Dynamic Capacity Allocation for Optimal Revenue Management: A ULCC Data Driven Case Study

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TU Delft

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by

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This thesis marks the end of my journey at the Delft University of Technology and officially marks the end of my time in Delft. I will greatly appreciate the time I spent in the small town, and all the growth that I have achieved.

Luis Gambetta
Atlanta, GA, August 2022

Contents

List of Figures

List of Tables

List of Abbreviations

D^3	Demand Driven Disptach
AGIFORS	Airline Group of the International Federation of Operational Research Societies
ARIMA	Autoregressive Integrative Moving Average
ASK	Available Seat Kilometers
DAVN	Displacement Adjusted Virtual Nesting
DOT	US Department of Transportation
EMSR	Expected Marginal Seat Revenue
FAA	US Federal Aviation Administration
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
KPI	Key Performance Indicator
LF	Load Factor
MAPE	Mean Absolute Percentage Error
ProBP	Probabilistic Bid Price Control
RM	Revenue Management
RPK	Revenue Passenger Kilometers

Introduction

Departing flights that leave with unsold seats is referred to as spoilage [3], on the other side flights where passengers are turned away because there are zero available seats is referred to as spillage [1]. Both of these scenarios are incredibly common scenarios in the airline industry. Each scenario is an undesired event by the airline. The airline aims to sell every seat in their inventory to the right customer at the right time and at the right price. This ensures that each flight leaves with no spoiled seats, and revenue maximized and no high-yielding passenger turned away. This idyllic scenario can not always be the case and many times flights depart with empty seats, or spoiled inventory, or they depart being unable to accept high paying customers at the last minute as they have sold all of their available inventory. This leaves revenue behind or misuses the available space. By working to ensure that inventory usage is optimized, revenue can also be maximized and even more, additional passengers can be taken on which allows for the fuel burn efficiency in aircraft to increase [2]. The research in this thesis aims to close this gap and help identify more areas in which an airline or operator can more effectively use the space that they have and help increase their revenue created as well as the amount of passengers that they are able to transport.

The area of interest for this thesis is how to be able to dynamically allocate capacity among different flights. That is, how can one enable certain flights to increase the capacity or decrease capacity as needed. This area has been researched before, but with limited existing research, it is the goal to help further advance this subject. One key way that this research aims to make advancements, is by introducing a revenue management application to the decision making methodology. By introducing a revenue management application, this methodology is able to incorporate decisions made by such a tool to help ensure that the right mix of passengers are accepted and that revenue is maximized for each individual flight. This application paired with a dynamic tool that is able to reallocate capacity, it is aimed that each flight can be further tailored to its specific needs from the beginning of its journey until the end when the flight has departed full of passengers.

This research aims to build upon existing research by Cots [4] and Fry [5] where both have set the foundation for what can be achieved in this area. This area of research further builds upon the concept of demand driven dispatch [6] using a so called rubber aircraft. This rubber aircraft and area of research take advantage of aircraft fleet types with varying capacity, but with the same qualifications. Such common examples are the Boeing 737 family or the Airbus A320 family. These two sets of aircraft have varying sub-variants of different lengths and capacity, but share commonality which allows the same pilot to fly all the varying aircraft type in the family. This eliminates extra restrictions that already take place in the airline industry, such as crew constraints. By allowing the same pilot to fly each aircraft, there are no issues if one were to swap one aircraft type for another on a certain flight. This specific capability allows for this area of research to take-off.

This thesis looks to continue building on the existing foundation by enhancing the methodology and introducing revenue management to the methodology. This research aims to additionally incorporate operational data, to help ensure that the results that are driven are based off of realistic operations and scenarios. By becoming data-driven this thesis is able to further emphasize any results that are delivered. Furthermore, this thesis looks to add elements of machine learning to help guide and drive any decisions that must be made. By pairing the obtained data with a machine learning algorithm, the aim is to ensure that this methodology is as realistic as possible and that the results that are delivered are as accurate as possible. The main points of contribution to this research then becomes integrating a revenue management framework to the methodology, as well as adding machine learning to the decision making process.

This thesis is divided into three main parts. Part I contains the scientific paper and is the main part of this paper, which contains necessary background information, the methodology, the results and conclusions that were found. Part II contains the literature study which was performed at the start of this thesis, to help identify the work that has already been done, as well as the areas that have not been researched and need to be investigated. The final part, Part III, contains a detailed and more throughout analysis of the results that were found throughout this thesis.

I

Scientific Paper

Dynamic Capacity Allocation Paired with Optimal Revenue Management: A ULCC Data Driven Case Study

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Abstract

In the airline industry revenue and inventory is managed tightly, with the intent to sell each seat at the right price to the right customer at the right time. This does not always go to plan and seats remain unsold, or demand can be greater than what is available. The question then becomes how can capacity and revenue be managed more efficiently? How can capacity and revenue be maximized to ensure that seat spoilage is minimized. This thesis takes a look at this problem and aims to solve this problem by dynamically allocating capacity as well as becoming paired with revenue management processes. By being able to move capacity around to different flights, it is believed that revenue can be maximized and that seat spoilage can be minimized, creating a more effective use of a perishable product. The goal of this thesis is to show that increases are possible, even if by small margins. This thesis looks to use real-world data to help support its findings along with a random distribution to pair alongside a Monte Carlo simulation to help ensure accuracy. In this data driven methodological approach revenue management and a capacity swapping algorithm are integrated. The revenue management module creates a series of seat inventory allocations as well as demand forecasting. This information is then fed into a simulation which will then simulate the entire booking life-cycle of a fight. Here each flight will build its passenger load and will swap aircraft with other aircraft of varying capacities when the algorithm has determined it is necessary and would create a positive increase in revenue and passenger counts. To assist in this approach a further random forest model is developed to help make informed decisions. These changes are further evaluated by the algorithm to ensure that every change that was made was beneficial and if so will accept the swap and continue to build loads as this new flight. Different case studies were developed that introduced different timing scenarios as well as different decision making tools. The two different decision making tools would use either the random forest model that was developed or a simple logic model that would look at estimated final revenue and estimated final passenger loads. The timing scenarios would look to see when swapping would be needed, whether it is a true daily swap or if swaps can be performed once a month. Ultimately there were positive results, with each scenario tested yielding positive increases in the three KPIs examined (Load Factor, Passengers, Revenue). Each scenario involved testing either the simple logic, or random forest model with varying swapping intervals. The best performing scenario was one where flights were allowed to be swapped daily using a random forest decision model. In this best scenario load factor saw an increase of 1%, the number of passengers increased 1.4%, and revenue increased 0.9%; all against the baseline scenario where zero flights were swapped. This translates into a 36,000 USD weekly increase for a small sample in a route network. Across a full route network, even greater increases can be achieved.

1 Introduction

Airlines are an industry of tight margins and tight operations, with notoriously having some of the lowest margins compared to other industries. Additionally, in a world where efficiency is key and climate change is persistent, every action possible needs to be done in order to ensure that resources are not being wasted. One area of improvement for both of these problems shifts the focus to aircraft capacity, or inventory. Inventory is a scarce and perishable resource that is available to an airline. If a flight departs with an empty seat(s), that product becomes spoiled like spoiled fruit. It can no longer be sold and is figuratively thrown in the trash. Any potential from that seat is lost, this means that potential revenue is lost and additionally this means that the flight itself was not maximized to its full potential. The latter meaning that the fuel burn per passenger has suddenly increased and efficiency has suddenly dropped [Brandon Graver, 2021].

Airlines are notoriously low margin operations, but with operations having increased in efficiency significantly over the years, the area for improvement becomes minimal, and the areas that can be improved offer minimal revenue increases. However, multiple small changes can still add to a large change. One area that

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should be looked at is route capacity. With some routes having margins as low as 2 % [Yilmazkuday, 2021] it becomes an interesting area to see how that margin can become padded and revenue can be added. Looking at capacity, flights are typically static in these terms. A flight will be created and put out for sale anywhere from six months to a full year before its departure. When they are first put out for sale they are assigned an aircraft with a fixed capacity, and most airlines will keep that aircraft assigned to it until it departs, or will analyze the flight manually and make adjustments where needed. One key aspect to this point is fleet commonality, by using a similar aircraft type operations become simplified as any additional constraint such as a crew constraint is eliminated. These flexible rubber aircraft allow any crew that is type rated in the aircraft fleet family to fly the different sub-variants [Matthew E. Berge, 1993]. An additional aspect to an individual flight, is revenue management. This is a process where inventory and pricing is controlled in order to ensure maximum revenue per flight by ensuring that the right customers purchases the right seat at the right moment. This means that leisure customers can purchase a non-flexible ticket at a low price further out from departure, while a business customer can purchase a flexible ticket closer to departure. To combine this aspect with capacity management becomes the main area of interest.

Furthermore, ensuring that capacity is not wasted also ensures that fuel burn per passenger is maximized, lowering carbon emissions per passenger transported. This area of interest then pairs perfectly with the formerly mentioned problem.

Combining these two problems, the area of research then becomes how does one work to ensure that capacity and revenue is maximized for each flight. This brings two areas of operations together, capacity allocation and revenue management. How can one integrate dynamic capacity allocation with revenue management to increase revenue and maximize load factor? This is an area that has been researched before, but not extensively. This research hopes to contribute to existing works by introducing real world data as well as a multitude of different models to enhance a dynamic swapping environment. By introducing real world data this project becomes data driven and provides an aspect of real world operations that is difficult to come across.

The methodology for this research is one that looks to integrate revenue management with a dynamic capacity allocation algorithm. Such a methodology is data-driven, and thus also uses simulations and randomness to help ensure that results converge and results are consistent. The methodology has a flow that begins with incorporating the revenue management tool that creates a set of inventory allocations. Alongside this, demand forecasts are created for each simulation to help model the booking window of a flight. Throughout this booking window each flight builds its load as dictated by the inventory allocations created. At certain intervals each individual flight is then analyzed and checked for its load building progress. If any flight is showing enough performance that would warrant extra capacity, or if any flight is struggling and would warrant less capacity, then these flights are evaluated and other flights close to that departure time are searched for and then have their aircraft swapped. If this results in an overall positive change then the swapping algorithm would continue with this swap. This methodology ensures that this is all integrated seamlessly to help deliver the best results possible. Previous research has been shown to have positive results, but have not integrated revenue management into the research. This methodology aims to build upon prior research, while improving any results. Potential short-comings of this methodology do involve a narrow focus on only increasing certain metrics. Additionally, this methodology only works given certain criteria, such as fleet commonality. This further limits the application of this research.

The main research scope of this project then becomes **How much additional revenue and increase in load factor can an airline generate over its route network by dynamically reallocating capacity using information from an optimal revenue management model?**. This question then becomes supported with the research goals of finding an optimal timing strategy and an optimal model. Such timing strategies suggested are from daily to monthly and in between. These are the times in which a swap is analyzed. The model that becomes suggested involves a model created by artificial intelligence or a model that is a simple rule based model. These questions and goals should help answer the main research question and should allow this thesis to provide further insight into the problem at hand.

The structure of this scientific paper is as follows, firstly a brief literature review will be given that will go over the different aspects of this thesis and give the current status of research in those respective areas as well as for the combined study. Following this the problem definition will be stated in which a brief overview of the research and goals of the research will be given. Next will be the methodology, where the process and method of this research is described fully. Following this, the case studies that have been developed will be explained. These case studies will then be proceeded by the results and analysis that was produced. These results will be critical of what was found and will highlight both the negatives and positives. Ultimately this scientific paper will be finalized by the conclusions and recommendations for future work.

2 Literature Review

The goal of this research is to provide an updated and improved method in which dynamic capacity allocation can be improved for an airline. The concept of dynamic capacity allocation, also referred to as demand driven dispatch (D^3), has its roots from an early idea by Boeing ([Matthew E. Berge, 1993]). This idea aimed to take advantage of the *rubber* plane, or a plane that has a fleet commonality but with different versions each having a different capacity. Such an aircraft allows an airline or any operator to be able to maintain one set of pilots, but a different aircraft to serve a unique mission. By maintaining one set of pilots, an airline is able to save on training costs and is thus able to have a larger set of pilots. To contribute to this idea, this current research proposes to increase the original scope. Dynamic capacity allocation is investigated, as well as the effects of integrating an airlines revenue management methods. By allowing revenue management to be integrated, an airline will have better insight into how each flight is performing, thus ideally being able to make the best decision when it comes to capacity allocation. As this scope becomes more detailed, relevant literature becomes limited. Most current literature focuses on these two problems separately. There are limited examples in where these two topics are integrated, and two main papers have been written, by both [Cots, 1999] (delayed fleet type assignment) and [Fry, 2015] (bookings based swapping).

2.1 Revenue Management

The concept of revenue management, also previously known as yield management, is that of selling the right product to the right customer at the right price at the right time. Essentially this concept is ensuring that revenue for an airline is maximized and spillage and spoilage are avoided. This is the scientific application of analytics and operations research to help an airline manage revenue for their products and service.

The first model was introduced by [Littlewood, 2005], which looked at assigning inventory protection levels. Such an initial model consisted of a simple formula that looked at marginal yields:

$$(1 - P) \leq \frac{r}{R} \tag{1}$$

Where r is the low yield fare, R is the high yield fare, and P is the maximum risk that the acceptance of a low yield passenger will result in the subsequent rejection of a high yield passenger [Littlewood, 2005]. Low yielding requests should continue to be accepted until $1 - P$ reaches the value of the calculated ratio. This first model, although simple, set the framework for future development.

