AIR CARGO REVENUE MANAGEMENT SPOT ALLOCATION PROBLEM

by

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B.S., Industrial Engineering, Middle East Technical University, 2019

Submitted to the Institute for Graduate Studies in
Science and Engineering in partial fulfillment of
the requirements for the degree of
Master of Science

Graduate Program in Industrial Engineering
Boğaziçi University
2022

ACKNOWLEDGEMENTS

I want to thank my thesis supervisor Prof. Z. Caner Taşkın, for showing me full support in helping me finalize my thesis. During my thesis, he has been an excellent guide with his knowledge and inspired me with his hardworking attitude. These behaviors have helped me to motivate throughout this period. Foremost, I would also like to thank Assoc. Prof. Ali Tamer Ünal, especially for working together on the thesis, showing enormous support, guiding me with his ideas, and accepting to take a role in my thesis committee.

Also, I am thankful to Prof. Mehmet Güray Güler for his participation in my thesis committee.

Finally, I would also like to thank TUBITAK for being supported by the 2210-A scholarship program during my education.

ABSTRACT

AIR CARGO REVENUE MANAGEMENT SPOT ALLOCATION PROBLEM

The focus of Air Cargo Revenue Management (ACRM) is to best estimate cargo capacity, forecast future demand, and take accept or reject decisions on the bookings accordingly. ACRM is a different problem than passenger revenue management due to uncertainty of cargo capacity, business, operations, and cargo booking behavior. These factors add additional complexity to a problem and make traditional revenue management approaches inadequate. Certain additional models need to be developed to solve the ACRM problem. The purposes of this thesis are to discuss the processes of air cargo revenue management and develop a spot allocation model.

In the thesis, we develop a spot allocation optimization model. In necessary booking control conditions, this model is solved repetitively to decide on allocating expected demand to cargo capacity. A simulation study is performed after the optimization model to compare the results of our optimization model with a commonly used heuristic, First-Come First-Served, under defined scenarios and other test problem settings. Finally, we conclude that our model performed better than 26 out of 27 scenarios according to t-test statistics with a 95% confidence level.

ÖZET

HAVACILIK KARGO GELİR YÖNETİMİNDE SPOT PİYASASI KAPASİTE ALOKASYONU PROBLEMİ

Kargo gelir yönetiminin en temel amacı kapasite ve talep tahmini ve bu tahminleri kullanarak rezervasyon kontrolü olarak anlatılabilir. Kargo gelir yönetimi problemi, yolcu gelir yönetimi probleminden birçok faktörde farklılık gösterir. Bunlar kargo kapasitesinin belirsizliği, yönetim operasyonları ve kargo rezervasyon davranışları olarak özetlenebilir. Bu faktörler kargo gelir yönetimi problemine ilave zorluk katmaktadır ve geleneksel gelir yönetimi çözümlerini yetersiz kılmaktadır. Bu sebeple, kargo gelir yönetimi modelleri ayrıca geliştirilmelidir. Bu tezin hedefleri kargo gelir yönetimi süreçlerini tartışmak ve spot piyasası için alokasyon modeli geliştirmek olarak özetlenebilir.

Bu tezde, bir spot alokasyonu optimizasyon modeli geliştirilir. Bu model rezervasyon kontrolü için gerekli görülen durumlarda tekrar çözülüp beklenen talebin kargo kapasitesine alokasyonunu gerçekleştirmektedir. Performans testleri için örnek test havaalanı ağı, farklı senaryolar ve performans metrikleri oluşturulup test ortamında geliştirilen model ile sektörde yaygınca kullanılan bir sezgisel yöntem olan "ilk gelen ilk alır" karşılaştırması için simülasyon çalışması yapılır. Simülasyon sonucunda elde ettiğimiz %95 güven aralığındaki t-testi istatistiklerine göre, geliştirilen optimizasyon modeli sezgisel yönteme göre 27 test senaryosunun 26 sında daha iyi sonuç vermektedir.

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LIST OF ACRONYMS/ABBREVIATIONS

2-D	Two Dimensional
ACRM	Air-Cargo Revenue Management
CSA	Cuckoo Search Algorithm
DBP	Deterministic Bid Price
DP	Dynamic Programming
EMD	Empirical Mode Decomposition
FCFS	First-Come First Served
FD	Finite Differences
IATA	International Air Transportation Association
ICAO	The International Civil Aviation Organization
JAH	Joint Approximation Heuristic
LP	Linear Programming
MC	Markov Chain
PLP	Probabilistic Linear Programming
RBP	Randomized Bid Price
RM	Revenue Management
SDE	Secondary Decomposition Ensemble
SE	Sample Entropy
VMD	Variational Mode Decomposition

1. INTRODUCTION

Revenue management (RM) can be defined as a discipline of analyzing previous analytics and performance data to draw future conclusions about consumer behavior. In aviation, revenue management is mainly focused on passenger and cargo services.

Earlier in aviation history, airline revenue management was mainly focused on passenger revenue management. Practical solutions obtained by experience were popular as the demand for Air-Cargo was much lower. Lower destination diversity and, less often flight occurrences generated a smaller set of itineraries, which also helped to work with practical methods easier.

With the help of growing institutional demand for international transportation and the proliferation of internet booking, it has become more challenging to utilize flight capacities. According to Boeing World Air Cargo Forecast for 2022-2041, which is retrieved from [1], world air cargo traffic has been growing 4.3% in the last ten years (2012-2021), and the growth is expected to be 4% per year over the next 20 years (2022-2041). An increasing number of flights and count of destinations have made it even more challenging to work with traditional methods. As such, air cargo revenue management has become the center of focus in the aviation sector.

On the other hand, only a few significant airlines practice ACRM, and these RM solutions are still in the early phases compared to passenger revenue management systems. Hence, there is room for improvement in airline cargo revenue management in the future.

1.1. Air Cargo Industry Background

There are three main types of users in Air Cargo, asset providers, shippers, and intermediaries, as stated in [2]. Service providers are air carriers such as Lufthansa

Cargo AG, FedEx Express, UPS Airlines, and Turkish Cargo. Customers that use air-carrier services are called shippers. Unlike passenger RM, most air-cargo spaces are purchased by institutions, namely HP, Dell, Samsung, etc. Institutions prefer to use air transportation through freight forwarding companies called intermediaries. Intermediaries operate with trucks and offer door-to-door service to shippers. Furthermore, intermediaries provide cargo consolidation, packing, loading, and third-party logistics services.

Cargo carriers sell their available capacity in two ways: guaranteed capacity contracts and free sales. Guaranteed capacity contracts, also referred to as allotments or long-term agreements, are the reservation agreement of cargo capacity, which is usually predefined in weight and volume, between providers and shippers on a specific flight. In addition to guaranteed capacity contracts, air cargo operators can sell their cargo capacity on the spot market, sometimes referred to as the black market or free sales. [3] mentions that free sales usually occur a few days before the flight and include more uncertainty. As a result, spot prices are higher than long-term contracts.

Since free-sale does not guarantee capacity filling, airlines tend to sell more space than the actual capacity to reduce the effect of variable tendering, no-shows, low-shows, or cancellations. This part of business practice is named overbooking. Upon the arrival of demand in the spot market, air cargo companies must decide whether to accept the current booking or reserve the capacity for a more profitable booking that may arrive in the future. It is stated in [3] that unit revenue of the booking, demand forecast, and the current sales profile are essential factors affecting acceptance/rejection decision.

1.2. Air Cargo Revenue Management vs. Passenger Revenue Management

Even though Air Cargo Revenue Management and Passenger Revenue Management are used in the same sector, they should be handled differently due to following reasons:

(i) Revenue from selling capacity is not only affected by the unit price but also depends on weight and volume capacity.

(ii) Passenger RM is focused on retail passengers, whereas air cargo usually operates with institutions. As a result, they have different demand curve patterns.

(iii) Intermediaries have detailed information on their hands and behave strategically. In contrast, passenger RM is mainly used by myopic passengers.

(iv) Air cargo business consists of two different markets: the guaranteed contract market and the spot market. These markets have diverse sales channels and customers.

(v) Unlike passenger revenue management, there often is a list of available routes to carry cargo. While choosing the optimal route, certain embargo restrictions should be considered.

(vi) The capacity of air cargo depends on the number of passengers on the flight, which is another stochastic information.

1.3. Thesis Organization

This thesis contains seven chapters. So far, the introduction to air cargo revenue management and the comparison of passenger RM with cargo RM are covered in this chapter. Chapter 2 contains a literature review related to the scope of our problem. The literature review is further grouped into passenger RM and cargo RM. Cargo RM includes references for the qualitative overview, overbooking, demand forecast, long-term demand allocation, short-term demand allocation, and simulation study. In Chapter 3, the airline cargo revenue management process is defined in detail, a verbal definition of the problem is given, and its scope is summarized in three different sub-sections. In Chapter 4, solution methods, class diagram, data generation steps, and mathematical model for spot allocation are introduced. Chapter 5 describes the numerical experiments conducted. In this chapter, the performances of the mathematical model, described in the previous chapter, and First Come First Served, a commonly used heuristic method, are compared. Test problem data generation, scenario settings, simulation steps, and performance metrics are defined, which leads to results obtained in the last part of this chapter. Chapter 6 summarizes the study and gives insight into future studies.

2. LITERATURE REVIEW

2.1. Airline Passenger Revenue Management

Revenue Management is defined in [3] as the method of appreciation, expectation, and persuasion of consumer behavior to maximize profit or revenue of the resource. The research on RM goes way back to 1972 and originates from the air carrier business, according to [4]. On the other hand, the scope of the revenue management research in reservations control was limited to overbooking in the past. According to [5], overbooking estimations were based on predicting the probability distributions of the number of passengers who would catch and successfully board the flight before flight time. [5] remarks that studies of overbooking have also led to various valuable research on disaggregate forecasting of passenger cancellations and no-shows. As a result, forecasting and overbooking studies successfully established ground rules for today's airline revenue management processes and developed scientific approaches to reservations control policies.

After the Airline Deregulation Act in 1978, air carriers gained control of prices and could change their schedule and services accordingly. Air carriers offered various products, such as business and economy class, to survive and develop in free market conditions. This innovation has led to attracting more price-sensitive customers and selling seats that would otherwise be empty. Littlewood's rule was presented in [6], which suggests that discounted bookings should be considered as long as it increases the total expected revenue. Following Littlewood's Rule, a single-leg allocation model with multiple fare classes EMSR model was discussed in [6]. EMSR has been extensively in demand for RM systems, and other models, such as EMSRb, have been developed.

All the literature involved above included restrictive assumptions, and these assumptions created implementation difficulties. Since the 1980s, the expansion of the Hub and Spoke network has increased the number of passengers that are involved in multiple flight legs. Origin-Destination Control problem, as defined in [7], includes the interdependence of flights and deterministic passenger demands. The article formulated a minimum-cost hub and spoke network, and its model was implemented at Frontier Airlines. Furthermore, a multi-leg itinerary capacity allocation problem introduced in [8] combines the fixed assignment of multi-leg itinerary seats and spot allocation of the remaining seats to provide flexible assignment.

Finally, the above literature review is limited to the seat allocation problem in passenger RM since it is relevant to our problem. For other research categories, including forecasting, overbooking, pricing, and real-life implementations, we refer to [9].

2.2. Air Cargo Revenue Management

In this section, ACRM studies in the literature are discussed in detail. This section comprises qualitative research, overbooking, demand forecast, long-term demand allocation, short-term demand allocation, and simulation study subsections.

