2}\right) = \log(\text{E}[X]) - \frac{1}{2}\sigma^2$$

Now we can generate realisations $y$ of r.v. $Y \sim \logN(\mu, \sigma^2)$ by generating $x$ from r.v. $X \sim N(\mu, \sigma^2)$ distribution, and return $y = e^x$.

B Simulating a Poisson Process

A PP $N(t)$ denotes the number of events in the time interval $(0, t]$. The number of events within this time period has a Poisson distribution with parameter $\lambda t$, which has the following probability mass function:

$$P(N(t) = k) = \frac{e^{-\lambda t}(\lambda t)^k}{k!}, k = 0, 1, \ldots$$

Simulating a PP: A PP with rate $\lambda$ has exponentially distributed interarrival times, with parameter $\lambda$. Therefore, we need to simulate realisations from a $\text{Exp}(\lambda)$ distribution until the booking period has ended.
Realisations of an exponential distribution can be generated with the inverse-transformation method [2]. By finding the inverse of the cumulative distribution function $F(\cdot)$ we can generate exponentially distributed realisations from a random number between 0 and 1. Let $u$ be a randomly generated number on the interval $(0,1)$ ($u \sim U(0,1)$), and $F(x)$ the cumulative distribution function. Then we want to find an expression for $F^{-1}(u) = x$. For the exponential distribution, this is given by:

\[
\begin{align*}
F(x) &= u \\
    u &= 1 - e^{-\lambda x} \\
   1 - u &= e^{-\lambda x} \\
\log(1 - u) &= -\lambda x \\
x &= -\frac{\log(1 - u)}{\lambda} = -\frac{\log(u)}{\lambda}
\end{align*}
\]

Where the last equality follows from the fact that $U \overset{d}{\sim} 1 - U$. 