Work has since progressed significantly since this initial model, allowing for the development of expected marginal seat revenue (EMSR). This model, developed by [Belobaba, 1987], was a more robust model that was able to handle a multi-class system. Similar to [Littlewood, 2005], this model looked at determining inventory protection levels, and when to stop selling seats at a certain fare class (bucket) to allow for more sales in a higher bucket. To help determine these levels, the following equation was developed:

$$EMSR(S_i) = f_i \cdot \overline{P}_i(S_i) \tag{2}$$

Where the EMSR for the S_ith seat is dependent on the probability that the S_ith seat will be sold at bucket level i, and f_i is the fare that has been assigned to that bucket. A visual representation of this concept can be seen below:

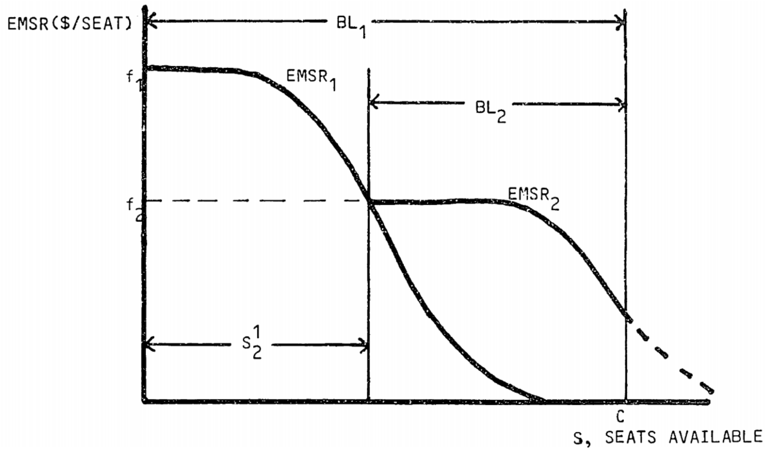


Figure 1: 2-Class nested EMSR example [Belobaba, 1987]

This initial model was developed further, and a separate model was created and coined as EMSRb (with the first model being coined EMSRa). The main criticism for the first model was that it was too conservative and left and left a large number of lower fare bookings unavailable. Equation 2 was kept to ensure the EMSR, but with variables being rewritten to allow for more buckets leaving the following equation:

$$EMSR_n(S_j^n) = \overline{P_n}(s_j^n) \cdot f_n = f_j \tag{3}$$

where s_j^n is the total seats protected for all classes $n < j$. Booking limits for each bucket lower than j is given by the following:

$$BL_i = C - s_j^n \quad \forall j > 1 \tag{4}$$

where C is the capacity of the aircraft.

2.2 Delayed Fleet Type Assignment

[Cots, 1999] proposed an early approach to the problem. His proposition considered looking at airline fleet assignment as a step that is solved later on in the booking curve (the period in which bookings build up for a specific flight). This proposition would create a network, release flights and put them out for sale, but assign no aircraft type to these flights, therefore there is no fixed capacity. This solution leads to multiple issues, the main one being that if there is no capacity set, then proper fare class protection levels can not be set. This leads to a non-optimal solution where revenue is not maximized and passengers which should not have been accepted, become accepted. The solution that was proposed, was to create a set of virtual capacities. This has the main benefit that an airline would not have to run their fleet assignment model multiple times, as that is a large complex model that costs the airlines time and money.

To begin, this model was set so that each flight would have their virtual capacity set at the maximum capacity. In this regard, each flight would be able to build their load throughout the booking curve and would not be restricted. In order to prevent any spillage (or passenger demand that is turned away) a constraint was set in place that prevented any flight to be assigned the lower capacity. Thus, once an aircraft has reached the lower capacity with bookings, they would be assigned a higher capacity to continue throughout the booking curve until the day of departure. Therefore, this dynamic model would create an initial high virtual capacity, and then as the flights build load, the model would assign fixed aircraft. This research proved to be promising and showed an increase in both total passengers being booked per flight (or load factor) as well as revenue generated. When looking at a flight level basis, positive revenue and passenger increase is noted, with an increase of about 1 % in both passengers and revenue. Although these increases are minimal, on an entire flight network these increases can be significant. One drawback mentioned by this report, is that by virtually assigning the largest capacity to each flight, there is a greater possibility for spillage as there are not enough high capacity aircraft available. Thus theoretically each flight could be fill to this higher capacity aircraft when in reality some flights will have to be forced into a downgauge.

2.3 Bookings Based Swapping

The most recent literature is a model proposed by [Fry, 2015] in where a future outlook is used. This futuristic outlook aims to use an estimate of bookings by departure to help make its decisions. Different to the previously mentioned model by Cots, this model does plan its network and assign a fleet type to each flight at the creation of the schedule. This means that the airline will sell its flights as if it had that final capacity, however the advantage here is that the airline can perform a swap whenever they will have determined necessary. This means that at certain points throughout the booking curve, if a flight is booking well, and is forecasted to have a high amount of bookings, the model can decide to upgauge the flight. In the case that a flight is not performing well, then the model can downgauge the flight. With this methodology, flights will be swapped according to their booking performance, and each flight would have an almost tailored capacity determined.

This particular research looked into introducing bookings based swapping in a competitive setting. Results were positive, with either of the competing head to head airlines having an increase in revenue. If both airlines were to implement this strategy then both would experience and increase in revenue, but at a smaller rate. The main reason for this is that if one airline implements this efficient strategy, they would be able to ensure that passengers are maximized for their airline, thus increasing their overall revenue. If both airlines were to implement this, then both would be maximizing their revenue but there are less customers to be able to take from the other.

2.4 Research Gap

Given that there is limited research in the space of dynamic capacity allocation, there are of course current gaps that should still be investigated. Work done by [Cots, 1999] and [Fry, 2015] showed that there is merit in the space of dynamic capacity allocation. [Cots, 1999] focused on more of a feasibility of this study, while [Fry, 2015] focused more on the competition aspect of this problem. Thus the gaps left are that of how can the revenue management aspect be improved to ensure that revenue is maximized and seats are not spoiled, how can the strategy of swapping be improved,how forecasting could be improved, and more importantly, how can all of these elements be integrated together to become a more streamlined process. Which then becomes the focus of this project, with the formal research questions as given in Section 1.

3 Problem Definition

Airline network scheduling is a complex process that is typically done well in advance before those sets of flights are scheduled to depart. Large airlines typically publish these schedules well in advance, typically over 180 days before a flights departure date. This process sets the a departure time, an arrival time, and an aircraft type for a certain flight between two cities. What this then does is that it sets a capacity outlook for a flight far in advance of when this flight is actually scheduled to fly. Typically, an airline will work off of enough historical data and other constraints to ensure that the assigned capacity is as close to the expected demand as possible. Airlines can and will routinely reevaluate the schedule that is currently out for sale and make adjustments as needed, but this process requires analysts to reevaluate the schedule and look at what adjustments can be made. This process is not perfect and requires more manual intervention.

The scope of this research then becomes how to better perfect this process and how to deliver better results with minimal manual input. These results should be simple to analyze and positive changes should be easily identified. This research aims to create a process that delivers these results and gives only positive recommendations. There are many dynamic elements to this problem, but the aim is to easily integrate into existing revenue management practices and data to help provide the best and most up-to-date information. Current revenue, current loads, and current capacity can be combined to provide the best understanding of how a flight is performing. This will give information as to whether a flight is on track for a full load factor or not. These elements show whether or not a flight might need stimulation to get closer to a full load factor or not. These are the key performance indicators for a flight in terms of the business angle. These elements provide a snapshot of flight performance and can help guide a swapping recommendation. However, given that simply swapping one aircraft for another can lead to positioning problems, this research also aims to take care of that by ensuring that down-line aircraft are swapped until needed. These swaps are also taken into consideration before committing to a final swap.

Ultimately this research problem ensures that revenue and load factor is maximized. Revenue management ensures that revenue is maximized, by limiting the different number of tickets available at different price points. This combined with a swapping tool will ensure that loads are maximized, by seeing where certain flights may have extra capacity and where other flights may need more capacity. The most important metrics for this problem are then flight level revenue, load factor, amount of passengers carried system wide, and the amount of times a flight is swapped. The amount of times a flight is swapped is looked at, to ensure that a flight is not being over-swapped and that resources are not being wasted.

4 Methodology

In this section, a data driven methodological approach is proposed and outlined. This methodology was chosen for the main reason that having industry observed data will ensure a realistic model. A significant amount of data was sourced to help properly simulate airline bookings. The first step is to introduce a forecasting model based on historical bookings. With the introduction of a forecasting model, randomness was allowed to be introduced to help further emulate a real world scenario. As randomness was able to be introduced, the next step was to make this methodology simulation based. The concept of Monte Carlo simulation was introduced to help derive a clear answer. This means that an accurate solution can be provided, with results that can be expected in real world scenarios. Finally, the final piece of this methodology introduces a machine learning, specifically a random forest algorithm, module to help create a more detailed and informed decision when it comes to swapping. This methodology and framework relies on Python to fully support all aspects of this project, from initial setup, model development, and final case study analysis. With this information at hand, a framework was able to be created, this can be visualized below:

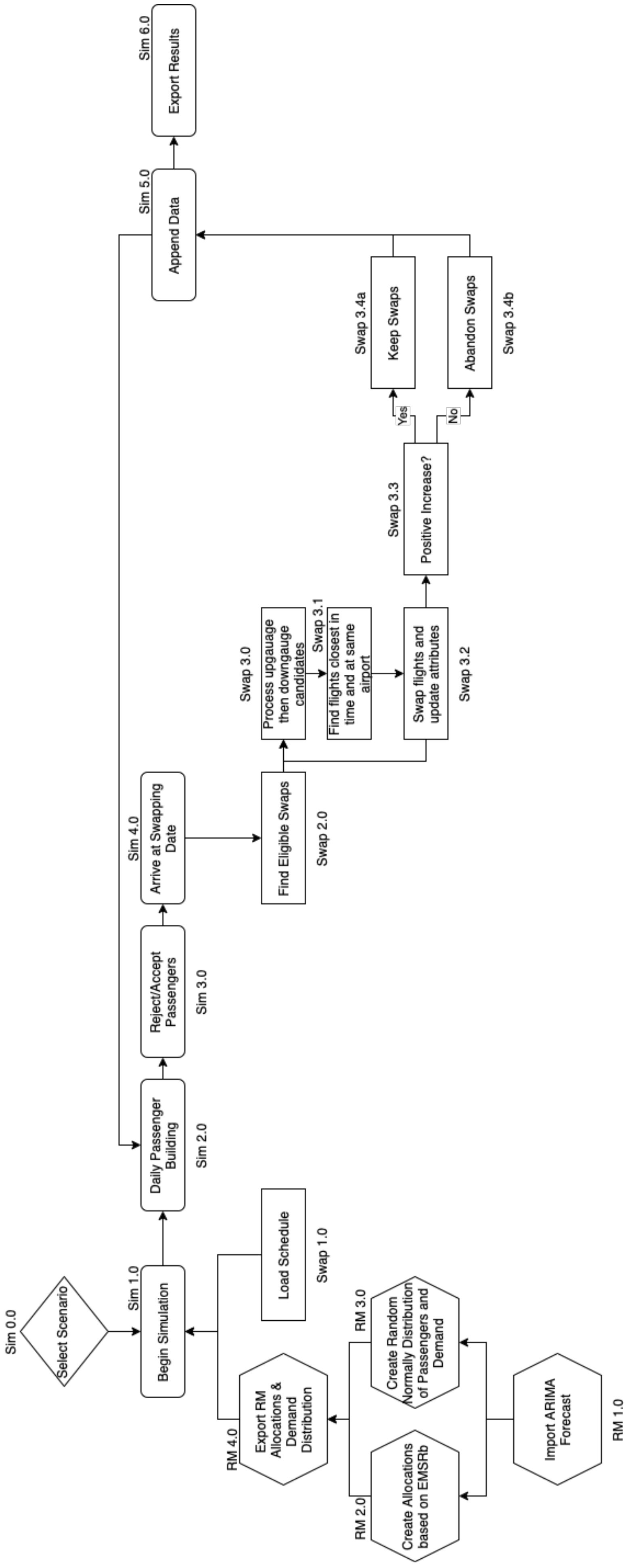


Figure 2: Framework

4.1 Revenue Management Module

The first module to be developed an implemented is the revenue management (RM) module (RM 1.0 - RM 4.0 in Figure 2). This module helps simulate an airlines RM practices. This job is typically done by an analyst to help further maximize a flights revenue, but at its basis is a model that has been researched and developed. As discussed in Section 2.1, RM has had significant development over time. For this project an EMSRb model for inventory booking limits has been created, to be paired with obtained data. RM has developed since this model, but in order to properly focus on the swapping logic and the gains that can be obtained from swapping, the EMSRb model was determined to be a good basis model. In addition to creating an EMSRb model, a forecasting module was created in order to be able to add stochasticity to the methodology. This stochasticity is needed for the allocations that will be used during the simulation of a flight while it builds its load throughout its out for sale window.

4.1.1 Forecasting Module

As booking demand follows a time series representation, time series models were investigated to find the best and most representative module. Ultimately the time series model that was chosen was the autoregressive integrative moving average model, or ARIMA. This model was chosen due to its robust nature and for its ability to react to seasonality, which can be true in some cases of demand. An ARIMA model has three different portions to it, which can thus be written as $ARIMA(p, d, q)$ where p is the order of the autoregressive model, d is the degree of differencing, and q is the order of the moving average of the model.

As this project is data driven, and supported with real world data, there is a significant amount of data to be processed. As has been previously mentioned, there are three hubs that have been selected and each hub has a number of weekly flights that are scheduled to be operated. Data for each of these origin and destinations (OD) has been split and gathered. In order to ensure proper accuracy, this data has been further broken into departure day of week. In total there were close to one thousand individual markets that had daily demand data for the full sale window of the flight. This of course is a large number to be able to manually process. Therefore the solution was proposed to create a Python script that would gather all of the necessary demand data, and feed this through a variety of ARIMA configurations. Each configuration would be sampled and processed, and the configuration that aligned closest to the data (highest accuracy) would be noted and a final model would then be created.