2.2.1. Qualitative Overview

Air Cargo RM and Passenger RM are studied as two different problems. Factors including uncertain capacity, three-dimensional capacity, itinerary control, and allotments increase the complexity of the ACRM problem. Characteristics and complexities of cargo RM and differences with passenger RM are further discussed in [10] and [11].

The cargo revenue management process consists of four main steps. These steps can be named capacity forecasting, allotment allocation, overbooking, and spot allocation. The Cargo RM process is also described in detail in [10].

The real-life implementation of cargo RM systems is another point of interest in the literature. [12] shares their experience of implementing a live cargo RM system in KLM Cargo and emphasizes the critical factors in ACRM success. Similarly, [13] describes the process of implementing Sabre's CargoMax as the Revenue Management system at various airlines, including Lufthansa Cargo, the benefits achieved from this, and also the complexities and pitfalls. Critical success factors for future implementation projects are derived from those experiences.

2.2.2. Overbooking

In ACRM, overbooking is defined as intentionally selling more space than available to compensate for no-shows, cancellations, and variable tendering. Regarding the stochastic nature of the cargo capacity in cargo RM and show-up-rate-estimations, an expected cargo capacity usage is calculated, and the expected remaining capacity tends to be overbooked. [14] presents an economic overbooking model under stochastic capacity, which minimizes the expected overage and underage cost. Although the capacity is assumed stochastic, the two-dimensional nature of cargo overbooking is not addressed.

Offload of air cargo may be the result of exceeded weight capacity as well as volume capacity. Therefore, a two-dimensional overbooking model must address the show-up volume and weight dependency. This problem is first discussed in [15]. An overbooking curve is introduced in this model, which obtains two different optimal results in two dimensions.

2.2.3. Demand Forecast

Demand forecasting estimates future demand with the statistical analysis of past data. [16] discusses a new secondary decomposition-ensemble approach with cuckoo search optimization for air cargo forecasting. A new secondary decomposition-ensemble method with a cuckoo search algorithm is defined in [16] for cargo demand forecasting. In particular, the original air cargo time series is divided into parts by an enhanced decomposition formwork. Enhanced decomposition formwork comprises variational mode decomposition, sample entropy, and empirical mode decomposition.

2.2.4. Long-Term Demand Allocation

Long-Term Demand (Allotment) Allocation is one of the cargo RM process steps. According to [10], after cargo capacity forecasting and itinerary generation, the available capacity is first allocated to allotments (long-term contracts). The process then continues with overbooking the remaining capacity and short-term (spot) allocation of the overbooked capacity.

Long-Term demand is protected via options contracts between forwarders or large-size customers and air carriers. These contracts intend to sell the cargo capacity less expensive than the spot market as they sell the "guaranteed capacity" and decrease the stochasticity-related risks of the process. [2] introduces a long-term agreement contract of the cargo capacity. This contract suggests that each forwarder reports the capacity use estimation and pays the reservation in advance. After the actual demand, which should be smaller than the reserved capacity, is realized, an additional execution fee is paid regarding the realized cargo capacity. Though it mainly shifts the risk from air carriers to forwarders, [2] also focuses on reducing their default risks of them by solving the unused capacity fee problem.

2.2.5. Short-Term Demand Allocation

Alternative to long-term agreements, air cargo operators observe short-term demand through the spot market. Spot requests arrive quickly, usually 1-2 weeks before the flight departure. Air carriers decide whether to accept or reject booking after monitoring the demand capacity, available capacity, and offered price. Unlike long-term contracts, counterparties do not agree on guaranteed capacity, so there may be no-shows, low-shows, and variable tendering. Short-Term spot demands bring more risk to air-carrier and are often more expensive than long-term contracts. As a result, airlines that can sell more capacity on the spot market tend to generate more revenue per unit capacity. Despite the dynamic state of the problem and the importance of real-life implementation on the balance sheets, only a few studies in the literature are involved in this area.

The first line of research often involved single-leg models focused on deterministic dynamic programming problems. Later, these studies were extended to stochastic dynamic programming models and Markov Chain processes. [17] develops a discrete-time dynamic programming model for finding an optimal booking policy. Their solution is discussed as a base case and extended in many articles.

Second, single-leg models with deterministic demand are covered. Another single-leg model discussed in [18] aims to maximize the expected contribution. Since they use Markov Decision Process, an exact solution is impractical, and they develop six other heuristics to overcome this difficulty. The weight and volume of the demand were approximated by average values in the heuristics to avoid the curse of dimensionality. Similarly, [19] proposes a discrete-time Markovian model for the booking request/acceptance/rejection process, which is followed by the bid-control policy. The problem discussed in [19] possesses a dynamic control policy as they accept bookings only when the revenue from accepting it exceeds the opportunity cost, which is calculated based on bid prices. Furthermore, [20] develops a single-leg solution by approximating the expected revenue function in the DP model while taking into account the stochastic volume and weight of shipments. They obtain the results by de-coupling weight and volume components.

Later, studies were extended to deterministic, multi-leg models. [21] improves the single-leg model [17] discussed above to a multi-dimensional dynamic programming model to present a network RM problem for air cargo. They proposed two models: dynamic programming, which obtains the exact solution, and linear programming (LP) approximation heuristic to overcome computational complexity. They assume finite numbers of cargo and neglect the two-dimensional nature of cargo capacity. Similarly, [22] formulated a deterministic dynamic programming approach that captures both passenger and cargo revenue management. Although they consider weight, volume, container capacities, and time dimensions, they assume that expected demand is used in the model.

Finally, probabilistic multi-leg models in the literature are covered. [23] takes short-term demand allocation as the scope and uses a bid-price control policy. [23] also claims that bid-price control policy is asymptotically optimal in short-term demand allocation problems. However, they use bid prices which are the mean value of the results of all simulations.

Multi-leg models have been extended from single-leg models to include more complexity to the problem. The complexity is even more increased if the probabilistic demands are used. Regarding the complexity in passenger RM, [24] came up with a claim that simple deterministic approximation methods based on average demand often outperform more advanced probabilistic heuristics. To test this phenomenon, [25] study carefully examines the trade-off between computation time and the aggregation level of demand uncertainty with examples of a multi-leg flight and a single-hub network.

2.2.6. Simulation Study

Simulation is performed to compare the performances of the policies under stochastic control variables. The numerical experiment test problem settings are often commonly-held in literature. Also, first-come-first-served (FCFS) is chosen as the base-case policy while comparing the performance of the policies.

First of all, [18] develops a simulation environment to test the performance of the six heuristics previously developed in their article. The test problem settings of this study assumed random volume but deterministic weight. Also, each product category followed a lognormal distribution. They also assumed ten different product categories and that the revenue function is piecewise linear. Other parameters were sixty days of the decision period, and capacity parameters were obtained from Boeing-747 technical data. Finally, they used FCFS as a base policy to compare the heuristics. [20] conducted a simulation study following the development of their approximate algorithm for the two-dimensional air cargo revenue management problem. First, [20] extends the 2-D DP model at [18] and discusses its intractability for most practical problems and proposes one of the six heuristics in [18], named as HD, to overcome the curse of dimensionality. Later, they develop the Joint Approximation Heuristic and design a numerical experiment to test the performance of their heuristic. Some settings of this study were based on [18]. They also used FCFS as a base policy. They used three rate classes, nine cargo product groups, and 60 days simulation period for test problem settings and compared JAH, HD, and FCFS policies.

[19] uses a Markov model for single-leg air cargo revenue management under a bid-price policy. First, they define the problem as a Markov process and use a bid-price approach similar to that of [23] to manage the booking requests. Then, they give a large-scale MIP formulation and a discrete-time Markov chain formulation with a bid-price control policy. After providing a theorem for the airline's expected revenue until period n, they compare the results of different policies, namely the discrete-time Markov-chain formulation described in this paper, algorithm in [23] and FCFS policies. Comparison is made based on a simulation procedure based on Boeing-747 technical data, ten days of the simulation period, log-normally distributed demand weight, inverse density, volume, and demand to arrive at non Homogeneous Poisson Process.

The classic dynamic programming methods are not suitable for the ACRM problem of a realistic size due to the curse of dimensionality. Many heuristic approaches, such as the well-known bid-price control method, approximate reservation control decisions according to different static formulations. These mathematical formulations then need to be solved again to take into account the dynamic features of the problem. [26] discusses the asymptotic optimality of the randomized linear program for network revenue management and then conducts a numerical experiment study. First, they define the problem verbally and write the Hamilton–Jacobi–Bellman equation for the problem. Then, they formulate the deterministic bid price heuristic and well-known randomized LP. Finally, they compare the performance of three solution methods, Randomized bid price heuristic, Deterministic bid price heuristic, and Deterministic bid price heuristic with finite differences.

Furthermore, a different method is presented in a simulation experiment summarized in [27], where no problem re-solving is required. This method is defined as the parameterized function approach. According to [27] results, the parameterized function method is an excellent alternative to the bid-price control method, which requires frequent resolving of the problem for favorable outcomes. The numerical experiment was performed in 18-time units. A small hub and spoke network with four nodes and only one-way flight movement were considered, resulting in 5 origin and destination pairs and 20 associated fares. In addition, they used a non-homogeneous Poisson process, which led to a triangular-shaped demand intensity vs. time graphic, to simulate booking arrivals and created a different peak arrival time for each fare class.

3. PROBLEM DEFINITION

Air Cargo Revenue Management is interested in many factors, including flight schedule, itinerary generation, demand allocation, and booking control. The process chart of the problem environment can be seen in Figure 3.1 below.

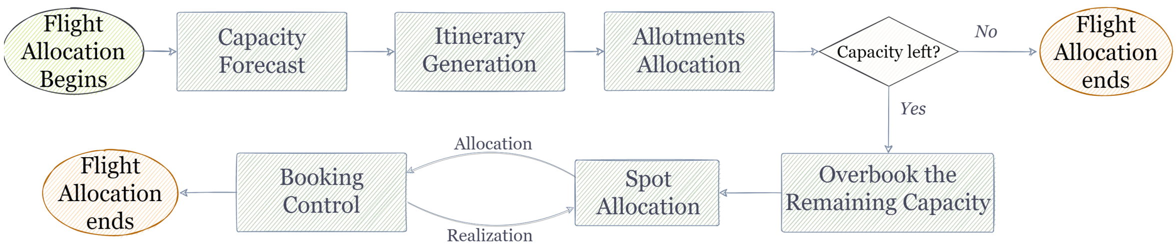

Figure 3.1: Air Cargo Revenue Management Decision Process Flow

The process flow can be analyzed in detail in three different categories. The first category generates route and cargo capacity estimations, the second process category allocates allotment decisions, and the final process allocates spot decisions and alters these allocations regarding the booking arrivals.

3.1. Determining Cargo Capacities and Itineraries

Given the flight schedule, assigned aircraft, and itinerary generation rules, this section provides detailed information on capacity forecasts and itinerary generation.

3.1.1. Capacity Forecasting

Once the flight schedule is published, and aircraft are assigned to flights, capacity forecasts are generated. Each aircraft type has varying weight and volume capacities. Aircraft weight components that are defined in [28] in detail mainly consist of fuel weight, total payload, and empty operational weight. A brief diagram of aircraft weights and components can be seen in Figure 3.2 below. Excluding what is necessary for operation and fuel, each aircraft has a specific weight capacity called payload.

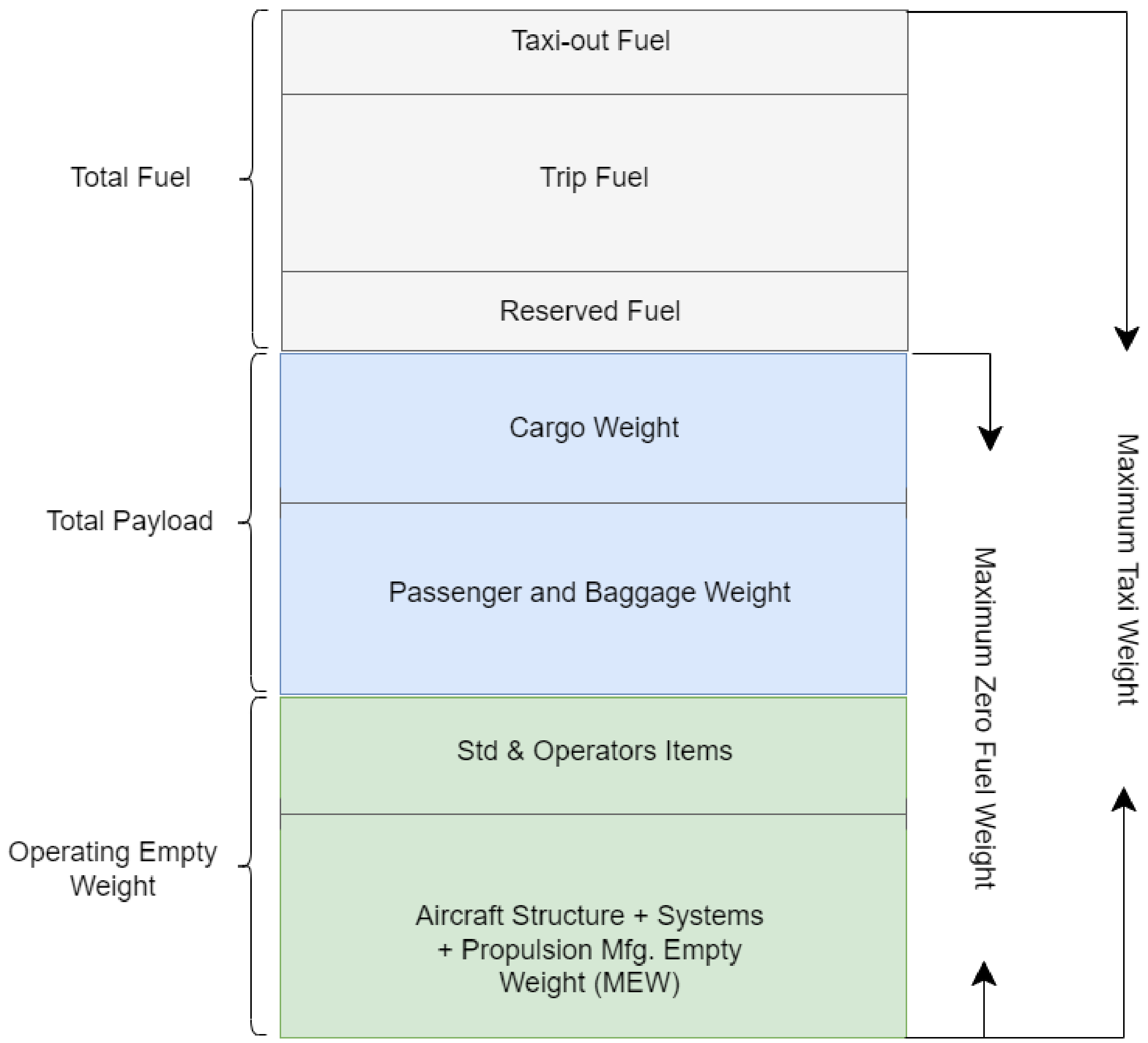

Figure 3.2: Aircraft Weight Components

Payload is divided into cargo and passenger in passenger aircraft, whereas it is mainly devoted to air cargo in cargo aircraft.

Weight and volume of the cargo are the two most important factors affecting the cost of shipment. Air carriers often use chargeable weight, which is the maximum weight and dimensional weight. Dimensional weight is the weight equivalent value of the volume. In air freight, 6000 cubic cm is equivalent to 1 kg in terms of the metric units of measurement, defined by the International Air Transportation Association (IATA) and accessible in [29].

Although most of the aircraft components presented in Figure 3.2 are static for aircraft, many components, including passenger weight, baggage weight, and fuel weight, are changeable and hence forecasted. The left-off weight is referred to as the cargo weight capacity forecast. Similar calculations can be made to generate cargo volume capacity forecasts for an aircraft.

Weight and volume capacities also differ in aircraft types. Whether the aircraft is a narrow body or wide body affects cargo capacity. Furthermore, some airplanes are purely devoted to cargo, and cargo capacities for these aircrafts may be up to payload level for weight and volume.

3.1.2. Itinerary Generation

Before going into detail about this section, specific aviation terminologies need to be introduced. A leg, also known as a flight leg, is a direct flight from one airport to another. A segment is a leg or combination of legs with the same airport number from one airport to another. On the other hand, an itinerary is defined in [30] as a nonstop or connecting path through an airport network to travel from origin to destination. Itineraries include but are not limited to segments since various legs with different flight numbers can be included in an itinerary.

The International Civil Aviation Organization (ICAO) is a multinational organization founded by 193 national governments for cooperation and diplomacy in air traffic in 1944. Brief information about ICAO can be obtained in [31]. Two main constraints of aviation nature apply while generating itineraries: fifth freedom and minimum connection time. ICAO defines all nine of the freedom rights in [32] and classifies beyond the Fifth as so-called since only the first five freedoms have been agreed upon by international treaty. An airline needs to have fifth freedom rights to fly from one country to another country if the airline is based in neither of these countries. Fifth freedom flights are often less expensive and less crowded due to their positioning. Every airport has set an amount of time, called minimum connection time, defined as the minimum time required to transfer from arriving to departing aircraft. Thus, we generate itineraries considering these constraints.

A brief methodology of itinerary generation, which is used as input to an air-cargo revenue management problem, is introduced in the data generation section. K-means clustering may be used to generate k itineraries between a given origin and destination, and it can be evaluated for all origin destinations in the network.

3.2. Allotments and Overbooking Processes

A detailed process flow is presented in Figure 3.3 to summarize the allotment and overbooking decisions. This part of the process takes itinerary and flight legs with capacity forecasts as input and gives the overbooked remaining weight and volume capacities as output. This part of the process is not included in the scope of this thesis.

3.2.1. Allotments Allocation

As mentioned in the introduction, there are mainly two types of air-cargo sales: allotment and spot. Allotments are spaces reserved for big customers. These deals often constitute most cargo capacity sales depending on the air-cargo provider. Cargo capacity is reserved with long-term contracts. Sometimes, “low-show” or “no-show” may occur, so each customer has a show-up rate estimation.

The allotment is often signed way before the flight time. Cargo providers must consider allotment demand forecasts before deciding on the agreement for a long-term contract. Airlines widely benefit from signing a capacity agreement since it resolves the low-capacity utilization, increases the load factor, penalizes guaranteed capacity deviations, and attracts more shippers because of long-term low-cost contracts. Furthermore, long-term agreements include a higher level of communication between airlines and customers, and information sharing improves the efficiency of cargo allocation.

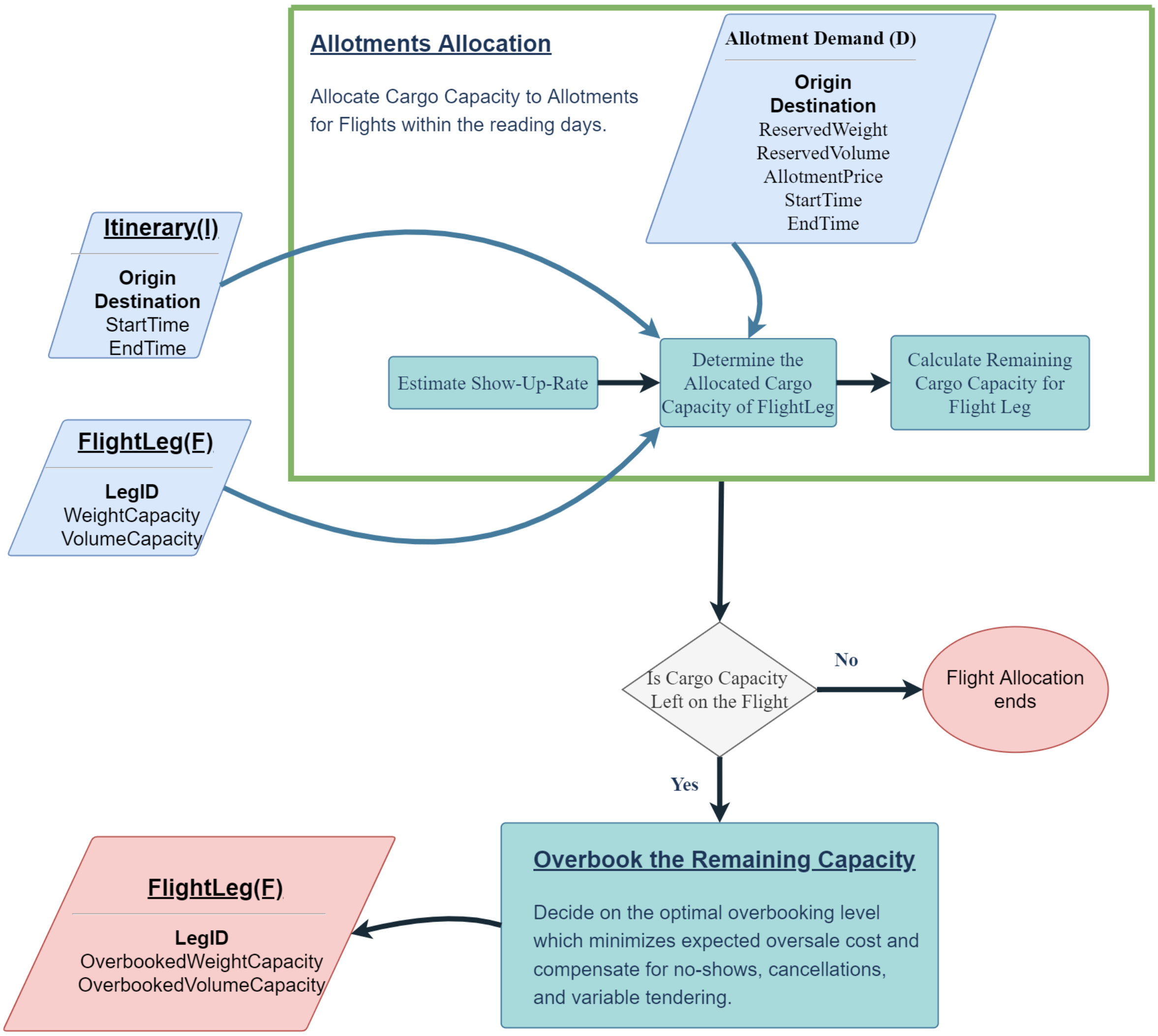

Figure 3.3: Allotments Allocation and Overbooking

The allotment allocation process begins with estimating the show-up rate of each customer. Show-up rate estimations of customers are often generated using the projection of past data. Allotment demand is another stochastic input of this process. Some long-term agreements may have already been settled, but other allotments are forecasted to date. Allotment demand forecasts are usually made regarding past data. After allotment demand, itinerary and capacity forecasts are given for a flight, its allotment allocation is determined. Allotment allocation is another part of the literature interest, and the optimization model discussed in [3] gives excellent insight into the problem.