These models would then be used and fed into the RM demand predictor. Different models were produced for total bookings, fare bucket trends, as well as ancillary demand. Each of these will help feed into the RM model. Most important are the total bookings and fare bucket trends, as this will give an estimate to how many passengers a flight can expect, and the fare class trends will give an estimate as to where each passenger will land in terms of bid price. All of this information stored as an ARIMA model will help enable further stochasticity and allow for a true Monte Carlo simulation to be performed during case studies. This ultimately leads to block RM 1.0 in Figure 2, as well as helps in block RM 2.0 to create a random distribution of passengers.

4.1.2 EMSRb Module

To ultimately begin optimizing and maximizing revenue per flight, an EMSRb model will need to be developed (RM 2.0). This module, discussed in Section 2.1, is to be implemented and fed through the final model. This module will take as input the previously discussed forecasting model, which will output an estimate of how many passengers a certain OD can expect. This normally distributed random estimate is given in the form of a daily list of expected bookings. Alongside this is the estimated fare per passenger, this is again a normally distributed random estimate and is given in the form of a daily list where each passenger is given a price point based on how far out in the booking curve they are. With both of these lists produced, data is then broken out and a collection of how many passengers at how many different price points is then collected and appended. As EMSRb is the second iteration of the EMSR method, the formula has evolved into the following [Kalyan T. Talluri, 2004]:

$$P(S_j > y_j) = \frac{p_{j+1}}{\bar{p}_j} \tag{5}$$

Where S_j is the aggregated future demand for class j, y_j is the protection level for class j, and p_j is the revenue for class j and $\bar{p}_j$ is the weighted average revenues from each bucket from 1 to j and is given as:

$$\bar{p}_j = \frac{\sum_{k=1}^{j} p_k E[D_k]}{\sum_{k=1}^{j} E[D_k]} \tag{6}$$

Where p_k is the revenue for each bucket from 1 to j and D_k is the demand for classes 1 to j and $E[D_k]$ is the expectation of demand for classes 1 to j.

This data is calculated and then fed into the given equation and inventory levels for each bucket are then calculate. These buckets are nested, which means that each lower and cheaper bucket is nested into the following higher bucket. Nesting was integrated as this additional RM structure helps ensure that each bucket is used to its full potential, and thus each revenue tier is maximized. This helps protect revenue from being taken away by the lower buckets and additionally simplifies the available inventory. This can be visualized below :

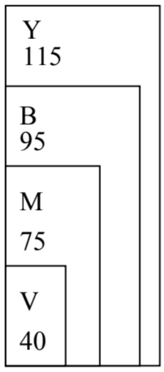


Figure 3: Nested buckets [Chapuis, 2008]

This ensures that the highest bucket available (the highest fare) has all available inventory at its disposal, and each lowering bucket has less and less inventory. Following this example, bucket V would only be allowed to sell 40 seats before the next passenger would have to pay the fare from bucket M. This calculation is done for each flight, giving each individual flight a tailored estimate of how many seats to see and at which price point, given the demand that was assumed from the original data. To give a further sample of just how this module works, the pseudo-code is provided below:

Algorithm 1 Calculation of Expected Marginal Seat Revenue (EMSRb) heuristic

Input Flight Routing, Aircraft Capacity
Import routing ARIMA forecasting model files
Load ARIMA model and create a daily normal distribution for demand and fares
Calculate mean and standard distribution for fares and demand
Create empty dictionary to gather frequency of passengers at different fare buckets
for $i = 1$ to $MaxDaysOut$ **do**
  Append amount of passengers at different fare classes to dictionary
end for
for $i = 1$ to $FareBuckets$ **do**
  Calculate weighted average of fares
end for
for $Fare$ in $FareBuckets$ **do**
  Find protection level for each bucket
end for
return $allocations$, $list(dailydemandpassengers)$
Output Inventory bucket protection levels, estimate of daily passengers

These determined allocations are then exported in RM 4.0, to be used in the main simulation (Sim 1.0).

4.2 Capacity Swapping Module

The next block of this methodology, is the capacity swapping block (Swap 1.0 - Swap 3.4b in Figure 2). This is the logic that will look through a set of given aircraft tails and their routes and make the decision to swap certain aircraft and place them onto different flights given one flight a higher capacity and the other flight a lower capacity. This module is the crucial part and will ultimately drive the network to bring higher revenue than planned.

What must first be defined, is how does a swap take place? What must be defined and what must be inputted in order to create a proper legal swap? It must be made sure that a swap makes functional sense, and that an aircraft is not stolen from one city creating an infeasible solution. One of the benefits of the data sourced, is that on the whole, most aircraft will return to their assigned base each night. This means that an aircraft will originate from its base in the morning, perform a set of flights throughout the day, and return to its starting point at the end of the day. This is a feature that saves in complexity of design, and allows for more swaps to be created, as there is no worry about any far down-line effects. Additionally, given that this data contains elements of a low cost carrier, there are less features to worry about, such as fleet type and mixed class cabin. This data contains a single fleet type, namely the A319 and A320, as well as a single cabin full economy configuration. This additional information means that different cabins and their capacity do not need to be taken into consideration when looking at creating swaps.

Following all of these clarifications and definitions, how a swap takes place can begin to be defined. Given that all aircraft are assigned to one base and begin and end their journeys at that base, this means that we can look at all of these aircraft as one set. Each base has a variety of aircraft that are assigned to perform different routes that day. Most of the time, these aircraft will perform out and backs, that is they fly to one city and return to base, and continue this pattern until the end of the day. Thus when looking to perform a swap, all aircraft assigned to a base are considered eligible candidates.

The first element that is done (Swap 2.0), is each flight is analyzed to see whether or not they would be considered a candidate for an upgauge or downgauge. This is eventually done for each flight, and a list of all eligible flights is compiled. Next, if a set of rotations from one base is noted as having a flight that is eligible for an upgauge or downgauge, then that flight is pulled into the swapping algorithm. Alongside these eligibility requirements, further requirements are set in place to avoid overswapping. Such requirements are that the average load factor for each set of rotations is not less than 25 %.

When looking at each set of rotations, firstly a list of all upgauge candidates are processed (Swap 3.0). Flights are looked at one by one, depending on their position in the rotation. Flights that have the most potential to benefit from an equipment swap are processed first. The flight is then processed and an eligible candidate is searched for. In the case of an upgauge, an aircraft with a higher capacity is sought for, firstly searched for within the list of downgauge flights. There is a requirement for all flights that they must both be at the same airport and that the other flight departs at the same time or at least within 45 minutes of that flight (Swap 3.1). If such a candidate exists then that flight is processed and the two are swapped as well as all down-line flights until the two aircraft are back at the same airport (Swap 3.2). From that point on the two aircraft resume to their original schedules. In the case that a flight isn't at exactly the same scheduled departure time then the two flights have their departure times adjusted. Down-line flights are also adjusted and are ensured that at least a minimum of 30 minutes are given to turn each aircraft around. Both of these flights are then removed from a list of eligible aircraft to be swapped and the process continues. Once the list of all upgauge candidates has been processed, the algorithm continues onto the downgauge candidates. As all upgauge flights have been processed, this list of downgauge flights searches through the list of all other flights, that is those that have not been marked for processing. The same logic as before is done until there are no more aircraft left that have been marked as a downgauge or downgauge. To ensure that the changes made were positive (Swap 3.3), the average physical load factor is compared to the set of rotations that were had prior to the swap. In the case that the average load factor has not improved, then this new set of rotations is rejected , and the old set of rotations is maintained (Swap 3.4b). This ensures that schedules remain the same and that each flight remains on the same original capacity, as when the swap was performed there were no noticeable improvements. In the case that a swap was shown to have an increase in average load factor, then those swaps are accepted and processed (Swap 3.4a). To give a further example of how this algorithm works, the following pseudo-code is provided below:

This algorithm was created to be simple to understand, so that any future person would be able to interpret and implement when needed. In reality there are various nuances that must be taken into account and written so that no single step is missed and so that there are no infeasible solutions to each flight. This swapping algorithm, along with the revenue management module, are key to this methodology and each will be key to ensuring that a positive solution is had, with improvements to KPIs as mentioned in Section 1.

4.3 Random Forest Module

The first two modules (Section 4.1, Section 4.2) are the key modules for this research. The first module allows for revenue to be maximized for each flight, while the second allows for flights to be swapped and capacity to be optimized. However, these modules do need further assistance which is where this following module is introduced, the random forest model development. This random forest (RF) module will help determine when a

Algorithm 2 Capacity swapping algorithm

```
1: Input Set of aircraft tail rotations for a given base on a given day
2: Identify all flights in each set of rotations and append those marked for upgauge or downgauge. Append all
   other flights in a separate list
3: while length(upgauge flights) > 0 and length(downgauge flights + remainder flights) > 0 do
4:    Identify flight with most potential to benefit from an upgauge
5:    for i = 1 to MaxDowngaugeFlights do
6:       Find flight with same departure airport and closest departure time (within 45 minutes)
7:       if No Downgauge eligible flights then
8:          Iterate through list of all remainder flights
9:       end if
10:   end for
11:   Change all attributes of both flights
12:   Adjust departure and arrival times of all flights as necessary to ensure a minimum of a 30 minute turn
      around time
13:   Change all downline flights until both aircraft are back in the same airport and are within 45 minutes of
      each others departure times
14:   Mark all flights as having been swapped, increase swap counter +1
15:   Remove all changed flights from lists
16: end while
17: Return to line 3 with list of downgauge flights and filter through remainder flights for eligible candidates
18: Run through all aircraft tails and create new list of rotations for each aircraft with updated information
19: Find if any flights have been changed and create a list
20: return Rotation, listOfChanged, amountOfFlightsSwapped
21: Output If list of changed status is 0, return original set. Else return new set of aircraft rotations for a
    given base
```

flight should be eligible for an upgauge or downgauge. Simpler methods can of course be used for this decision, such as when load has reached a certain level. However, given that there is a large sample of data available, specifically detailed demand data, it was decided that this data could be used to the advantage of this project.

To help predict an upgauge or downgauge decision, data that is on hand will need to be used. Such data in this instance can be the amount of passengers booked at the time of decision, the days out from departure at the time of decision, the day of week (Monday, Tuesday, etc.), the type of haul (short, medium, long), the load factor, and the estimated final passenger count. This is key data that is known for each flight, as well as real world data that is actually on hand.

For this particular methodology, the sklearn package for Python was used. This package is a tried and tested package for Python, with wide use across the any field. This model was used, and a variety of combinations were developed. To test accuracy, the mean absolute percentage error (MAPE) was calculated. This is the difference between the model results against the data results. This was calculated for both the split dataset as well as the dataset to its entirety. MAPE can be calculated using the following formula:

$$MAPE = \frac{100\%}{n} \cdot \sum_{t=1}^{n} |\frac{A_t - F_t}{A_t}| \tag{7}$$

Where A_t is the actual value, F_t is the forecasted value, and n is the number of fitted points.

The first element determined was the upgauge or downgauge decision. This could have been modeled a few different ways, and each way was tried and tested. Firstly capacity was thought to have been the label to have tested for, with different combinations of variables helping to predict this model. When attempting to test this however, it was seen that this model was too conservative and would mostly stick to the original capacity of the flight and would not give any other limits. Given that this was too conservative for this methodology, the next label that was to be tested was that of the final passenger count. This label was tested with various different features, including that of day of week, days out from departure, and the amount of passengers booked at that point in the booking curve. Other variables were tested such as the type of haul (short, medium, long), however such variables were seen to have not played a significant factor in the decision making of the model. Regardless, this model showed a MAPE of again over 90%, which proves to be a very satisfactory model. To avoid over-modeling, restrictions were set in place to ensure that this model would have satisfactory performance and would not be a bottleneck. Limitations created were around the amount of estimators and depth of the tree. The final amount of estimators and depth was set at 750 and 7 respectively. These values were tested within a range, but a decision had to be made, as ultimately if the values are too low then the model might not be robust enough and may give simple decisions, but if the values are too high then the model would be robust but with poor performance, namely run-time. These set limits were found to be robust to the degree that this project needed, but did not increase run-time significantly. Such limits ensured that the predictions were accurate and took as much information as needed to help create a final decision. The final decision tree ends up showing a series of possible criteria, where each input must either be true or false against the decision. This then flows to the bottom of the tree where a final decision can be made based on the original input that was given at the time of decision. The final decision tree that was created can be seen below:

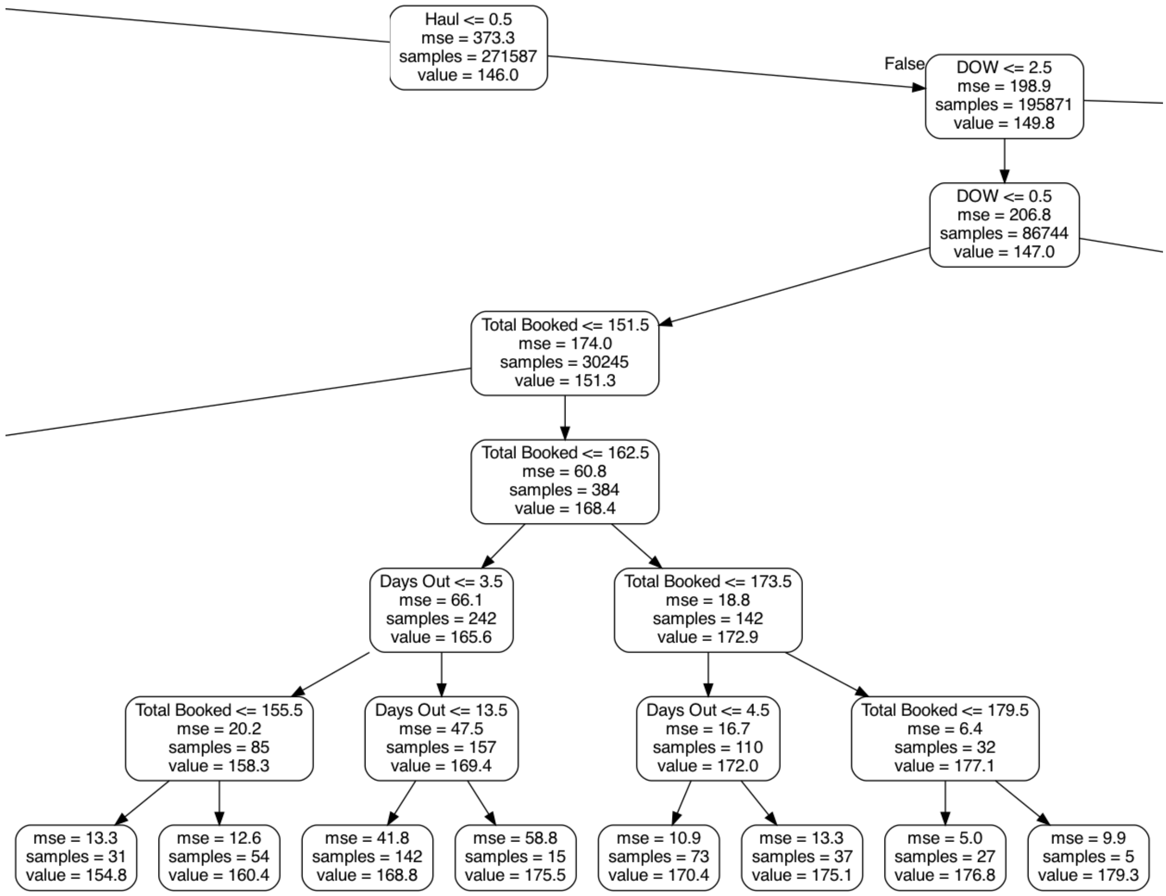


Figure 4: Upgauge/downgauge random forest excerpt

Where *mse* is the mean squared error, the samples are the amount of observations that have made it to that part of the tree, and the value is the desired output at that point in the tree.