Whether to sell the cargo space for a long-term contract at a given price or to save the area for the spot market is often the topic of broad interest among air-cargo providers. Some carriers prefer lower levels of allotment allocation to aim large profits at black market sales, while others minimize their risk and uncertainty by largely allocating their sales capacity to allotments. Hence, deciding on the optimal allotment/spot ratio is often considered part of this process and is usually included as a decision parameter in mathematical models such as the model discussed in [2].

3.2.2. Overbooking

Like passenger overbooking, air carriers usually overbook cargo capacity to fill expected empty capacity by low-show, no-show, cancellations, or variable tendering. As the name implies, low-show refers to the case when a lower level of cargo than the long-term agreement amount is realized. Similarly, a no-show describes the case when an agreement is made, but the shipment does not show up. Variable tendering describes cargo that shows up less or more than the agreed amount.

The optimal overbooking level should minimize the expected over-sale cost and the underutilization caused by no-shows, cancellations, and variable tendering. A brief discussion of air-cargo overbooking and a cost model under a specific capacity is presented in [10].

3.3. Demand Forecast, Spot Allocation and Booking Control

Given itineraries, flight legs, and remaining capacity forecasts after allotment allocation and overbooking, this section provides the spot market demand forecast, allocation, and booking control. Later in the next chapter, a mathematical model will be developed for spot allocation. The process flow can be seen in detail in Figure 3.4.

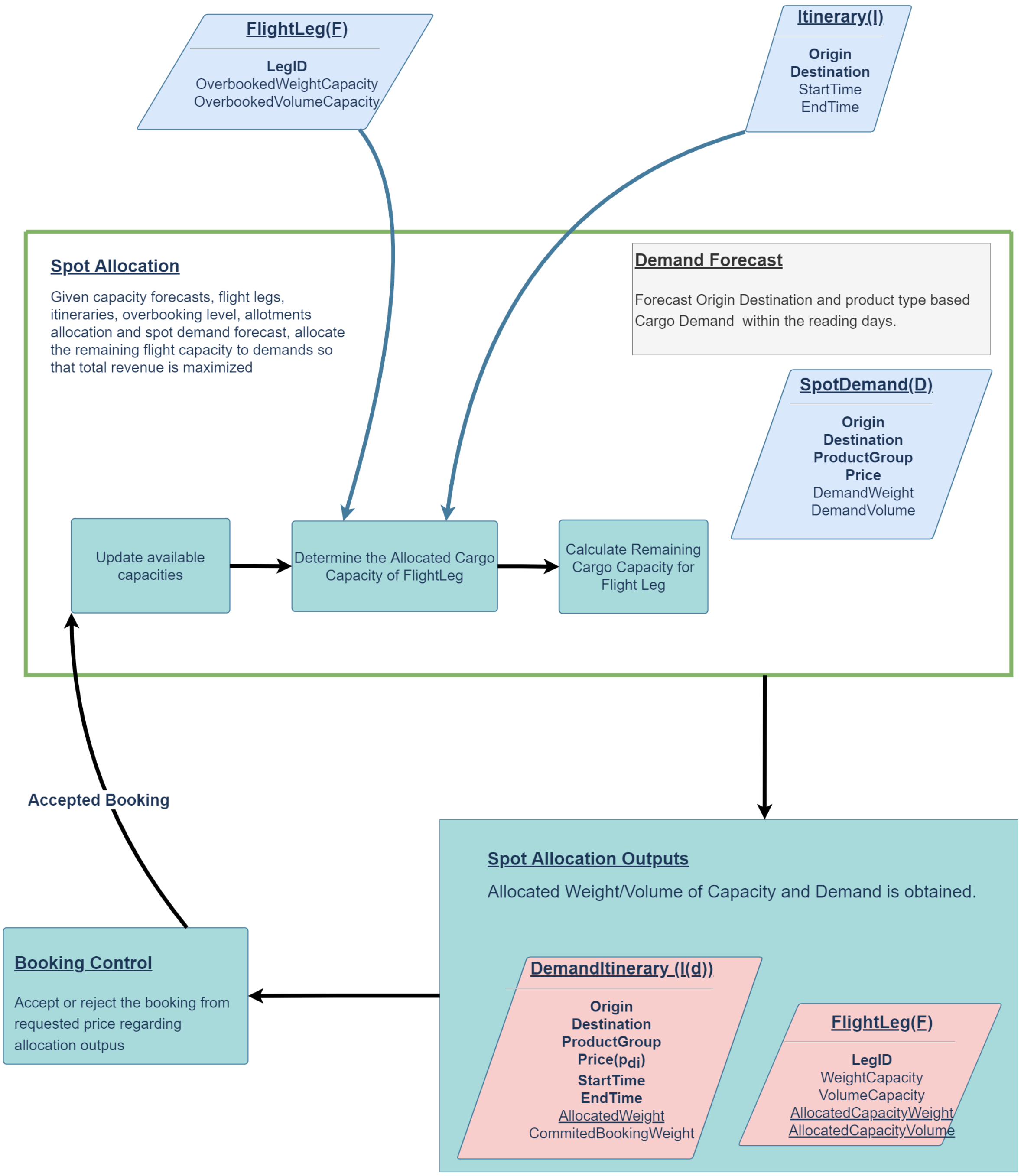

Figure 3.4: Demand Forecasting and Spot Allocation Updated

3.3.1. Demand Forecast

Unlike demand forecasting for allotments, spot market demand forecasting includes but is not limited to historical demand projection, short-term pre-departure booking information, historical realization profiles, and allocation feedback.

Various methods are used in demand forecast price parameter estimation, and rate-class methodology is widely used in literature. In this method, unit prices are divided into k price levels, called rate classes, and these price levels are located at points where historical sales price data point distances are minimized.

Unit cost and revenue of cargo transportation depend on location and product group. Small-distance flights consume less fuel and should have a lower unit cost. Different product types have additional handling costs, and the carrying charge for live animals or delicate products is much higher than for standard cargo. Hence, assuming that the historical data sample is large enough to describe each factor independently, generating a separate forecast for each should generate more accurate results.

3.3.2. Spot Allocation

After allotments are allocated, the remaining capacity of an aircraft is devoted to spot allocation. Spot allocation is briefly the devotion of expected remaining capacity to future booking sales. Its output directly affects and is affected by the booking control policy. Bookings are accepted or rejected regarding different policy rules. Accepted bookings require the assignment of an itinerary and a decrease in the itinerary's leg capacities.

The main objective of spot allocation is to find the optimal demand allocation to maximize the expected total revenue. It requires capacity forecasts after allotment allocation and overbooking, itinerary, and demand forecast. Its output should display an allocated weight of each demand's itinerary. It can also give allocated capacity in each flight leg.

3.3.3. Booking Control

Given the allocated capacities, booking control is the process that makes booking accept/reject decisions and rate requests in the spot market according to a set of predefined criteria. The spot market is where cargo providers and their customers meet to find a settlement on the carrying price of a booking. Customers offer a bid price for their cargo, and air carriers may make another price offer considering rate classes. An airline may also put the empty cargo space for sale on the spot market to utilize its capacity.

Booking arrival is a stochastic process defined in [33] as a non-homogeneous Poisson process that peaks at 3-5 days before take-off. Weight, inverse density, and volume of a booking are distributed lognormally, as stated in [4], [20], [34].

Many bid price control algorithms are presented in the literature. For instance, [33] presents a two-phase formulation; phase 1 includes the static formulation of the optimal allocation of the cargo capacity under a non-homogeneous Poisson process of demand arrival, and phase 2 demonstrates a dynamic programming model which accepts/rejects spot orders as they arrive. The formulation is only solvable for small problem sizes due to computational complexity. [20] presents a bid price control policy by joint approximation heuristic and compares it with other policies in the numerical experiment section.

Finally, comparisons of policies are made under certain numerical experiment settings in [18] is used as a base setting for many other articles. Three different models are presented in the previous sections. They are compared with First Come First Served Policy, a widely used policy by most air-cargo providers, and many articles as base policy. Furthermore, [27] compares the performance of different policies in a test environment similar to [18].

The processes, summarized in the three sections above, contain complete information on air-cargo revenue management. This thesis focuses mainly on the third section, Demand Forecast, Spot Allocation and Booking Control. As explained above, the problem has a dynamic solution, and some factors, including demand, capacity, weight, and volume, are stochastic. Furthermore, airport network, flight schedule, aircraft assignment, and itinerary sample data are necessary to construct a multi-leg network optimization problem. The generation of sample data for the optimization model and booking control policies are discussed in the data generation section in detail.

To draw a more clear perspective on the problem, the following assumptions and simplifications are made:

- Time horizon for the test problem setting is set as 30 days. On day 0 of the simulation, all cargo capacities that are open to free-sale bookings are available.
- Inverse Demand Density is distributed as log-normal with mean $\mu_{1/d}$ and variance $\sigma^2_{1/d}$.
- Demand Weight is distributed as log-normal with mean μ_w and variance σ^2_w. Then, Demand Volume is also distributed as log normal.
- Unit Revenue from a booking is calculated as the summation of rate classes of the flight/s of selected itinerary. RateClass capacities are determined. Booking requests start to be committed from the smallest to the largest until the capacity is reached.
- Cargo weight and cargo volume capacity of each flight are assumed to be Truncated Exponential(λ) in the interval [0,1].
- It is assumed that every cargo has a 100% Show-Up Rate.
- It is assumed that the air-cargo provider does not apply overbooking.
- Each flight has three different rate-class levels. Unit revenue from a booking is calculated as the summation of the selected flights' rate classes evaluated over these levels.

A small airport network is described in Figure 3.5 below. This network is also used in spot allocation and numerical experiment chapters. It makes it possible to apply many concepts to the problem, including itinerary generation, fifth freedom in international flights, and a summary of the significant air traffic in İstanbul Airport, which is taken as a hub station. Please note that it is not a pure hub-and-spoke network. The network is defined as small as possible since a large network size affects problem complexity drastically.

There are ten airports and 13 different flight routes in the network. It is possible to connect 45 different origin-destination pairs using itineraries. Flights in both directions are possible, and the network is classified as an undirected graph.