Given that this model would only produce final passenger counts instead of a capacity recommendation, logic was needed to ensure that a recommendation could be created. Such logic was simple, but effective. The different capacities would be gathered at the start of the program to see what capacities are available. With this information, and the final passenger prediction, upgauge and downgauge decisions can be created by finding the closest aircraft capacity to the prediction. Following this, a recommendation can be given and flights can be marked accordingly. These marked flights are then able to go through the previously mentioned swap algorithm and fed into the overall methodology for processing.

The random forest model to help forecast the final LF was developed to help give an estimation as to how a flight will finish out in terms of final amount of passengers over capacity. Each flight has the aim of filling up to 100% LF, that is that every seat available is filled. Of course this becomes more complex as it intertwines with RM to ensure that revenue is maximized as well, ensuring that each seat sold is sold to the right customer at the right price. However, if there are any seats left unsold then this means that some seats will be spoiled, and there is revenue potential that is missed. Therefore, this RF LF prediction model will be useful to estimate final loads. This model again would use the data that was originally sourced. The final LF would be used as the final label, and a series of different variables would be used as features to help estimate the final load factor. Eventually it was found that a combination of aircraft capacity, flight haul type, day of week, and days out led to the best result with a MAPE of over 90%. Testing this model with the full methodology confirmed the accuracy and helpfulness. Ultimately this model was not used for any decision making, but this model can be used for future developments to help ensure that the RM model is maximizing its potential and not missing out on any customers in the lower fare buckets. Similar limitations were given to this model, which include a maximum depth of 7 levels, and the number of estimators set to 750. These values used were found to be robust enough to deliver a confident answer for each different flight tested but did not add to the run-time significantly.

4.4 Simulation Module

The final module of this methodology, is that of the simulation module (Sim 0.0 - Sim 6.0 from Figure 2). This module helps ensure accuracy in results. The specific type of simulation that is used is the Monte Carlo simulation (MC simulation). This style of simulation uses an increased number of random simulation runs, in order to drown out any of the noise that may come when using a random normal distribution. By using a larger amount of simulations, these values can be ran and the frequencies of certain results can be appended and a converging point can be found. As the results begin to converge, one can see that those results would be the expected results as a whole with a general use case.

In order to create a simulation, the first process that must be done is the loading of the original schedule, this is the beginning of the simulation (Sim 1.0). The schedule is imported from a csv and is the same each time. Each flight begins its life with the same times, and unique aircraft (tail number and capacity). This means that each different simulation run is identical, which helps when processing the results. Following this, each aircraft is ran through the RM module. The RM module will use the flight characteristics to load the ARIMA forecasting model. Each flight is characterized based off of the origin, destination, and day of week. This ARIMA model is then used to find the average amount of passengers and the fare given by each passenger. This information is then used by the RM module to assign allocations to each fare bucket, where each bucket is nested into the higher bucket meaning that the highest bucket will have all seats available to it. With the allocations then distributed, each flight is then assigned a random normally distributed daily demand list and fare list for each of the incoming passengers. Following this, flights are then processed daily (Sim 2.0). Each flight starts at the beginning of the booking window, which for the case of this sourced data, begins at approximately 250 days before departure. Flights are then processed daily and the however many passengers are given, are then taken. Alongside that, the corresponding fare is then given and in the case that there are enough seats at their fare bucket, they are allowed to purchase a ticket. If there are no seats at their fare bucket or a fare bucket that is at a lower price point, they are not allowed to purchase their ticket (Sim 3.0). This process continues throughout the life of the flight up until a decision to review all flights for capacity swaps is done (Sim 4.0). These points are different according to the methodology, and the research questions posed in Section 1. At the point of a capacity swap, each flight has temporarily stopped accepting any bookings, and each flight is then ran through the swapping algorithm. As mentioned in Section 4.2 in the case that the average LF for the flights in a given set of rotations is less than 25% then that set of rotations is not processed. This was a decision made to help unnecessary processing, as any load factor lower than this means that the flight has not had enough time to develop and may be processed inaccurately, or additionally may be sent through an unnecessary amount of swaps. In the case that the average LF for a rotation is greater than 25% then the set of rotations are processed and if a swap is to be made then it is done so, and assuming that the flight has a net positive benefit, the swap is accepted and the flights that have been swapped are tallied, in order to help with post data analysis.

Once a swap has been completed and the necessary data has been appended (Sim 5.0), the procedure is of course followed until each flight has reached zero days before departure and has finalized its booking window and has "departed". Such data includes capacity, aircraft type, load factor, revenue built up to that point, the amount of swaps, and departure and arrival times. This data is taken at an individual flight level, which is characterized by its flight number, origin, and destination, which is combined to create a flight key. This data is then exported into a csv for the particular simulation run, and the process is repeated until enough simulations have been run, which for this particular methodology was decided to be 500 simulation runs. This number has some basis as well as it was the amount of simulations ran by [Cots, 1999]. With such a large number of simulations it is expected that there will be a converging point and a set of expected results can be obtained.

5 Case Studies

In order to properly test the methodology that has been written above in Section 4, case studies were designed. Multiple case studies were generated in order to thoroughly test out the research question, and see just where are the limitations and where do results converge, if they converge. As has been mentioned, this thesis was able to source real world data, from an ultra low cost carrier (ULCC). Therefore it was decided to model case studies using the ULCC business model. Given the plethora of options in network options that could have been available, it was decided to limit the scope and concentrate on just a few areas of deployment. A select few hubs were picked, and destinations from each of these cities were chosen. The summary of hub cities is described below:

City	IATA Code	AC Types	Capacities
Orlando, FL, USA	SFB	A319 A320	156 177 186
Cincinnati, OH, USA	CVG	A319 A320	156 177 186
Las Vegas, NV, USA	LAS	A319 A320	156 177

Table 1: Selected Bases and their Aircraft/Capacities

As can be seen, each city has two versions of aircraft available to it, each with varying capacities, which allows for the testing of this methodology. In addition to having varying capacities, there is a significant benefit in having a single aircraft family (A319/A320) as one of the biggest constraints, pilots, is eliminated due to fleet commonality. Once the select bases with their varying types of aircraft have been established, the next thing that was needed was to establish the various case studies that could be performed. The first case study to be developed is the baseline no swap model. This case study is simply the baseline and will be used as a reference for further case studies, given this it has been numbered Case Study 0 and will be described further in Section 5.1. Following this case study, a simple case study will be created that looks at a simple set of rules that the swapping logic will follow. This is further described in refssec:casestudy1. The final set of case studies to be generated, is that of the random forest, which was previously described in the methodology. This case study will be further defined and broken down in Section 5.3.

5.1 Case Study 0: No Swap Baseline

The baseline case is a necessary case that will highlight the original state of the data as well as the natural state of the revenue management capabilities. This case will use a MC simulation (500 runs), however with no swapping logic enabled. This means that each flight will be simulated using the same normally distributed passenger demand and fare demand as all other case studies. The difference that enables this to be used as the baseline is that each flight retains the original capacity that was assigned at loading. As the research question for this thesis primarily looks to investigate the effects of a dynamic capacity swap model, this particular case allows for future case studies to have a base to test against. This will allow results from a capacity swapping logic to be truly tested.

5.2 Case Study 1: Simple Rule Based

Before the more intense, more intelligent, and more capable logic is used, it was thought to create a simple swapping logic to see just how robust a simple logic could work. Such a simple logic could test initial feasibility of this concept, by simply seeing if there is any merit and any enhancements by performing aircraft swaps throughout the booking period. Additionally, a simple logic could be used by many before needing to invest in a more detailed model. This would greatly benefit those who do not have detailed data, and thus cannot afford to have a data driven model. This logic does not used the more advanced random forest algorithm, but instead uses a simple set of rules to determine up and downgauge eligibility. Such criteria for this methodology has been set at to upgauge if the flight is estimated to have a final load factor of 92.5 % or greater, and the flight is not already at the highest capacity available, or to downgauge if the flight has an estimated final load factor of 70 % or less and is not already at the lowest capacity available. This basic criteria can be altered and a further analysis can be done to see just what the optimal load factor criteria (or other KPI) should be in order to provide the best results. In addition to using the simple logic, this methodology is performed once every four weeks (or monthly), further analysis can be done to see how often a swap should be done using the simple rules.

5.3 Case Study 2: Random Forest

The main focus of the methodology, lies with the capacity swapping logic. This is an in depth detailed logic that has been previously discussed, and allows for a certain flight at a certain base on a certain day to be swapped for another larger or smaller aircraft, without interrupting the schedule, that is all remainder flights and aircraft are all accommodated to fit for this swap. However, flights cannot get to this step without actually being marked for swapping consideration. The previous case study took this problem and applied a simple solution to help mark a flight to be considered. The main area of interest is this case study, and that is to use an advanced machine learning algorithm to help make that decision. Given that there is a significant amount of booking data available for this project, it is wanted to use this data to help the methodology. This data can be used in machine learning algorithms, specifically the random forest algorithm provided by scikit-learn (sklearn) in Python. This algorithm is a regression model, which means that it uses sets of labels to help piece together a formula to determine a final answer, which in this case is the final amount of passengers to be booked on a flight.

Once the random forest model has been developed the next step was to create different strategies on how to use this module. These strategies are the key piece of this methodology and will allow for one to determine just how effective swapping is. These strategies are discussed below but namely vary in time. By varying in time, the methodology can prove how effective that strategy is and if it's necessary or at which point is it necessary until.

5.3.1 Continuous Daily Monitoring

The first sub case study to test is what can be considered by some as the true dynamic version. This model will look at a flight daily and will make a decision to swap, as well as perform the swapping module daily once each flight has had a full 24 hours of booking and has not yet been worked on by a revenue management analyst.

5.3.2 Monthly Monitoring

The final sub case study strategy to be implemented is that of a monthly swapping application. This will analyze a flight once every month, or more specifically, once every four weeks. This is expected to have weaker results than the previous three sub case studies, but it is of interest to see how the results differ. This can then help interpret just how many swapping points are needed in order to produce a meaningful outcome.

6 Results & Analysis

In order to test the methodology that has been previously described, the case studies that were previously mentioned were needed to be put to the test. In this section the results from those individual case studies will be described and analyzed. As has been mentioned, this is a data-driven thesis. Every crucial aspect of this project has been done with the assistance of real-world airline data from an ultra low cost carrier. This means that the results have also been created with the assistance of this data. To help ensure that the data was not simply copied and that there is some variation - time-series models were created and Monte Carlo simulations were used with a normal distribution.

Given that this thesis looks to follow a real world model and be as close to normal operations as possible, while not expanding the scope and intending to answer the question initially set out to answer, there have been some assumptions taken. The assumptions and simplifications are listed below :

- Crew and maintenance scheduling is ignored - In reality this is taken into consideration to accommodate for any additional constraints such as crew and maintenance. However, this can complicate the ability to swap and thus would expand the scope of the thesis if such constraints must be accommodated for.
- An automated revenue management (RM) system - In reality, this is a full time task and requires deep involvement. However, the main scope and goal of this thesis is to test how well a swapping module would work when paired with an RM system. Therefore, with this methodology, a basic RM inventory management system was built which will serve as the main decision make for any RM related decisions.
- No overbookings are permitted - Overbooking is a practice where revenue management systems will allow for more customers to book over the available inventory. This helps reduce spoilage as generally not all customers will board, leaving empty seats on the flight. In this thesis an overbooking model is not created to avoid any scenarios that may arise, leaving the RM system to be simple and focus on the swapping model.
- A simplified forecasting model - This thesis and methodology uses an ARIMA time series model once and only once. Demand for both customers and their price points is generated once at the beginning of the booking curve and is used for the entirety of the booking curve until 0 days from departure.
- Point to Point model - This is an assumption based off of the data that was sourced. This allows for a simpler pricing structure, as each flight is priced and managed independently. Additionally this allows for

a simpler model when swapping as it is known that the aircraft will always return to its base at the end of the day, not having to worry about any repositioning elements.