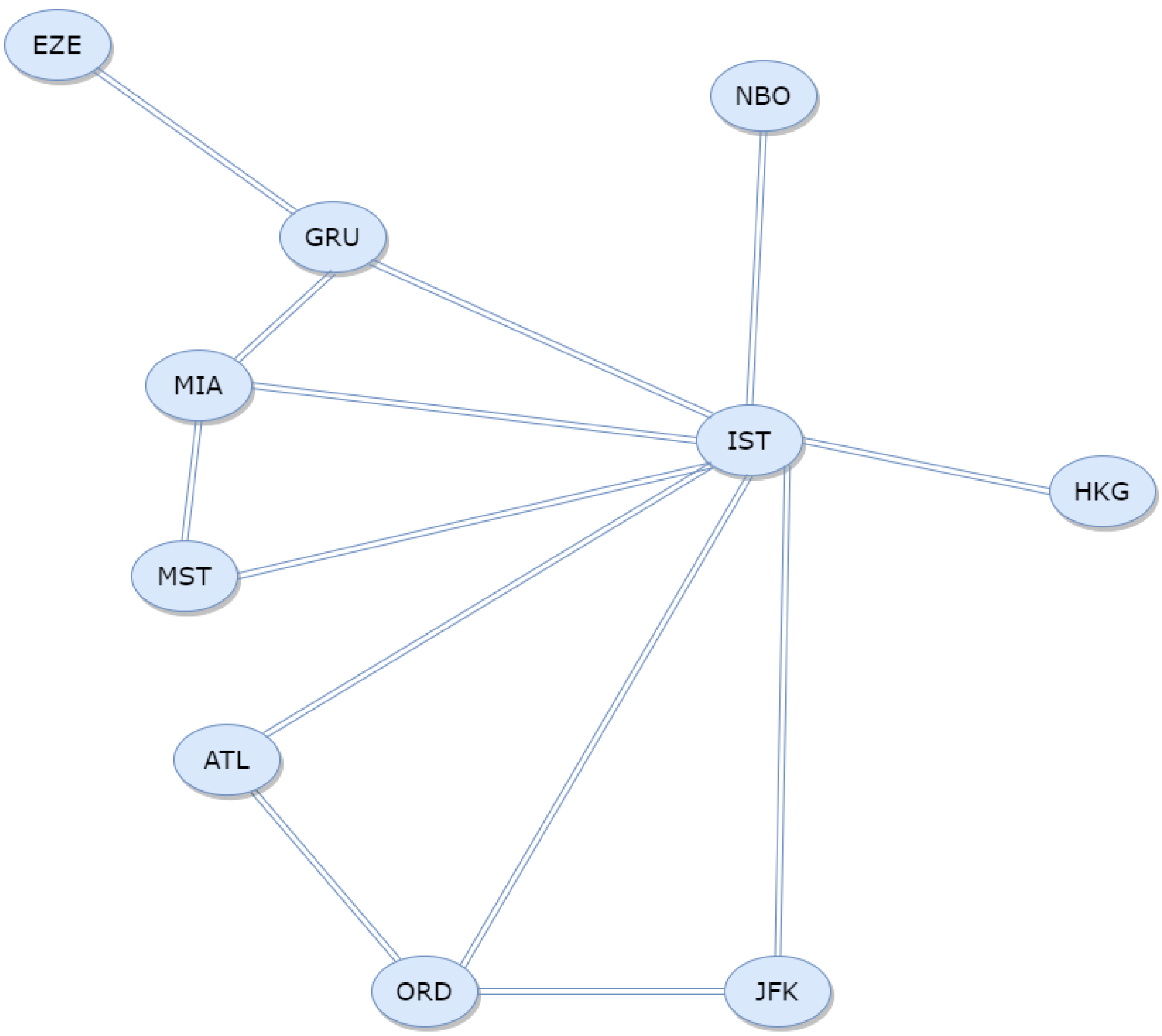

Figure 3.5: Sample Airport Network

In light of the above information, the definition of the problem is to find a revenue management approach that:

- Maximizes the expected allocated total revenue of spot sales
- Minimizes the effect of uncertainty
- Maximizes the revenue per unit capacity
- Utilizes air cargo effectively

4. SOLUTION METHODS

4.1. Class Diagram and Data Generation

Given the cargo capacities and demand forecasts, the objective of the spot allocation model is to allocate the cargo demand to a set of itineraries so that total revenue is maximized.

4.1.1. Class Diagram

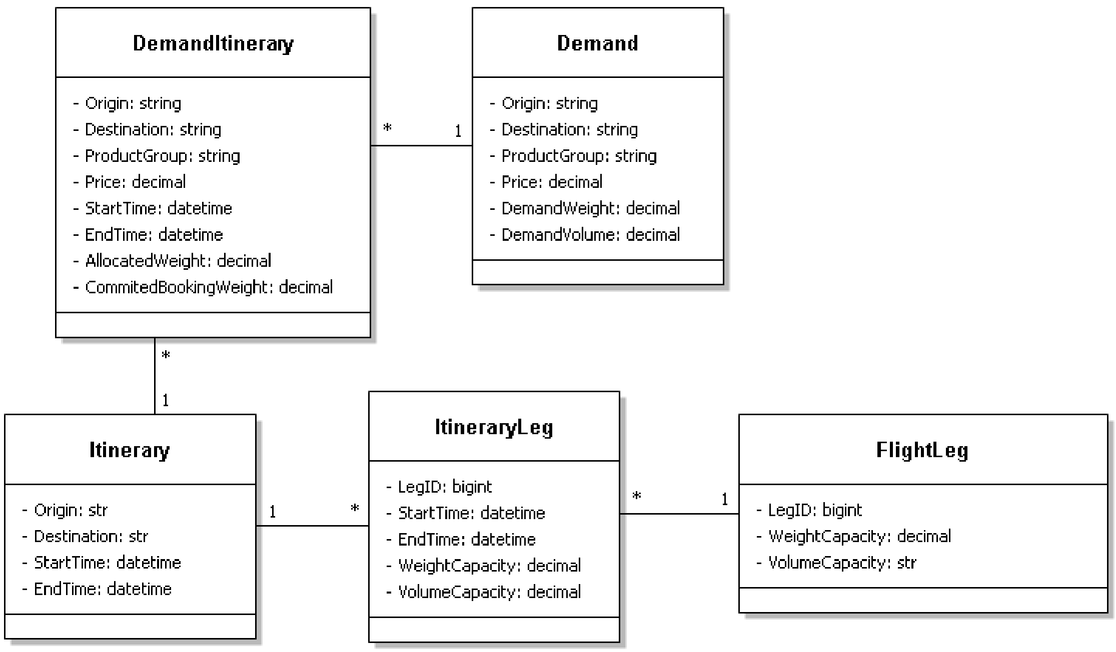

Figure 4.1: Class Diagram of Data Used in Optimization Model

A class diagram for the spot allocation problem is introduced in Figure 4.1 above. A FlightLeg class has Origin, Destination, FlightDate, and FlightNo fields described in LegID and capacity forecasts for weight and volume, demonstrated as WeightCapacity and VolumeCapacity. The itinerary class is created by the meaningful connection of routes in FlightLeg class. Each Itinerary is then assigned a StartTime and EndTime from the minimum departure dates and maximum arrival dates of the FlightLegs in the

Itinerary. Then, ItineraryLeg, the joining class of Itinerary and FlightLeg, is created to describe capacity forecast information for each leg item in an itinerary. Demand class is a descriptive form of demand forecast created for spot demand. Demand forecast data contains the weight, volume, and density forecast for each origin, destination, product type, rate class, and day. The origin and destination airports do not have to have a direct route. DemandItinerary class is created as a join of Demand and Itinerary classes to match each demand with possible itineraries. Finally, the allocated capacity weight field in the DemandItinerary class is set as a decision variable. The data generation procedure of each class is explained in the following subsection.

4.1.2. Data Generation

A data generation algorithm is created to generate statistically consistent data for each class. Sample flight schedule data set is taken from Turkish Airlines. The pseudo-code of steps taken for each class is briefly summarized below. Steps to generate flight legs given airport network and flight schedule sample:

(i) Pick a random origin and destination from the Origin Destination list, which is created considering fifth freedom rights and direct flight availability.
(ii) Generate departure time, randomly selected within the time horizon. Then, assign arrival time by adding E(Flight Time) + ϵ where the error term ϵ is distributed as Normal$(0, \sigma^2)$
(iii) Randomly pick an aircraft from the previously used aircrafts list of the flight leg.
(iv) Generate weight and volume capacity forecast. The ratio of cargo capacity to total capacity is distributed exponentially with the rate λ, which is based on [35] reference. Truncated exponential distribution, defined in [35], is used to limit generated random variables in [0,1] intervals.

To generate itineraries from previously generated flight legs and airport pair networks:

(i) Determine possible paths from a given origin to destination by using flight distances as a weight parameter.

(ii) Order by total weight and take up to the k-th shortest path to be added to itineraries.

(iii) Apply (i) and (ii) for all possible origin destinations.

Finally, demand forecasts are generated from previous bookings samples as follows:

(i) Group past bookings in each day per origin, destination, and product type and summarize the weight and volume of the grouped bookings; call it Demand Sample. Then generate n rate classes from previous rates by using k-means clustering centroids.

(ii) For given origin, destination, product type, day, and rate class, generate demand weight and volume using the lognormal distribution of previously constructed Demand Sample.

(iii) Repeat (i) and (ii) for all days, origin destinations, product types, and rate classes.

Having generated data necessary for the problem, the mathematical model is defined in the next section.

4.2. Spot Allocation Model

Table 4.1: List of Symbols

Sets	
I	set of itineraries, indexed by i
F	set of flight legs, indexed by f
D	set of demands, indexed by d
$I(d) \subseteq I$	set of itineraries to which demand $d \in D$ can be assigned
$D(i) \subseteq D$	set of demands that can be assigned to itinerary $i \in I$
$F(i) \subseteq F$	set of flight legs that is contained in itinerary $i \in I$
Parameters	
p_{di}	unit price of using itinerary $I(d)$ to satisfy Demand $d \in D$
DW_d	forecasted demand weight of demand $d \in D$
d_d	average density of demand $d \in D$
CW_{if}	weight capacity of the flight leg $f \in F(i)$ which is included in itinerary $i \in I$
CV_{if}	volume capacity of the flight leg $f \in F(i)$ which is included in itinerary $i \in I$
Decision Variables	
x_{di}	allocated weight capacity of itinerary $i \in I(d)$ to demand $d \in D$

4.2.1. Optimization Model

In this section, we introduce an LP model which maximizes the total allocated revenue regarding the demand forecast of each origin-destination and the weight and volume capacities of each flight leg constraint. Model sets, parameters, and decision variables are described in Table 4.1. in detail. Optimization model outputs are used in the booking control process to accept the booking if the corresponding capacity is available, and committed booking capacities are deducted from allocated capacity weight and volumes. The problem can be formulated as

$$
\begin{aligned}
\max \quad & \sum_{d \in D} \sum_{i \in I(d)} x_{di} p_{di}, && && (4.1)\\
\text{s.t.} \quad & \sum_{i \in I(d)} x_{di} \leq DW_d && \forall d \in D, && (4.2)\\
& \sum_{d \in D(i)} x_{di} \leq min_{f \in F(i)}(CW_{if}) && \forall i \in I, && (4.3)\\
& \sum_{d \in D(i)} (\frac{x_{di}}{d_d}) \leq min_{f \in F(i)}(CV_{if}) && \forall i \in I, && (4.4)\\
& x_{di} \geq 0 && \forall i \in I, \forall d \in D. && (4.5)
\end{aligned}
$$

Sets, parameters, and decision variables are defined in Table 4.1. Objective (4.1) maximizes the total allocated revenue of all demands and all itineraries of demands. Constraint (4.2) ensures that the total allocated weight of specific demand to its available itineraries is not greater than the forecasted weight. It is evaluated for all demands. Constraint (4.3) guarantees that the total allocated weight to a specific itinerary from all of its demands cannot be greater than the leg capacity with the minimum cargo weight capacity. Constraint (4.3) is written over all itineraries. Constraint (4.4) ensures the same condition for capacity volume. Allocated weight capacity is divided by volume on the left-hand side of the equation, and the minimum volume capacity of flight legs is taken on the right-hand side.