- Simplified fleet family (fleet commonality) - This is an assumption that helps with crew constraints and allows for a more feasible model to be created. By having a singular fleet family, pilots can be interchanged without having to worry about finding a new crew. Although this thesis already ignores crew scheduling, this is still an important assumption and simplification to make in order to provide accuracy for real world modeling.

6.1 Baseline Model

The baseline case primarily serves as a comparison for the future case studies that were tested. Nonetheless, it is important to describe what results were see from this case study, to help understand how the network is performing and how the RM system is working. This also serves as a test for the RM system as well as the forecasting modules, in how well they were able to process the originally sourced data. To note, this section contains no swapping and is purely the original schedule built out from the beginning of the booking curve until the end when the flight has reached zero days from departure (or departed).

For the baseline model the same methodology was used as is planned for the case studies. This means that a Monte Carlo simulation was used inclusive of an ARIMA forecasting module to help simulate varying demand for all of the individual flights that was sourced. As would be expected for any network, there are flights that have performed very well, flights that performed poorly, and flights that have performed in between (or average). As there were over 2,250 individual flights, the top, bottom, and average performing flights will be selected and highlighted. This data is presented in terms of three different KPIs; load factor, number of passengers, and revenue generated. This should set expectations for the the future case studies. In order to provide secrecy and to protect competition, numbers will be given in categories and for future case studies the differences will be given in percentages only. This should give a good understanding of baseline performance and will give a good understanding to future case study performance improvements. The categories for load factor (LF), passengers, and revenue are given below:

LF (%)	**Category**
0-10	**1**
11-20	**2**
21-30	**3**
31-40	**4**
41-50	**5**
51-60	**6**
61-70	**7**
71-80	**8**
81-90	**9**
91-100	**10**

Table 2: Load Factor Categories

Passengers	**Category**
0-20	**1**
21-40	**2**
41-60	**3**
61-80	**4**
81-100	**5**
101-120	**6**
121-140	**7**
141-160	**8**
161-180	**9**
181-186	**10**

Table 3: Passenger Categories

Revenue (USD)	**Category**
0-5,000	**1**
5,001 - 10,000	**2**
10,000 - 15,000	**3**
15,001 - 20,000	**4**
20,001 - 25,000	**5**
25,001 - 30,000	**6**
30,001 - 35,000	**7**
35,001 - 40,000	**8**
40,001 - 45,000	**9**
45,001 - 50,000	**10**

Table 4: Revenue Categories

In terms of load factor, these are the three top(bottom) flights from their perspective category:

Flight (Day of Week)	**LF**	Passengers	Revenue
Top:			
PIE - CVG (Saturday)	8	7	7
SFB - GRR (Wednesday)	8	7	4
SGF - LAS (Wednesday)	8	6	5
Mid:			
AVL - SFB (Tuesday)	6	5	2
AUS - CVG (Friday)	6	5	2
SFB - FNT (Thursday)	5	4	3
Low:			
LAS - BLI (Friday)	2	1	3
LAX - LAS (Wednesday)	2	1	1
LAX - LAS (Saturday)	1	1	1

In terms of passengers, these are the three top(bottom) flights from their perspective category:

Flight (Day of Week)	LF	**Passengers**	Revenue
Top:			
PIE - CVG (Saturday)	8	7	7
SFB - GRR (Wednesday)	8	7	4
LAS - TYS(Sunday)	7	7	10
Mid:			
FSD - LAS (Friday)	6	5	4
MFE - LAS (Wednesday)	6	5	5
CVG - SAV (Friday)	5	5	3
Low:			
GSO - SFB (Tuesday)	2	2	1
LAS - BLI(Friday)	2	1	3
LAX - LAS (Wednesday)	2	1	1

In terms of revenue, these are the three top(bottom) flights from their perspective category:

Flight (Day of Week)	LF	Passengers	**Revenue**
Top:			
LAS - TYS (Sunday)	7	7	10
SFB - MFE (Sunday)	5	4	9
MFE - LAS (Monday)	5	4	9
Mid:			
SFB - OKC (Tuesday)	4	4	3
SFB - FAR (Monday)	4	4	3
SFB - SWF (Friday)	4	4	3
Low:			
LAS - LAX(Saturday)	4	3	1
LAX- LAS (Wednesday)	2	1	1
LAX- LAS (Saturday)	1	1	1

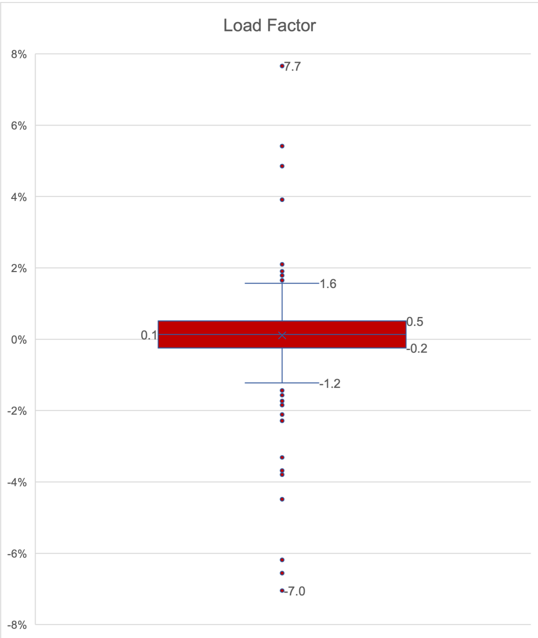
What can be inferred from these tables is that although some of these flights perform well, they are not exceptional and do rank lower than one would expect. On average one would expect a flight to perform and leave with a load factor of 80 % or greater [James D. Dana Jr, 2019]. However, most of these flights, whichever way they become sliced, depart with a load factor lower than 70 %. This could of course be to a weakened demand environment provided by the data, or this could also be by a tough revenue management system. This tough revenue management system may need a more modern methodology in order to ensure that enough bookings are created and revenue is fully maximized. The results from the baseline show that all flights are leaving with empty seats, which translates to spoiled seats and missed revenue. This means that although the revenue management system worked, it should have been softened to allow bookings at lower price points. By allowing just a few more bookings at lower price points, the LF can increase and revenue can also increase. By doing so, revenue might not increase significantly, but by ensuring that LF does increase this helps environmentally as the per passenger fuel burn is reduced. This scenario can thus be seen as a win-win by either stakeholder (airline and public).
Looking at each slice of the baseline data, the results are not as expected and have come in under expectations. Expectations were that the RM system would achieve over 80 % load factor, but this was not achieved. However, this is still the baseline and the more important aspect of swapping is still yet to be measured and tried. This will be reviewed in the next sections and will ultimately provide the answer to the central research question.

6.2 Simple Rule Based Model

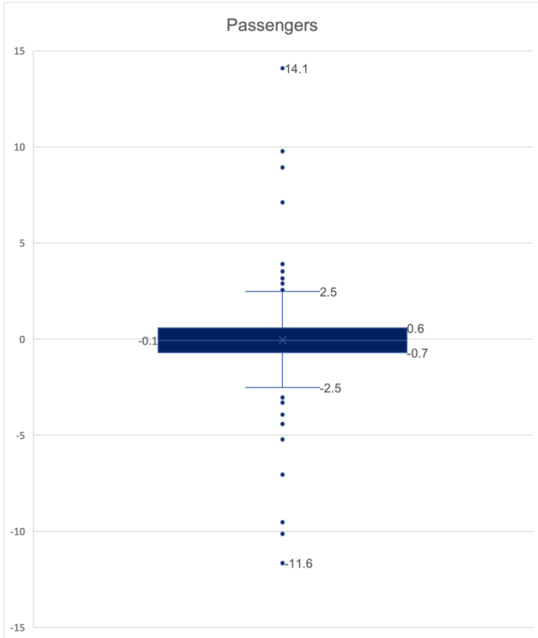
This model uses the same swapping methodology that has been described and formulated in Section 4.2. The main difference between this model and the model in Section 6.3 is the way that a flight is marked for a swap. With this model, a flight is given a basic review. Each flight is evaluated at various different points throughout the booking curve, for this particular scenario each flight is reviewed every four weeks. At the point of review, the flight's current LF is taken, as well as how it is performing based off of an average booking curve for that flight. If the flight is performing above average (meaning it is expected to end the booking curve above average) then it would be considered for an upgauge given that it is currently expected to end at a LF greater than or equal to 95 % and has less capacity than the highest gauge. Alternatively, a flight would be considered for a downgauge if the LF is expected to be less than 70 % and has a capacity higher than the smallest gauge.

Given that in this scenario swaps have occurred, only the results of the subset of which flights that have been swapped will be analyzed. As this methodology did use Monte Carlo simulations, only flights that have been swapped for at least 20 % of the simulations will be considered for analysis.

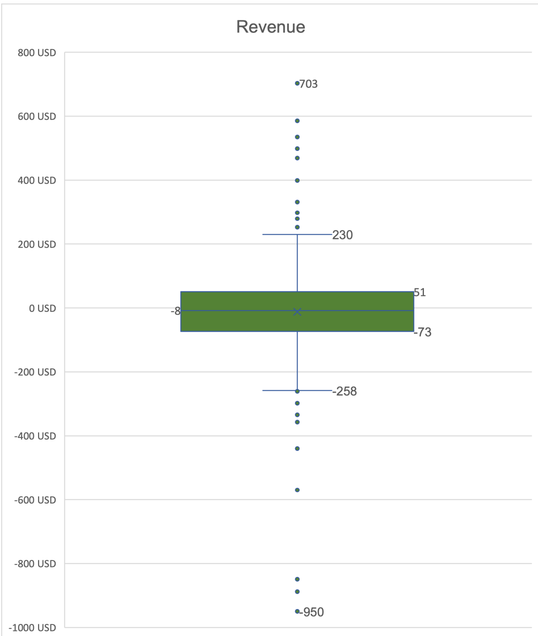
To help easily view results by KPI, box and whisker plots were created to show the distribution of results. The first plot shows the spread of load factor in red (Figure 5(a)). This shows a large spread ranging from close to positive 8 % gain in load factor, down to -7 % loss in load factor per flight. This is a large spread that is undesired, but shows strength in the results that were achieved as the median is centered at a positive increase. Similar results can be seen with passenger and revenue increase, however in these cases the median results obtained are at decreases but are close to 0. These full plots can be seen below:



(a) Load Factor



(b) Passengers



(c) Revenue

Figure 5: Distribution of all flights that were swapped compared to the baseline

The next step to complete is to compare the results from these swapped flights against their baseline scenario equivalent. This highlights performance from the swapping algorithm itself as well as the simple swapping logic that would help bring a flight to the swapping algorithm. Looking at the KPIs, it is seen that average load factor per flight increased by 0.4 %, average passenger per flight increased by 1.4, and average revenue per flight increased by 110 USD. Furthermore, there were approximately 400 flights swapped per week, which then equates to an increase of 44,500 USD per week.

To put these results into further perspective, a radar chart was created that shows the percent increases against the baseline equivalent. In this radar chart the strength and weakness of the different KPIs is highlighted.

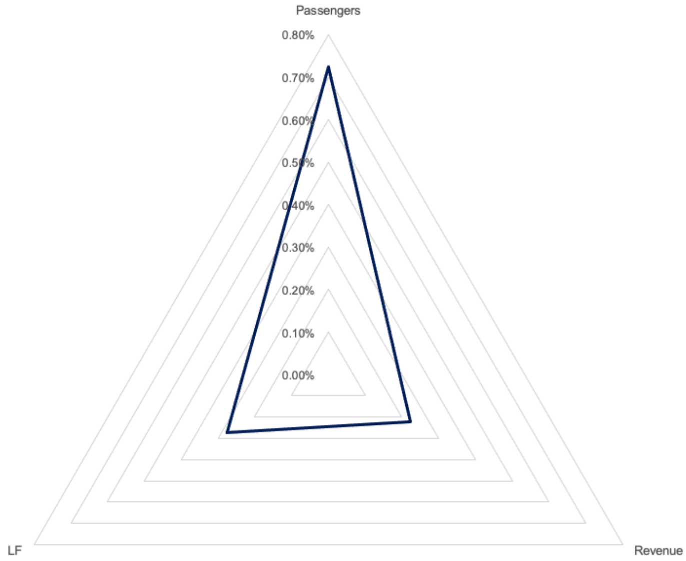


Figure 6: Radar Plot

The next element that is important for review, is just when did these swaps happen? The following chart shows the density of when swaps happened throughout the booking window:

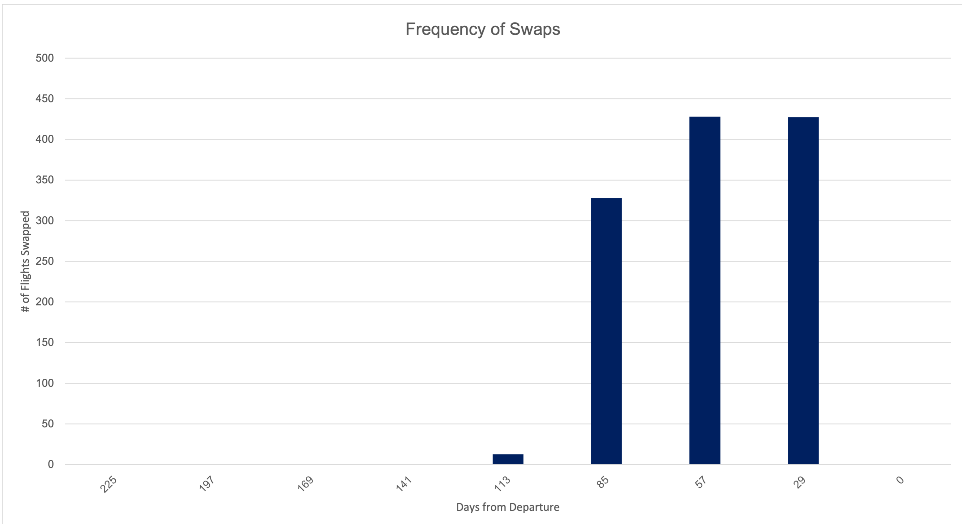


Figure 7: Density of Swapping Decisions

This chart highlights that most swaps happen closer to departure rather than the beginning of their selling window. As there were restrictions on when to swap, such as load factor, this then indicates that most flights do not begin to build load until they are closer to their departure date. This begins at around 113 days, or over half way through the booking window. These swaps then quickly ramp up at the next interval and levels off for the next set of intervals until the swapping window is closed due to the operational lock set in place.