The entire process of spot allocation and booking control is a stochastic dynamic problem with uncertain demand, weight, and volume capacities. There exist a maximum count of DxI decision variables in the model. Besides, the Constraint (4.2) count is equal to the number of demands in D. Counts of Constraints (4.3) - (4.4) are equivalent to the number of itineraries in I, but each inequality is evaluated a total of $F(i)$ times due to the right-hand side $min()$ expression. Hence, these constraints are evaluated for each flight leg in each itinerary. The size of the set of itineraries (I), set of demands (D), and set of flight legs (F) depend on the number of origin-destination pairs. If a new node and an edge are added to the problem, its complexity increases dramatically. Problem size is also dependent on the number of flights that are generated for an O&D pair as it does not only increase the size of set F but also the sizes of sets I and D. Other factors, such as increasing the count of product groups also increase the problem size, but it only affects the set's count D.

The optimization model introduced above needs to be resolved frequently to respond to the changes in stochastic parameters. A set of internal or external factors affect demand and capacity. For instance, a new passenger booking or cancellation is not a part of the cargo RM decision process. Still, it may affect the available cargo capacity of a flight in real-life. On the other hand, problem resolution requires a lot of computational time and effort for complex networks with a high degree. Hence, for an O&D network with less than 20 nodes and 30 edges, the optimization model can be resolved upon the arrival of each booking to ensure optimality. In contrast, it could be resolved on a regular time basis, with a frequency that holds the computational time vs. optimality trade-off.

5. NUMERICAL EXPERIMENTS AND RESULTS

In this chapter, the performances of two policies, Spot Allocation and FCFS, are evaluated under different scenarios. Spot Allocation sets aside a specific capacity for each flight to cargo demand expected to arrive in the upcoming days before the flight. Allocation decisions are based on the output of the mathematical model (4.1) - (4.5). It assumes the static bid price of the demand.

First Come First Served (FCFS), on the other hand, is considered as another policy as it is a base case used in many air-cargo providers with simple revenue management policy and is also used in [19] and [21] to evaluate performances of different policies. First Come First Served presents the lowest available rate-class for the booking upon their arrival time and commits every booking until the capacity of available itinerary/s is full. It can be viewed as zero bid price control policy with no previous allocation.

Both policies assume a 100% Show-Up Rate for the committed bookings and no overbooking. In the first section of this chapter, test problem settings for the simulation runs and simulation steps are introduced.

5.1. Test Problem Settings

Our test problem consists of the following:

- 10 nodes, 13 edges
- 45 Origin & Destination Pairs
- 3 Product Types
- 3 Rate Classes
- 30 days of booking horizon before the flight date

The same airport network, shown in Figure 3.5 in Problem Definition, is used to test FCFS and Spot Allocation policies. Next, test problem data generation and scenario settings are described in detail.

5.1.1. Test Problem Data Generation

Bookings arrive with a Non-Homogeneous Poisson Process with rate λ_{max}. Λ_{max} is calculated different for each Origin & Destination pair. Demand arrivals display a triangular-shaped Demand Intensity Pattern. The arrival rate starts from 0 on day 0 (30 days before the flight), reaches the maximum, and declines after the peak. Peak day is randomly chosen in each simulation run and origin & destination pair.

Three levels of rate class allocations are introduced, and the ratio of each group is chosen as different in scenario settings. The first level of the rate class defines the lowest possible acceptance rate, while the third level implies the highest rate for the flight. Early arrived bookings have the advantage of getting the first level of rate class. After a certain percentage of flight capacity is filled with committed bookings, second and third-level rate classes can be offered, respectively. Both policies start to fill flight capacity from the lowest available rate class.

Unit revenue of a booking is calculated as the summation of the minimum rate classes from flights of an itinerary that can be assigned to the booking. Even though rate classes are generated similarly in each policy, unit revenue of the same booking may differ in FCFS and Spot Allocation as FCFS starts filling the bookings from the itinerary with the highest available capacity. In contrast, spot allocation chooses the itinerary with the lowest available unit to first satisfy demand.

The generated data size largely depends on the test network and time horizon selected. Thus, forming a modest-sized but representative problem size is crucial regarding the problem's complexity and solution time.

5.1.2. Test Problem Scenario Settings

Different scenarios are presented for the test problem. Each scenario consists of a different combination of the following three factors; demand arrival intensity, peak demand time, and the ratio of the flight capacity allocated to the rate class scale. Each element has three key levels adding up to 27 different scenario settings.

Demand arrivals are categorized as low-intensity (smaller λ_{max}), medium-intensity (regular λ_{max}) and high-intensity demand arrival (larger λ_{max}). Medium-intensity uses regularly generated λ_{max} of each origin and destination. Regular λ_{max} are multiplied by 0.8 and 1.25 to create low-intensity and high-intensity demand arrival, respectively. The demand arrivals table can be seen below for reference. Regular demand intensity for each origin-destination can be seen in Table 5.1.

Table 5.1: Regular (Medium) Demand Intensities of Each O&D

Origin	Destination	λ_{max}
JFK	IST	31.1755
IST	JFK	25.1335
IST	HKG	13.7254
ORD	IST	11.3623
HKG	GRU	8.2445
HKG	IST	8.2005
MIA	GRU	15.3453
MIA	IST	13.6636
IST	ORD	12.3388
IST	MIA	10.7340
IST	GRU	10.1864
IST	ATL	9.9084
GRU	IST	9.8090
ATL	IST	7.9341
HKG	EZE	4.8829
NBO	MST	7.7727
HKG	MIA	6.6123
IST	EZE	3.2490
MIA	NBO	2.8466
IST	NBO	2.5401
GRU	HKG	1.9793
HKG	JFK	1.9720
IST	MST	1.8111

Origin	Destination	λ_{max}
ORD	NBO	1.8051
EZE	GRU	1.6806
JFK	NBO	1.5038
MIA	HKG	1.6198
EZE	IST	1.2672
GRU	EZE	1.2433
MST	IST	1.1040
HKG	ORD	1.1028
NBO	IST	1.0025
NBO	JFK	0.9501
NBO	MIA	1.1053
GRU	NBO	0.7680
ATL	NBO	0.7676
JFK	HKG	0.7405
EZE	HKG	0.5726
ATL	HKG	0.5410
HKG	NBO	0.5090
GRU	MIA	0.4818
NBO	ATL	0.4251
HKG	ATL	0.3930
ORD	HKG	0.3287
NBO	HKG	0.0050
ORD	GRU	0.0050

Peak booking arrival times are divided into three key levels: early, regular, and late peak times. Early peak times can happen (10-15) days before the flight. Regular peak times occur within (3-7) days before the flight. Finally, late peak times happen in the last three days (0,3) before the flight.

Rate class capacity allocation can be defined as allocating a flight's percentage capacity weight and volume to a previously determined rate. Three different scenarios are presented for rate-class allocation. First, in the low rate class allocation scenario, 80% of weight and volume capacities are allocated to first-level rate-class sales, 15% of the capacities are allocated to the second-level rate-classes sales, and the remaining 5% is allocated to the third-level rate-classes. Second, in the medium rate class allocation scenario, 70% of weight and volume capacities are allocated to first-level rate class sales, 20% of the capacities are allocated to the second-level rate class sales, and the remaining 10% is allocated to the third level rate-classes. Finally, in the high rate class allocation scenario, 50% of weight and volume capacities are allocated to first-level rate-classes sales, 30% of the capacities are allocated to the second-level rate-classes sales, and the remaining 20% is allocated to the third-level rate-classes.

Table 5.2: Demand Intensity, Peak Time and Rate Allocation Settings

Scenario	**Demand Intensity**	**Peak Demand Time**	**Rate-Class Allocation**
1	Low	Early	Low
2	Low	Early	Medium
3	Low	Early	High
4	Low	Regular	Low
5	Low	Regular	Medium
6	Low	Regular	High
7	Low	High	Low
8	Low	High	Medium
9	Low	High	High
10	Medium	Early	Low
11	Medium	Early	Medium
12	Medium	Early	High
13	Medium	Regular	Low
14	Medium	Regular	Medium
15	Medium	Regular	High
16	Medium	High	Low
17	Medium	High	Medium
18	Medium	High	High
19	High	Early	Low
20	High	Early	Medium
21	High	Early	High
22	High	Regular	Low
23	High	Regular	Medium
24	High	Regular	High
25	High	High	Low
26	High	High	Medium
27	High	High	High

5.2. Simulation Steps

The simulation study is necessary since booking decisions must be made frequently. Individual solution time and objective function are not relevant policy behaviors over a finite period matters. Besides, simulation gives clear insights on complex real-life problems. ACRM is a difficult problem to make progress with static problem testing.

The stochastic environment of the problem also makes it difficult for static problem testing. Some stochastic random variables, such as inter-arrival times between bookings, need to be regenerated in each simulation run. In contrast, other variables are used in the same random state for all runs.

Flight schedules, available itineraries, and demand forecasts are generated using the data generation algorithm in each simulation run. 27 different simulation runs for each scenario setting are conducted. Regarding the scenario setting, booking arrivals, their rate classes, and their allocations are created. Unit revenues are assigned regarding the policy rules previously discussed in test scenario data generation.

At least 100 samples of each simulation run are taken to stabilize output. Simulation steps can be summarized as follows:

(i) Booking Control: After flight dates and itineraries are generated using the test problem network and booking horizon, flight capacities and rate classes and their capacity allocations are generated. For booking acceptance, allocated demand capacities and rate class capacities are controlled.

For Spot allocation, upon the arrival of each booking, solve the optimization problem and determine allocated capacities. If there exists allocated capacity available, booking is accepted. Bookings start to be filled from the itinerary with the lowest unit revenue possible.

For FCFS, use flight and rate class capacities for acceptance. If an itinerary is available, booking is accepted. Bookings start to be filled from the highest itinerary possible. Partial allocation is not available for this policy.

(ii) Generate the demand scenarios (different demand intensities and peak times) for which the booking will arrive accordingly. Accept the arrivals regarding the constraints of various policies and update the corresponding allocated demand weight as committed booking. If rate class capacity is reached, search for the next lowest rate class. For Spot Allocation, if all rate classes capacities are committed, solve the Spot Allocation, including the last arrived booking, and give accept/reject decision accordingly. Upon booking arrival, after all available itinerary capacities are filled, partial allocation of the booking to itineraries is checked. For FCFS, reject the booking in that case.

(iii) Calculate and record the average of performance metric which is used in the comparison of policies.

(iv) Repeat steps 1-3 in each simulation run. Calculate average metrics and draw histograms for each scenario. Compare the histograms.

5.3. Performance Metrics

Total revenue, revenue per unit capacity, and cargo capacity utilization metrics are used to track the performances of FCFS and Spot Allocation policies. The first metric, total revenue, as the name implies, is the total revenue generated within a defined time horizon. The second metric, revenue per unit capacity, is calculated as the total revenue/total used capacity. The third metric, cargo capacity utilization, tracks the average utilization of each flight in each run.

The results of each simulation run are stored separately for both policies. The following section presents a heat map and histogram drawing of the simulation results. Results are expressed in terms of policy differences (Spot Allocation - FCFS) for comparative visualization and t-testing.

5.4. Results

The results section is divided into two different subsections. The first part gives histogram results of total revenue differences. We perform a t-test after the histogram results, while the second part briefly discusses scenario settings' effects on other performance metrics.

5.4.1. Histograms of Total Revenue Differences

The total revenue of Spot Allocation - FCFS histogram results are shown in Figures 5.1, 5.2, and 5.3. Each figure has a 3x3 matrix of rate class allocation and peak time scenarios for low, medium, and high demand intensities, respectively.