Given that one flight must swap with another flight in order to successfully change capacities as needed, this can translate into a delay from the scheduled times. In the swapping algorithm there were stop limits set in place to ensure that a delay was never significant. This was proven so, as when reviewing all of the flights it was seen that on average each flight incurred a delay of less than one minute, or just 38 seconds. This shows that the stop limit set worked as intended, and did not disrupt the schedule. Looking at the ends, it was seen that a vast majority of flights incurred no delay (82 %). On the other end it was seen that the maximum delay incurred was under 28 minutes, which is considerably less than the stop limit that was set (45 minutes). Although this delay can still be considered minor, would have minimal impact due to how far out this delay would have been seen, at over two weeks out due to the operational swap stop limit.

Having considered all of the various different aspects, such as KPIs, timeline density of swapping decisions, and delays, the conclusion is drawn that this particular case study meets the expectations of this research. Some particular aspects and metrics are not as strong as others, but they are balanced out and have net increases. Revenue and load factor have positive increases indicating successful accomplishments. Other aspects such as delays are created, but by creating a delay the amount of passengers able to be transported increases which can help offset any customer inconvenience. Additionally, the swapping timeline is as expected and swaps are halted before any major close-in inconvenience can be created.

6.3 Random Forest Model

In this section the results regarding the different scenarios using the random forest model will be discussed. This random forest model provides a recommendation as to what capacity a flight should have based on different variables such as day of week, days from departure, total booked at point in time, and the type of haul the flight is (distance-based). These variables are fed into the random forest model and a recommendation is given. If the recommendation is lower or higher than what is currently assigned to the flight then the flight is marked and recommended for a swap.

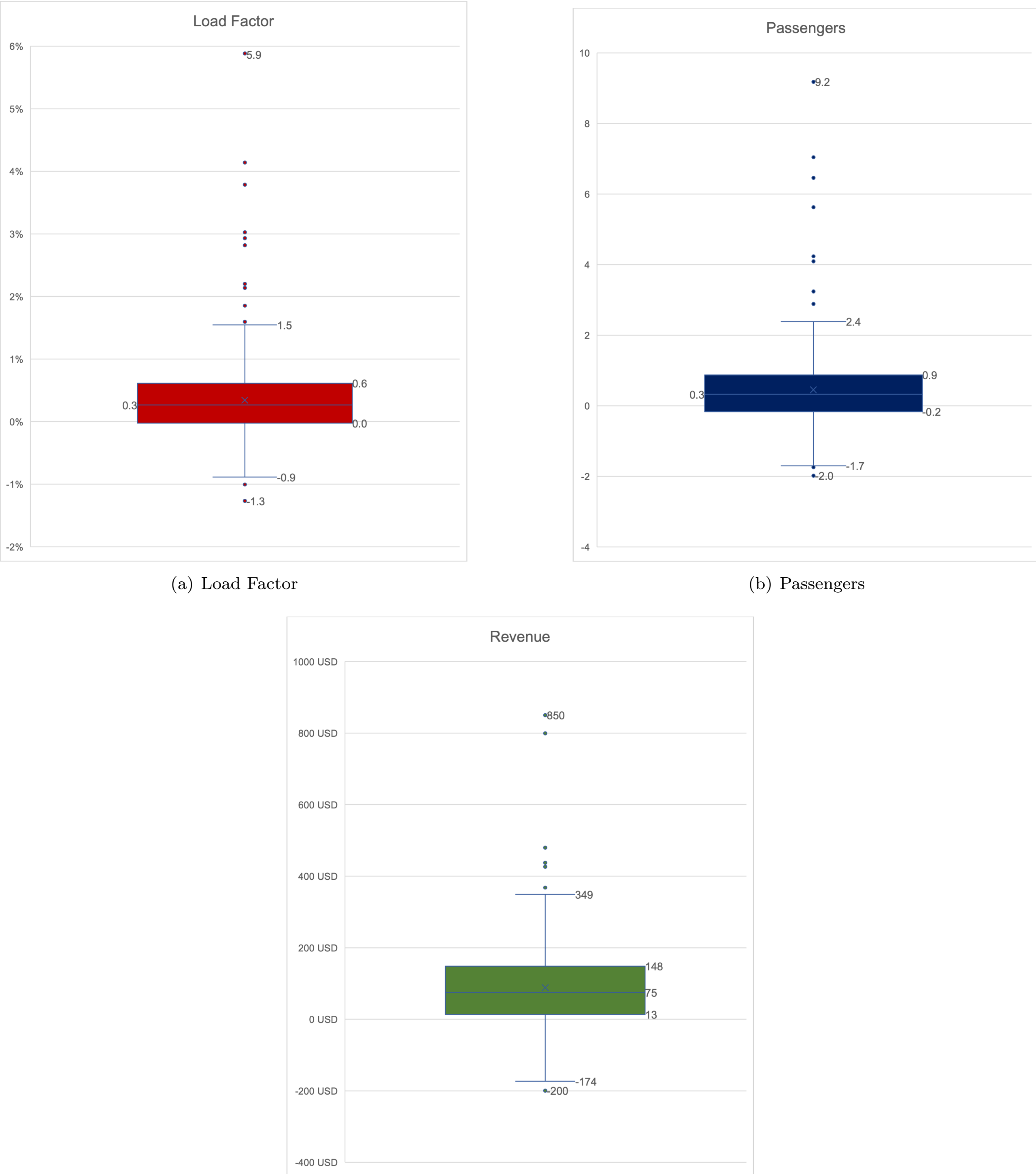
The different subsections in this section represent the different timing strategies. These strategies will vary from either accessing every day, or once a month. These different scenarios are taken to show the difference that can occur when you shift from swapping daily to monthly. In certain circumstances a daily approach may become too extreme for an operator, as by changing daily you may start to interrupt other activities such as maintenance scheduling. On the other hand, an operator may choose to ignore such restrictions and allow for a daily swap algorithm to take place and worry about such constraints when they arise.

In these scenarios, the same restrictions from Section 6.2 were used. This ensures that there result comparisons will be equal as no other variables are changed rather than the true intent of the research. These swapping restrictions included that each rotation must have an average of 25 % load factor and that swapping is closed two weeks prior to departure to give consideration into any operational constraints that may be had, such as crew or unplanned maintenance disruptions.

6.3.1 Daily Monitoring

In this section the results of swapping daily are given. On average each flight that was processed had a booking window of 250 days. In this particular scenario, this would indicate that there are 250 possible days to swap a flight, or a maximum of 250 swaps per flight. However, given the restrictions that were mentioned previously, such an amount of swaps would not be possible. Firstly, buy introducing a minimum load factor of 25 %, it was seen that the first swaps did not begin until 125 days, indicating that the first half of a flights booking window is sparsely booked and swaps during this time period are not necessary.

Firstly looking at the spread of results it is seen that these swaps have a much smaller negative tail, meaning that most swaps that took place were positive increases against their baseline counterpart. Additionally, each median from each KPI is positive and approximately 75 % of the results show positive increases when compared to their baseline. This highlights the scenario strength and shows that increases are most likely attainable if this timeline were to be fully implemented in a real operation.



(a) Load Factor

(b) Passengers

(c) Revenue

Figure 8: Distribution of all flights that were swapped compared to the baseline

Looking holistically at all of the swapped flights and comparing against their baseline, it is seen that there is an average load factor increase of 0.20 %, an average passenger increase of 0.6 passengers, and an average revenue increase of 100 USD per flight. Though these results are marginal, they do show strength in the algorithm and methodology. These results were only for the flights that were swapped (for at least 20 % of the simulations). In total there were close to 700 flights that were able to be swapped (for a two week period). Thus translating these revenue results into a weekly basis an additional 36,000 USD can be generated. This is less than the simple logic scenario, but given that the spread of these results were not as large, this scenario becomes more desired as the outcome becomes more certain. Furthermore, a radar plot is given below that helps indicate the increases for each KPI. In this scenario, the results have become more balanced with each KPI providing a 1 % increase over their baseline.

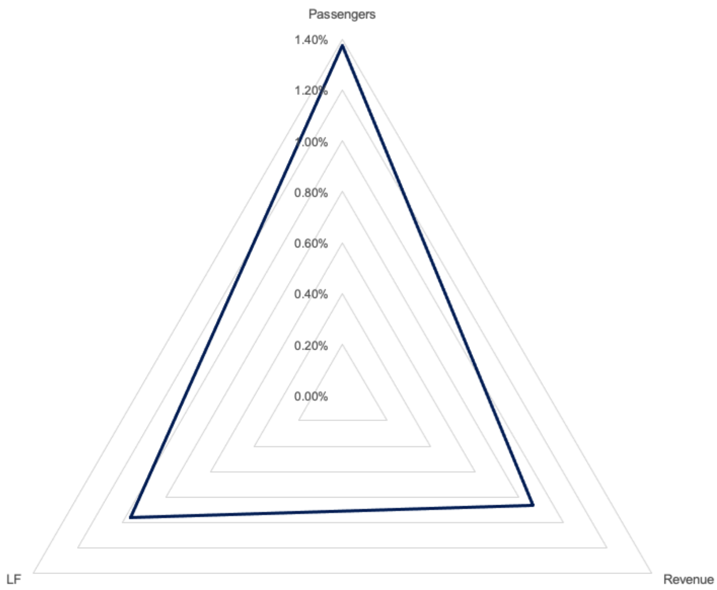


Figure 9: Radar Plot

Looking at the timeline of swaps, and considering when swaps are most likely to happen, it is seen below that there is a peak of swaps happening around 93 days from the scheduled departure date. It is also seen that these swaps have a rapid rise and a rapid decline, with most swaps stopping 62 days from departure. This is due to the restrictions that were set in place to help avoid excessive swapping. These restrictions do not mean that they are correct; although positive results were obtained in this scenario, it is likely that by creating different restrictions, or adding more swapping criteria, a more even spread of distributions can be had and potentially stronger results can be shown. This is a potential shortcoming of the methodology and may need additional review.

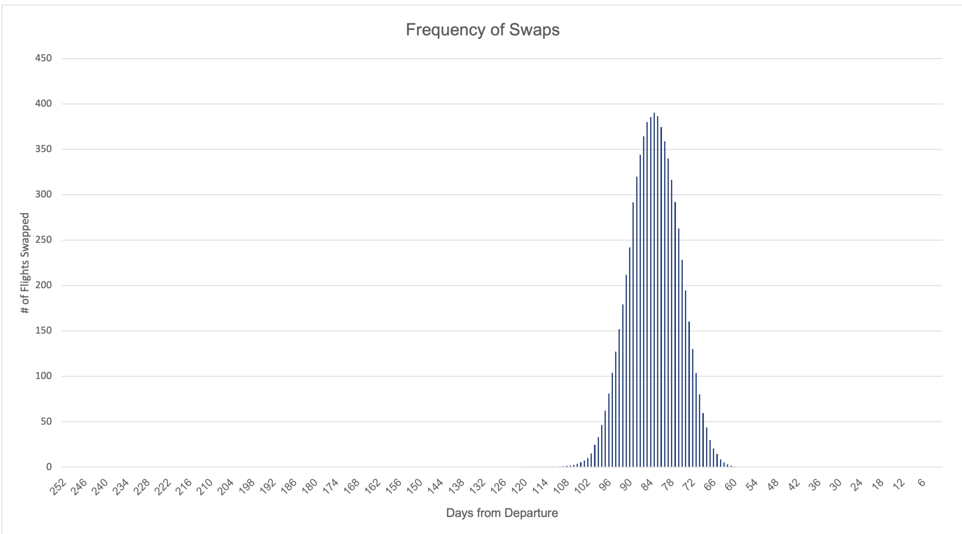


Figure 10: Density of Swapping Decisions

Considering any delays that may have happened as a result of a swap, it is seen that over 75 % of flights that were swapped faced zero delay, meaning they were able to keep their original scheduled departure time. This helps bring the average down to 1 and a half minutes for all swapped flights. Looking at the set of flights that were swapped and did face a delay, it is seen that the average delay created was less than 6 and a half minutes. The lower bound of these delays averages at just under one minute, while the upper bound is much higher at just under 44 minutes, which is closer to the limit that was set.

Overall this scenario has proven to be the strongest scenario tested yet. Although the weekly revenue increase was smaller than in the simple scenario, by having a smaller spread in the results, higher confidence is gained.

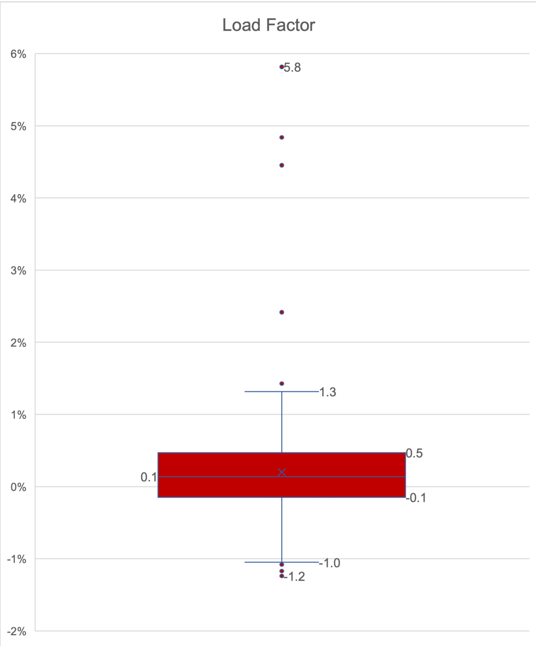
Decisions to swap are made with more information on hand which helps ensure that only the flights with the most potential are swapped when needed.