Simulation study results are displayed under each scenario in separate histograms. The x-axis refers to Spot Allocation - FCFS total revenue, while the y-axis represents the count of simulation runs corresponding to the bar.

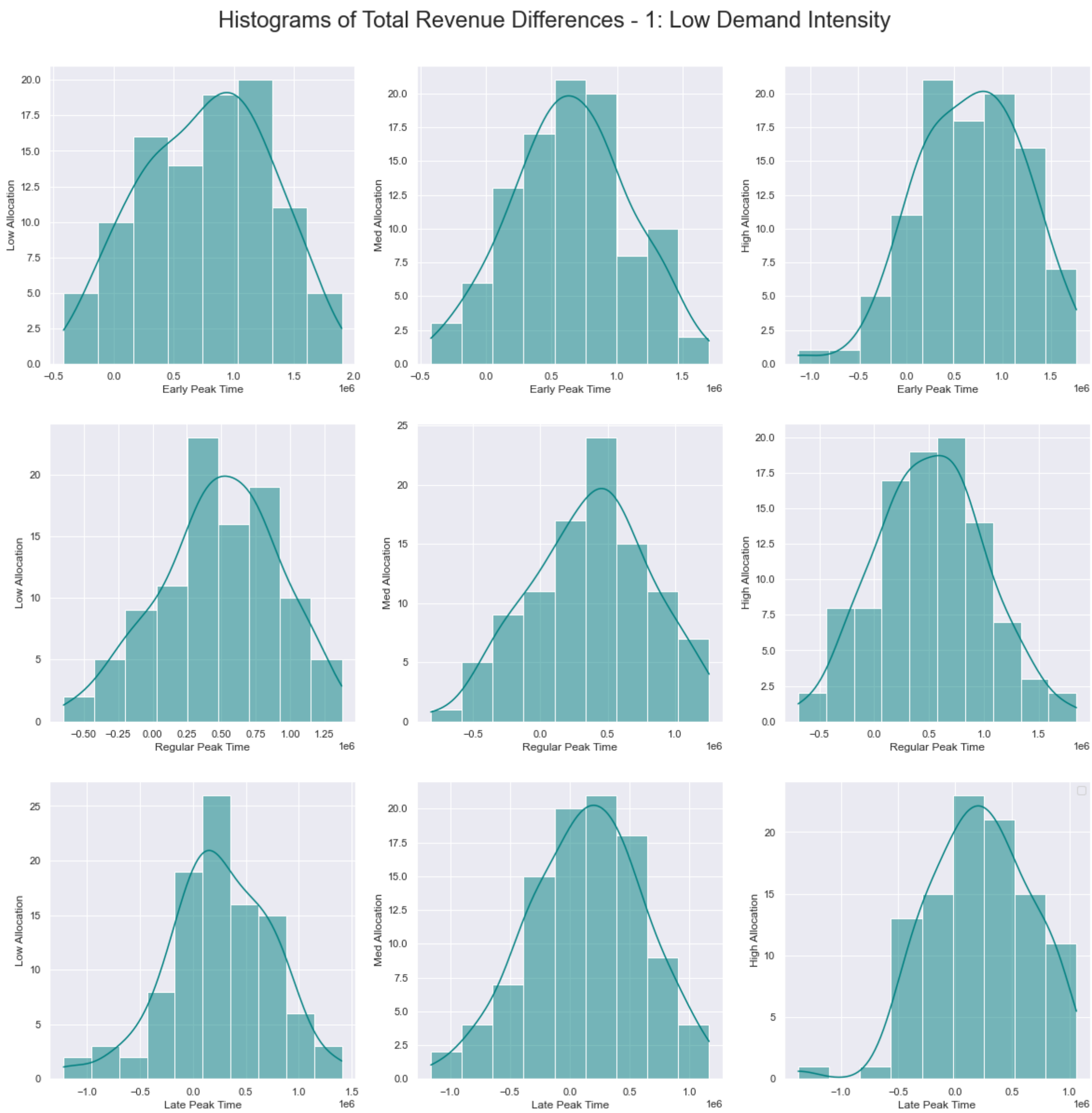

Figure 5.1: Total Revenue Differences in Low Demand Intensity

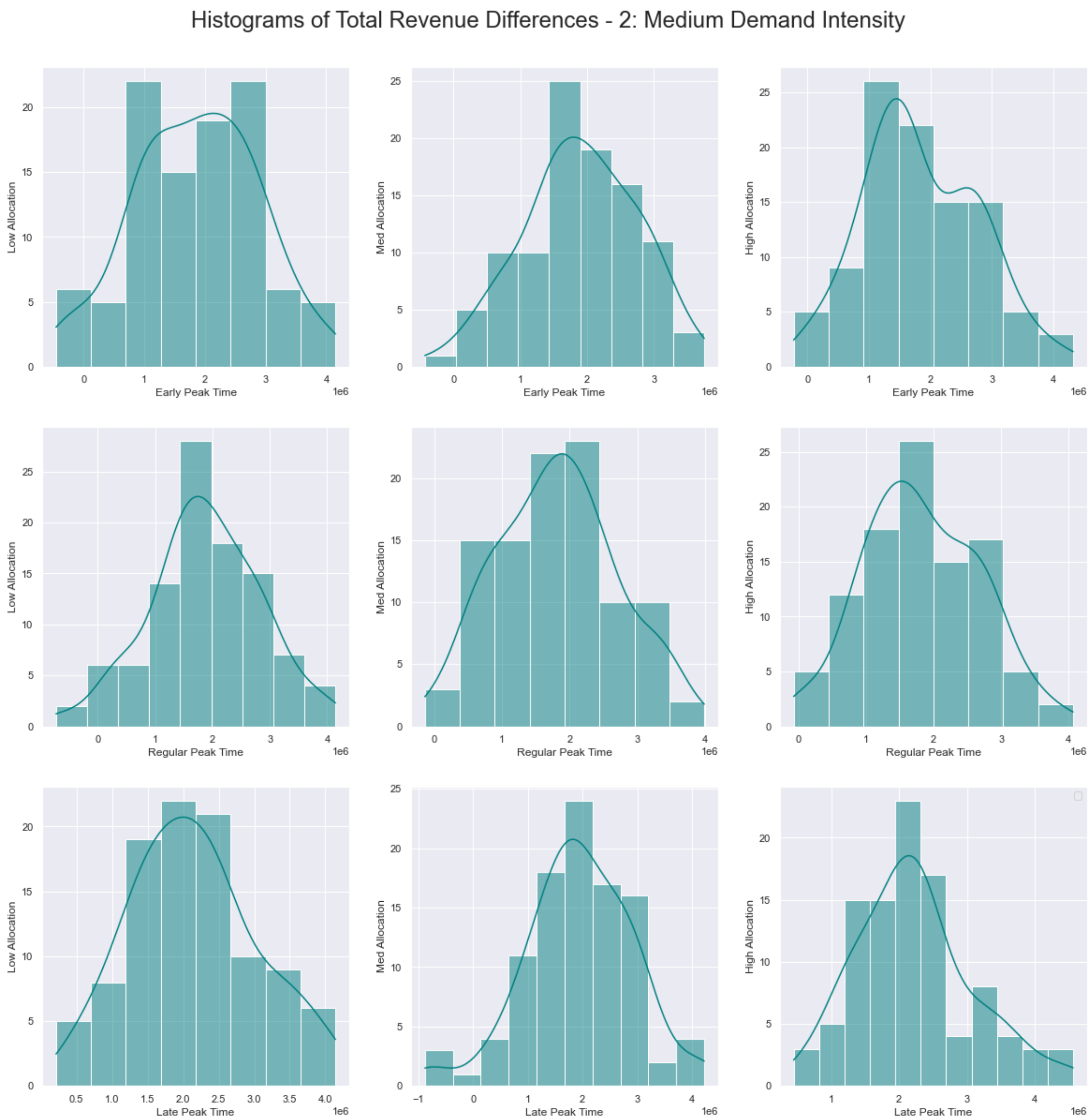

Figure 5.2: Total Revenue Differences in Medium Demand Intensity

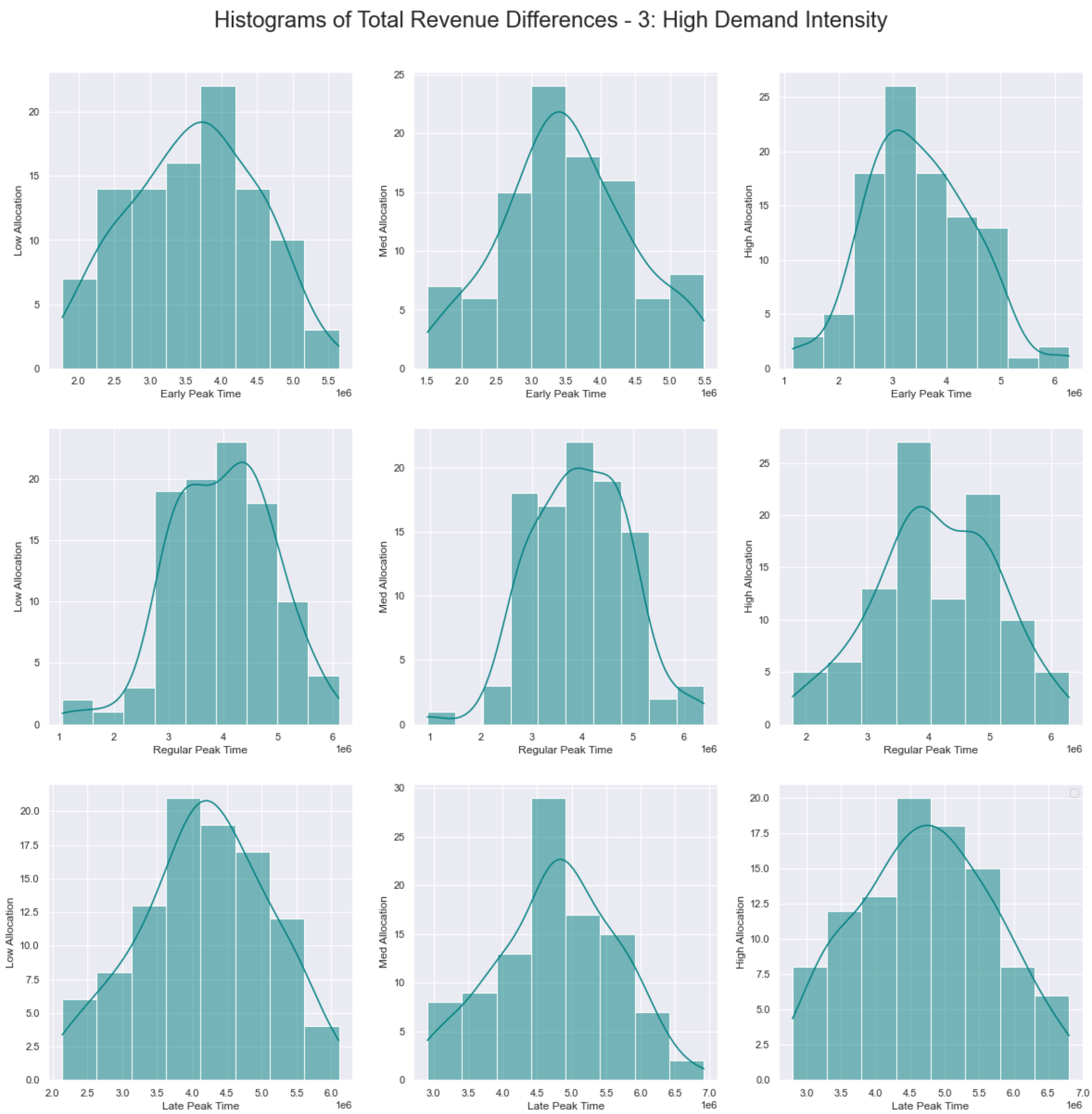

Figure 5.3: Total Revenue Differences in High Demand Intensity

As mentioned before, 100+ simulation runs are conducted so that outputs are stable. When we analyze histograms, their distributions look close to normal and we can assume that simulation results are stable. Low demand intensity histograms have some negative results, which indicates that FCFS policy performed better in that scenario in that simulation run. On the other hand, medium and high-demand intensity scenario histograms have almost zero nonpositive values.

Next, a t-test is performed to comment on the significance of the results. A hypothesis of total revenue difference is greater than zero is tested under a 95% confidence level. The results of the test are shared in Table 5.3.

When t-value results are analyzed in the table, only one scenario, scenario 8, has a t-value smaller than the critical value $t_{1-\alpha,df}$, and the other 26 out of 27 scenarios have significantly greater mean values than 0. Thus, test results have statistically confirmed that spot allocation in 26 out of 27 scenarios has significantly more mean total revenue value than First Come First Served policy under a 95% significance level.

On the other hand, in scenario 8, there is no stochastical evidence indicating that spot allocation is a better-performing policy than the FCFS policy.

Table 5.3: Mean, Standard Deviation and t-Value for Different Scenarios

Scenario	Mean (μ)	Standard Deviation (σ)	t-value
1	768158.97820	940274.72436	7.38362
2	658985.15230	937754.97827	6.22093
3	636498.38540	1036883.32675	7.65073
4	396708.70890	911580.88416	5.15585
5	388923.19520	918499.12354	5.10572
6	402508.78510	989548.24609	2.55494
7	258956.10800	881206.78324	3.69487
8	213878.99500	1069882.87861	0.69319
9	227895.84520	986078.45496	2.95589
10	2024579.70510	1020473.06739	18.25823
11	1897257.02550	853765.18482	22.26685
12	1922248.66230	931158.84382	19.82956
13	1789545.46400	964047.97279	19.53653
14	1883598.23100	885108.62673	20.49676
15	1831581.55500	855716.85723	21.39063
16	2010082.11230	893010.23632	24.03292
17	1994199.27120	986788.33856	19.69676
18	2131507.88950	862739.13149	25.79499
19	3571408.18850	887908.62684	40.59597
20	3548515.19080	919881.49624	38.18258
21	3556875.00980	970263.38607	35.99795
22	3880782.08910	929420.52505	42.81520
23	4017280.01850	949270.07109	41.68209
24	3979298.50610	986993.95899	41.73575
25	4256712.50610	911766.39638	45.84919
26	4695308.98050	865367.10030	55.27474
27	4682775.11520	974089.35739	48.52670

5.4.2. Heat Map Matrix of Results

The heat map matrix shown in Figure 5.4 summarizes the results. Each heat map cell consists of the mean differences in performance metrics. Heat map results are not normalized. The coloring range of each heat map is taken as $[-x, x]$ for each row so that 0 is the medium point and positive and negative results are in different color groups. Also, positive numbers (denoted by red color) imply that the Spot Allocation policy performs better. In contrast, negative results (shown in blue) mean FCFS gives better outcomes for the given performance metric in that scenario.

Each square in the heat map corresponds to a mean of simulation runs score of the performance metric, shown in the outer vertical axis. The inner horizontal, inner vertical, and external horizontal axes show peak demand time, rate-class allocation, and demand intensity scenarios, respectively.

We can conclude from the following statements when heat map results are analyzed. The total revenue difference is positive in all scenarios. The most considerable average difference occurs in high demand intensity, late peak time medium allocation with an average value of 4695308,9805. Furthermore, demand intensity significantly impacts determining the total revenue difference. Peak time and Rate Class Allocation have more minor impacts.

Revenue per capacity is the second metric analyzed. It has a mixed color distribution, and 8 out of 27 scenarios have resulted in negative average revenue per capacity difference value. The most significant average difference occurs in low demand intensity, late peak time, and low allocation scenarios with a value of -68792,1215. The main reason behind this difference could be the result of the two policies' unit revenue gap under low capacity utilization, as spot allocation assign bookings to itineraries with the lowest possible rate. Furthermore, all three factors seem to impact determining revenue per capacity significantly.

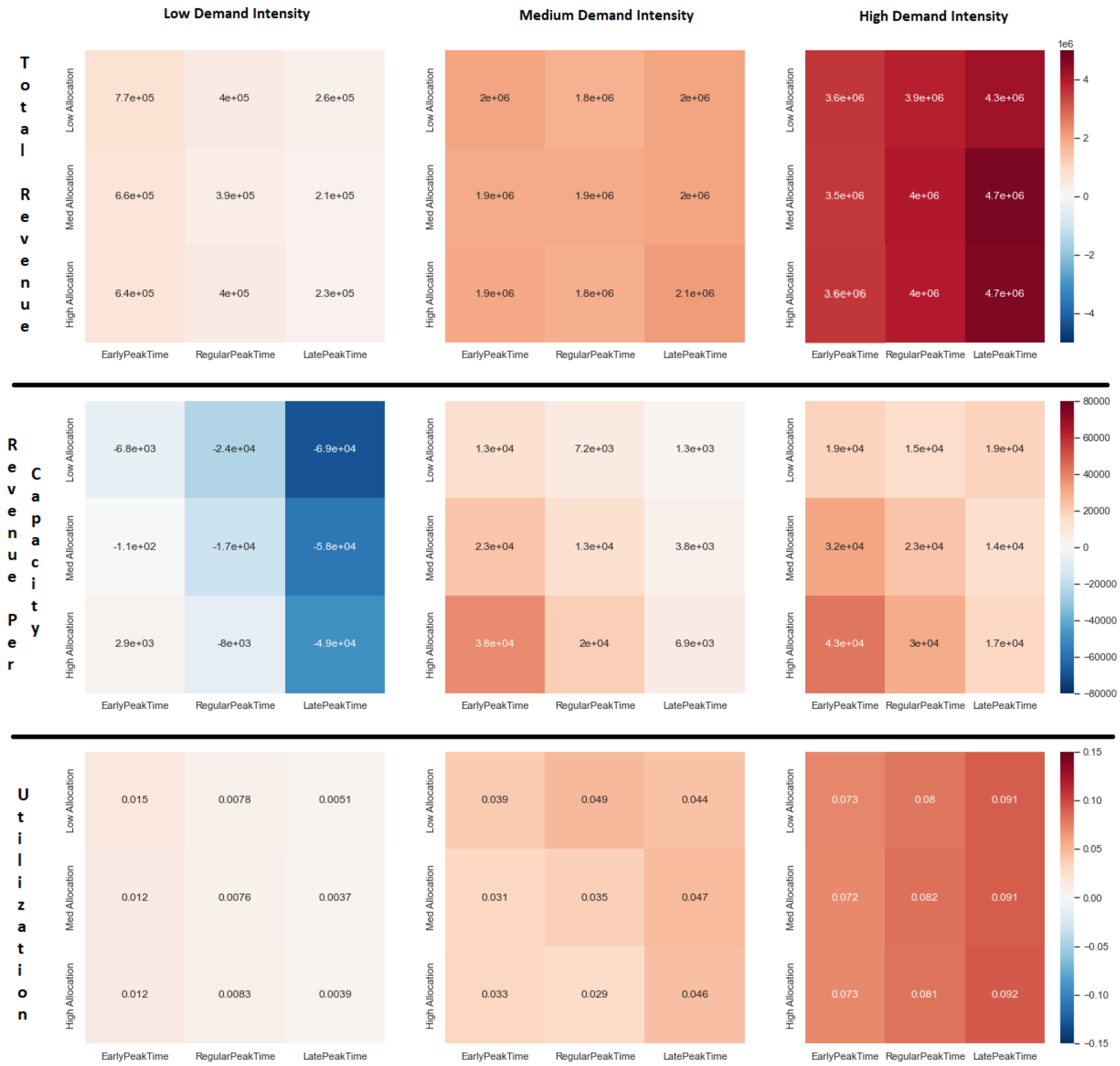

Figure 5.4: Heat Map of Spot Allocation - FCFS Performance Metrics

Cargo capacity utilization, calculated as filled cargo capacity / total capacity, is the final performance metric analyzed. All 27 average utilization differences have a positive sign, implying that spot allocation performed better in all scenarios. The highest difference occurred at high demand intensity, high rate class allocation, and late peak time scenario with 0,0923. Furthermore, demand intensity seems to impact utilization rates, while others have less significant effects.

6. CONCLUSIONS AND FUTURE WORK

Air cargo revenue management includes determining cargo capacities and available itineraries, allocating allotments and overbooking regarding the show-up rate estimations, demand forecasting, spot allocation, and booking control processes. The primary purpose of an air-cargo provider is to maximize the total profit generated by the system by minimizing its operational requirements and making booking bid price and allocation decisions.

A mathematical model definition of spot allocation is given in Chapter 4. Its objective is to maximize the total revenue regarding demand, capacity forecasts, and available itineraries. Allocation results of this model are then put into booking control. The process is also briefly shown in Figure 3.4.

Furthermore, after the test problem is constructed, performance metrics and scenario settings are defined. As mentioned before, a simulation study is conducted in Chapter 5. This study compares the performances of spot allocation and first come first served policies under different scenario settings. Comparing spot allocation with FCFS, it can be concluded that the difference in total revenue is significantly greater than zero in 26 out of 27 scenarios. Spot allocation optimization model generates more revenue according to t-test results. Also, a heat map of all performance metrics under all defined scenarios has summarized the expected differences for each. The heat map has shown that 72 out of 81 results were significantly greater than zero, indicating that the spot allocation has better results in these regions.

Having concluded the thesis about Air Cargo Revenue Management (ACRM), some concepts are left out of this study and may be a good point for future research. The definition of cargo revenue management, as explained in Chapter 3, is quite broad, so several assumptions and simplifications have been made. Some processes, including allotment allocation, were left out of this study's scope.

To begin with, allotments are an essential part of ACRM, and fewer studies are conducted about allotments compared to spot market allocation. This may be mainly due to the deterministic nature of long-term contracts, which makes the problem less complex and exciting. Nevertheless, its solution should provide an important output for revenue management decisions.

Second, show-up rate estimation and overbooking is other important part of ACRM. Cargo overbooking may look similar to passenger revenue management at first look. On the other hand, there is a slight difference in show-up rate estimations. Cargo transportation is usually popular among big customers. A show-up rate estimation is made for each customer in cargo RM, whereas passenger RM estimates the show-up rate metric for each flight. Hence, the difference in show-up rate metrics should separate these two problems, and more future work containing air cargo revenue management overbooking could be conducted.

Finally, capacity forecasting is another important problem that is often overlooked. Many decisions are made in cargo revenue management based on these forecasts, including allotment, spot allocations, and booking control. Furthermore, many components of cargo capacity, such as passenger, baggage, and fuel weights and volumes, are estimated, and these estimations depend on each other. More research on cargo capacity forecasting would shed light on the decisions of booking control, spot, and allotment allocations.

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