6.3.2 Monthly Monitoring

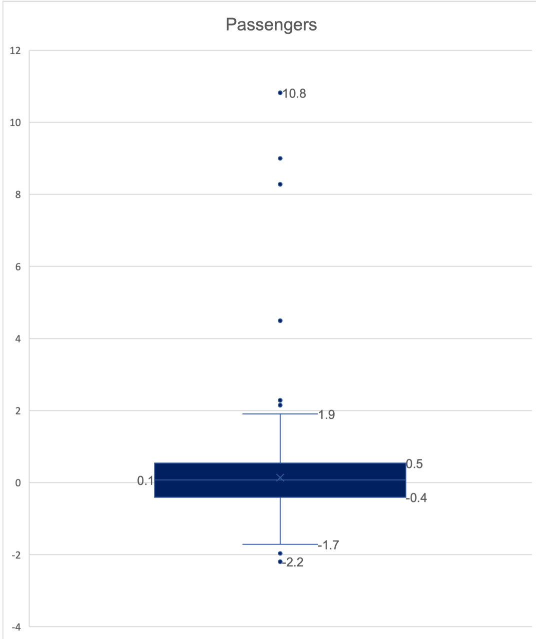
In this final scenario, we look at swapping a flight once a month (or once every four weeks). Combining this scenario with the same restrictions, such as stopping the swapping 14 days prior to departure and a 25 % LF minimum to begin swapping, the amount of opportunities to swap a flight has significantly decreased. In this scenario, most flights will be swapped around a maximum of only four times. In a variable demand market, this sometimes may not be enough. In cases of a higher flow of demand, or more variable demand, decisions may be made and a domino effect may happen. Such an example may be where a flight was performing strongly, was swapped accordingly, but suddenly the demand has weakened and now that flight may not be taking full advantage of the capacity whereas other flights may need it. By only swapping once a month, the other flight may miss out on a significant amount of demand because of this timing scenario. Such scenarios become possible by creating a large gap in decision making periods and these scenarios and outcomes need to be considered before any implementation.

Despite any possible negative scenarios that may occur, it is still possible that positive results can be achieved. It is noted that because of such scenarios, the results achieved may not be as strong as possible, but positive increases are still possible.

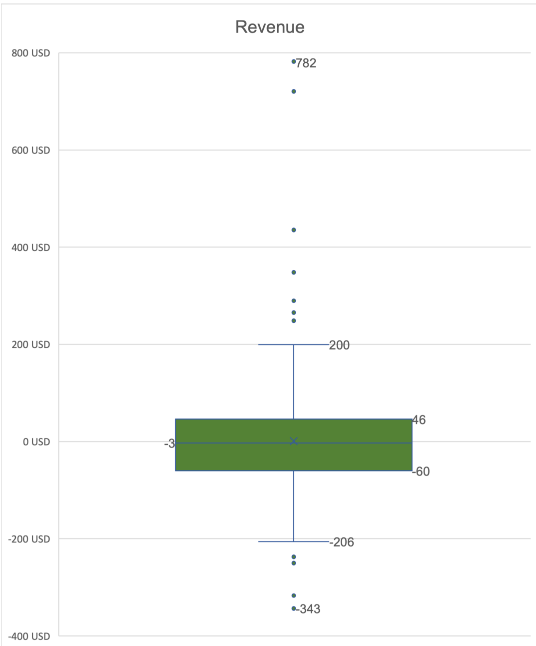
This is evident in the results that are given below. Looking at the spread of results, it is seen that approximately 50 % of all flights swapped have positive increases compared to their baseline equivalent. These results are not as great when comparing to the daily swapping scenario, but this can be attributed to a lack of enough decision making periods, as previously discussed. Regardless, by having minimal supervision, and positive increases, this shows the true strength that the swapping algorithm has. With minimal information, the swapping algorithm is still able to turn half of the flights around and ensure that their capacity is being optimized and that the flights revenue is being maximized. Additional positives from this scenario, is that the spread is not large or significant as was seen in the simple scenario. There is a larger spread towards the positive improvement region, but when looking at the negative decrease region, this spread is not large and is more concentrated. This continues to show strength in using an advanced random forest model to help create a decision for when a flight should be swapped or not.



(a) Load Factor



(b) Passengers



(c) Revenue

Figure 11: Distribution of all flights that were swapped compared to the baseline

To review all swapped flights against their baseline, we see an average increase of 0.4 % in load factor, an average increase of 0.17 increase in passengers, and an average increase of 1.6 USD per flight. Although the load factor increase that we see has nearly doubled from the daily scenario, the average passenger and revenue increase is significantly less. This is most likely due to a smaller amount of flights having been swapped. To translate the revenue into a weekly value, this would mean an additional 500 USD per week. Which is approximately 99 % less than the daily scenario. This indicates that a monthly swapping scenario is most likely too infrequent to achieve any significant results.

The final radar plot below shows degraded performance in revenue against the baseline. While passenger and load factor increases against the baseline are strong, revenue is seen to be a laggard. Seeing such a poor result would indicate that the methodology may be biased towards passenger amounts and load factor, and not enough towards revenue. In certain cases this may be acceptable, but for this research and for operators, this is not desired. Revenue is expected to grow as strongly as the passenger increases have grown.

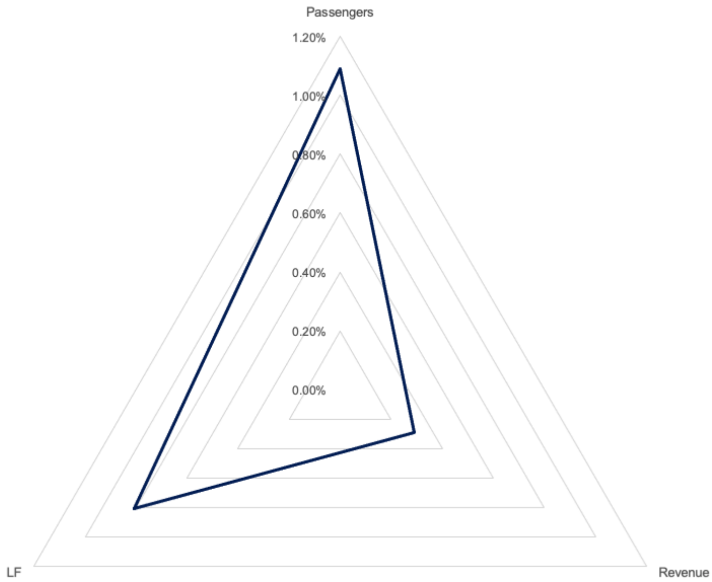


Figure 12: Radar Plot

When analyzing the density of swapping decisions below, it is seen that there are not many opportunities for a flight to be swapped. There are only four opportunities to be had given the restrictions, and most flights will only be swapped in three opportunities. Given that the swaps end at a peak, this further indicates that there is a benefit from creating additional swapping opportunities as more decisions can be made.

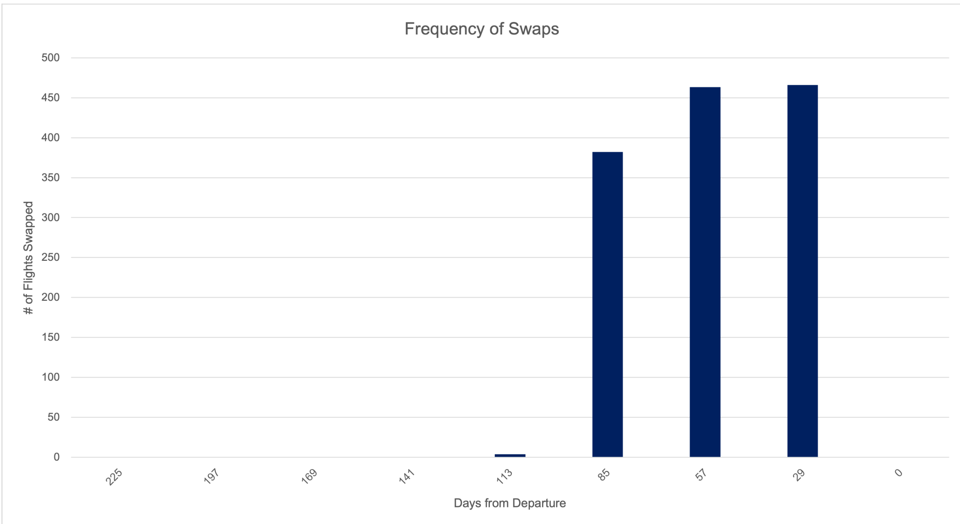


Figure 13: Density of Swapping Decisions

Considering delays that might have been incurred as a result of any swaps, it is recorded that 90 % of the flights that were swapped incurred no delay at all. This brings the average delay down to just less than 45 seconds which is a factor that would not be noticed at all. Looking at the 10 % of flights that were delayed, the average delay is brought up to 7 minutes. The low end of these delays is a delay of just one minute. To look at the other end, it is seen that the highest delay incurred is at just over 26 minutes. This delay would push outside of the on-time boundaries in a regular scenario, but given that this delay would be posted at a minimum of 14 days away from the departure date, the impact is again minimal.

To conclude from this scenario, the overall swapping algorithm and methodology shows positive results that align with the research goals and hypotheses that were originally set out. The swapping algorithm created is able to produce positive increases over the baseline standard. However, in this particular scenario, the results that were found were not as strong as previously achieved, showing great weakness in such a minimal timing strategy.

7 Conclusions & Recommendations

The implementation of a dynamic swapping capability paired with a proven revenue management model has been shown to deliver results with positive margins. The potential to increase in every measured KPI was proven in most scenarios that were ran. These KPIs (passenger counts, load factor, and revenue) are metrics that airlines constantly seek to improve. To be able to show net average positive increases is an achievement that is strongly desired. This capacity swap strategy used a logic-based method to help process swaps for any flight within a rotation that was deemed eligible. This methodology would take a flight as input along with all other eligible aircraft (and their rotations). The methodology further incorporates each different module, which are the revenue management module, capacity swapping module, and the simulation module. These are integrated seamlessly, and are aided by data to help produce a data-driven result. This integration allows for an updated perspective to help further highlight how well a dynamic capacity swap model can perform.

In the methodology, the decision module would help determine which flights would be best considered for an aircraft swap. The first model created used a simple logic based approach to help determine eligibility. The next approach took advantage of the data that was on hand to help create a random forest model. This random forest model assisted in determining the final amount of passengers for a given flight. Alongside the swapping capabilities was the revenue management module, which used the EMSRb algorithm. This revenue management model took the expected demand to help create allocations for the different various fare classes. This would help ensure that revenue was maximized and the right balance of customer was taken, namely that the low paying leisure passengers were accepted but without accepting too many low paying passengers that high paying late passengers would be rejected. This ensures that seats are maximized along with revenue by ensuring that there are not too many low paying customers accepted, and that there are not too many seats that may be spoiled. These elements were crucial in propelling this methodology forward and helped set it apart. Alongside these modules, the capacity swapping module would help ensure that aircraft can be swapped among flights with minimal interruption. If an interruption was incurred, the interruption was made sure to be minimal by creating a delay upper-limit as well as by stopping any swaps before the day of departure. Additionally, only swaps that showed positive gains were created and any other swap would be rejected.

There are a few main conclusions that can be taken away from this research. One of the first points that can be taken away is that the methodology is strong, and is able to deliver results with positive increases compared to the baseline. Each case study that was developed and analyzed has resulted in net positive increases compared to the baseline. Of course each case study is different than the other, and that is the next conclusion. When it comes to swapping, more decision points are very important and can make a difference. It was seen that the daily swapping scenario resulted in the best increases against the baseline. Such results translated to an average increase of 0.20 % in load factor, an average increase of 0.6 passengers per flight, and an average revenue increase of 100 USD per flight. Comparing this to the lowest swap interval tested (monthly), it was seen that 0.4 % increase in load factor was generated, along with 0.17 passengers extra per flight, and only 1.6 USD revenue increase per flight. The difference in revenue gain compared to the daily scenario is approximately 99 %, meaning that revenue gain is almost entirely lost. Although these results are still positive, it does indicate weakness in the case studies by having such a large gap between swaps.

The next conclusion that was noticed stemmed from the results during the simple logic scenario. This scenario involved simple logic to help create swapping recommendations and did not process any data to help its decision. Instead, information was taken from the flight itself, along with the average expectation for the flight, and this information along with simple hard limits would help create a decision. If a flight was expected to end with a high load factor but on a small gauge, then an upgauge would be recommended. If the the flight was expected to have a poor load factor and on a high gauge aircraft, then a downgauge was recommended. As this was not the focal point of this methodology, this scenario was tested with the spaced out monthly swapping timeline. As was noticed in the random forest scenarios, the monthly timeline did the poorest. Regardless, this simple scenario along with a monthly timeline proved to have exceptional results with an average passenger increase of 1.4 per flight, and average revenue increase of 110 USD. Which even rivals that of the daily random forest scenario. Of course given that only one scenario was ran, and simple logic was used this is an area that requires further research.

While reviewing the results, a key potential issue that was noticed was in the daily random forest scenario. In this scenario, and compared to others, it is noticed that the amount of swaps quickly reach a peak and then rapidly decline. This is not on trend with the other scenarios which indicates that potentially more swaps may lead to better results. Initially this was done purposefully, to help avoid swapping the same flight multiple times, thus avoiding redundant swaps. However, it is possible that the limit on how many times a flight can be swapped can be increased to see if any further gains would be possible. On the other hand, it may also be possible that the results are positive because of this limit. It may be the case that the limit helped avoid excessive swapping and that the increases are maximized. This will of course have to be further researched to truly understand what is the right path.

One other issue that was noticed, was in the monthly scenario. Along with poor results, it was noticed that the spread of results was larger than previously seen. This is a scenario that requires further research to help determine why such a large spread in results is happening. If such a spread can be reduced then this can help ensure that the results are kept tight and that a clear expectation can be set out every time. It may be worth considering adding any safeguards for these low frequency scenarios, such as additional limitations in terms of load factor or days from departure. The final conclusion that was drawn, was regarding the KPI of revenue. In most cases the other KPIs of passengers and load factor showed positive increases. However, when looking at revenue, there were increases to be had, but not at the level that was attained with passenger or load factor.

Therefore it is recommended to adapt the methodology to become more revenue focused. This can lead to even greater revenue increases and can help the swappings to become smarter and avoid unnecessary swaps. Other recommendations for the methodology would be to shift the focus towards environmental concerns. With the current climate of today, it is beneficial to be able to transport as many passengers as possible while burning as little emissions as possible. While this research showed positive results in passenger and load factor improvements, it is not necessarily the case that emissions per passenger would be reduced. There are multiple other factors that need to be taken into consideration such as length of flight, emissions per different aircraft sub variant, or alternative means of transportation. Such a methodology that would focus on integrating these elements would be beneficial for the industry. This research could focus on evaluating all options to ensure that emissions per passenger is minimized. By evaluating alternative transportation modes, smarter decisions can be made on where to allocate aircraft (capacity) to ensure that the passenger has the better option as well as global emissions become minimized. Further methodology recommendations would also look to reducing some of the restrictions created. The key restriction placed is fleet commonality, if this is removed then perhaps better results can be obtained. However, given the complexity of crew constraints, which is the main driver for the need of fleet commonality, it may be necessary to integrate this research with a crew scheduling application.

After having reviewed the results, it can be seen that the results were as expected and showed growth in revenue and load factor. This shows that the capacity swapping algorithm performs as expected and helps increase the total amount of passengers flown and the total amount of revenue generated. These results are meaningful, but further enhancements to the methodology can help excel this area of research even further. By incorporating other metrics such as environmental metrics, this methodology can help ensure that airlines and operators are further focused on the commitment to decrease carbon emissions. Further methodology enhancements such as reducing crew constraints can additionally help ensure that this methodology would become more widely adapted. These areas of enhancement to the methodology, are key in taking this area of research to the next level.

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Appendices

A IATA Airport Codes - USA

IATA	City	State
CVG	Cincinnati	Ohio
PIE	St. Petersburg	Florida
SFB	Orlando	Florida
LAS	Las Vegas	Nevada
GRR	Grand Rapids	Michigan
SGF	Springfield	Missouri
AVL	Asheville	North Carolina
AUS	Austin	Texas
FNT	Flint	Michigan
BLI	Bellingham	Washington
LAX	Los Angeles	California
TYS	Knoxville	Tennessee
FSD	Sioux Falls	South Dakota
MFE	McAllen	Texas
SAV	Savannah	Georgia
GSO	Greensboro	North Carolina
OKC	Oklahoma City	Oklahoma
FAR	Fargo	North Dakota
SWF	New York Stewart	New York

Table 5: IATA Airport Codes

II

Literature Study

previously graded under AE4020

1 Introduction

In the airline industry there are a number of problems that cost the company time and money. One of these problems is that of capacity allocation and uncertain demand. Flights typically leave with either too many or too little seats sold resulting in what is known as spillage and spoilage. This current problem is the main focus of revenue management. Revenue management is an integral part of any airline that aims to ensure that the right seat is sold to the right customer at the right time. Currently, revenue management uses historical data to create their forecast that helps estimate demand. This demand forecast is then used to help assign an aircraft to a certain flight. From the point of aircraft assignment, most of the time that aircraft will stick to that flight and will not be reassigned. However this method of using a static demand model might not be ideal. There are a number of factors that might influence the demand for a flight, therefore historical data may not always prove to be accurate. Therefore the question that becomes posed is, should a static demand model continue to be used? Is it possible to have flexibility when assigning aircraft? These questions lead to the integration of the topics of revenue management and dynamic capacity allocation, which lead to the formulation of this literature study and thesis research question.

This main objective that becomes posed is: *How to best combine revenue management tools and models with a dynamic capacity allocation model to ensure that each flight leg departs with its revenue potential maximized.*

This main objective then leads to a series of sub-goals and tasks that will help solve this stated objective. These sub-goals and tasks will additionally help with the analysis, ensuring that the results are of significance.

Firstly, what must be considered is who the stakeholders are, that is what departments and what group of people are going to be most impacted by this project? In addition to this, the integration and how that will be handled needs to be clearly defined, so as to avoid any uncertainty. These initial steps will provide a clear basis and foundation for the project.

Following this, an analysis of the different steps that are required throughout the entire process will need to be done. That is, throughout the period in which this model will be operational, what are the different steps and checkpoints that will help provide the best answers? This will find the different constraints and the different levers that can be used to help optimize the model and make it a practical model.

Once the model has been formulated, a case study will be performed with real information and data. This case study will provide results that will help determine model effectiveness. This paired with a sensitivity analysis will help further the research in this field, providing more answers and questions that will advance this topic.

With the overarching objective defined, the main research question that is formulated becomes: *How much additional revenue can an airline generate over its route network by dynamically reallocating capacity using information from an optimal revenue management model?*

With this question created, a series of sub-questions can be created. Each of these sub-questions will help towards the progress of the project and ensuring that the overarching question is answered. Each of these questions will reflect upon a different part of the model, helping lead to the development of the model.

1. What timing strategy will yield the best results?
   (a) Will it be better to perform a swap once or multiple times throughout the booking period?
   (b) How many weeks in advance should these swaps be performed?
2. Which swapping strategy will yield the best results?
   (a) Is it better to create a virtual maximum capacity cap and assign aircraft as bookings fill?
   (b) Is it better to swap based on bookings at the specified swap time?
3. Is a continuously updating forecast beneficial for revenue management?
   (a) Is it better to keep the original forecast or update the forecast as bookings begin to arrive?
4. How effective is the integration of revenue management with dynamic capacity allocation in terms of KPIs?
   (a) How does load factor change?
   (b) How many flights result in a swap?
   (c) What are the changes in ASK and RPK?
   (d) What are the changes in revenues, costs, and profits?

The structure of this literature study is as follows, firstly in chapter 2 the topic of dynamic capacity allocation will be covered, this will go over the history of dynamic capacity allocation and will then go over the works and advancements in this field, leading up to the current state of the industry. Following this in chapter 3, the topic of revenue management will be covered. This will again look at the history of revenue management which will then be followed by the milestones covered in that field, leading up to what is currently in place today. The next chapter, chapter 4, will look at the integration of the previous two topics, dynamic capacity allocation and revenue management. How these two problems have been integrated and what the current state of research in that field is will be covered, followed by what is missing and what can be done next. Following this, a description of the problem, its definitions, framework, and assumptions will be given in chapter 5. Lastly, a research proposal will be given in chapter 7 where the research timeline and expectations throughout the timeline will be given.

2

Dynamic Capacity Allocation

Dynamic capacity allocation is a way to update and change aircraft within a schedule as information is becoming continuously or periodically available to the decision maker. [42]. This means that as new information comes in, periodically or aperiodically, the schedule in question can be updated to better reflect the new information that is being brought in. The basis of dynamic capacity allocation involves a fleet assignment model, which can either be created manually or by a computer. A manual schedule can be quite an extensive task, especially when dealing with a large number of aircraft and routes. This leaves manually scheduling to relatively smaller airlines. The alternative to manually scheduling, is to use a computer. Using a computer and programming, there are two widely-known methods. The first method would be to use dynamic programming, and the second would be to use a time-space network. These two concepts are briefly described and discussed in section 2.2 and section 2.3.

2.1. History

Dynamic capacity allocation is a relatively new area, with the first publication being released by Berge and Hopperstad in 1990. This concept, titled Demand Driven Dispatch (further discussed in section 2.4) was a concept released by Boeing [8]. This concept would be a part of the airline planning process, taking part after the initial fleet planning and schedule development as seen in Figure 2.1. This concept took advantage of the so called "rubber" aircraft. That is a series of aircraft each with a varying capacity, but with the same foundations. This would mean that an airline could have a family of aircraft that could serve different markets, both large and small. In addition to this, the airline could use the same set of pilots without having to extensively retrain them, or in some cases they would not have to retrain them at all. Following the theoretical conception by Boeing, the next logical step was implementation at an airline. There have been several implementations at major airlines around the globe each showing promising results [31] [22]. Current research has been aimed at improving certain aspects of the overall model, which include creating a more detailed revenue management model. Knowing this, there are still gaps that have not yet made a major presence in dynamic capacity allocation. These gaps include maintenance constraints and expanding the area where this dynamic capacity allocation is applied. Current trends have looked at swappable loops within a network, or simple point to point schedules, and the stochastic nature of passenger demand [26] [9].

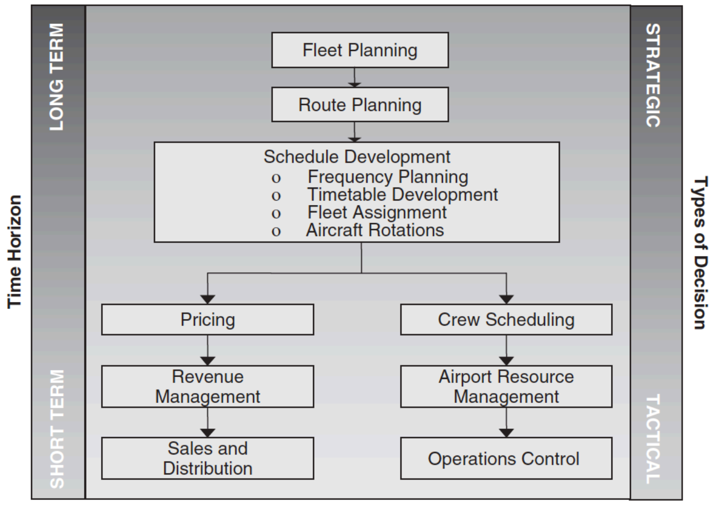

Figure 2.1: The airline planning process [4]

2.2. Dynamic Programming

Dynamic programming is a multi-stage decision process making tool, and an alternative to linear programming. Dynamic programming looks to take a large problem and reduce it in size and dimension, therefore making a complex process simpler for computer programs to use [15]. This technique uses a divide and conquer technique to create smaller sub-problems [13]. A visual representation of this can be seen in Figure 2.2

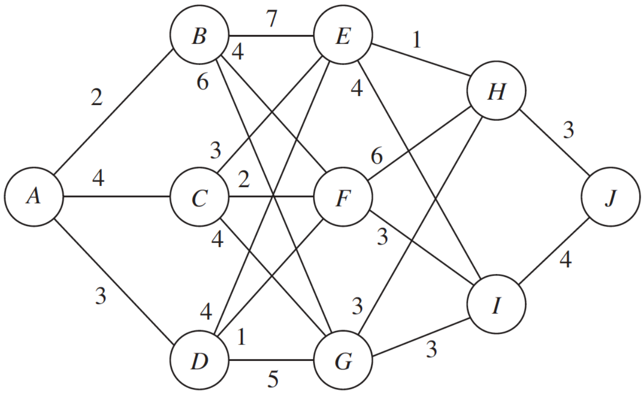

Figure 2.2: Dynamic programming [20]

Dynamic programming is one of a few ways that the fleet assignment problem can be handled, with the other being the use of a time-space network (as discussed in section 2.3). In scheduling, there is not a significant amount of research that looks at the use of dynamic programming as a tool. Most research has looked at using linear programming as a main tool. This is due to the fact that scheduling and fleet assignment is composed of linear constraints and integer decision variables, making linear programming a clear choice. This is not to say that there has been no research, one of the first publications that has looked at dynamic programming as a tool is that of *Bomberger (1966)*. This publication looked at minimizing the cost formulation for a network, and did find favorable results over the alternative at the time.

Additionally, there does not appear to be much if any research that uses dynamic programming as a tool for dynamic capacity allocation. Knowing that this gap exists, it could prove useful to include this method as the main method for the fleet assignment problem. It would thus be of interest to see whether or not dynamic programming is a useful method for dynamic capacity allocation. The main investigations would be to see whether or not there could be any time savings, and if a feasible solution can be achieved.

2.3. Time-Space Networks

Time-space networks are a method that is used to represent a schedule map with possible schedule alternatives. These networks are a key part of any fleet scheduling and allocation problem. These network diagrams are key for dynamic scheduling as they can be continuously manipulated and the effects are shown. Time-space networks are made up of different arcs and nodes, specifically with air transport there are two main arcs, these are called flight arcs and ground arcs. A flight arc represent a flight leg with a departure location and an arrival location, inclusive of this is the duration of the flight plus turn time. The turn time is represented by the arc's destination node. A ground arc represents the aircraft on the ground during the period spanned by the time associated with the end nodes of the arc [4]. A visual representation of a time-space network can be seen in Figure 2.3 where time is represented along the x-axis and the different vertical lines (BOS, LGA, ORD) are the different locations in space.

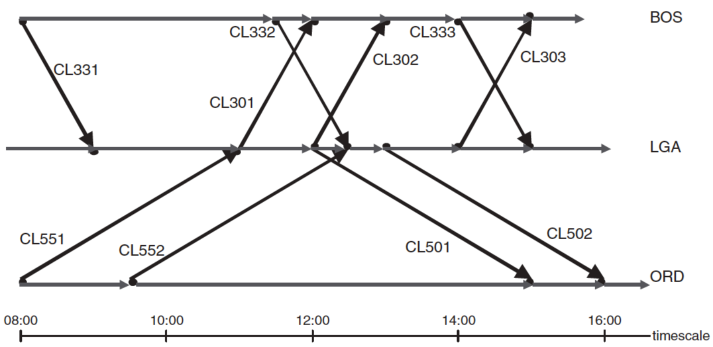

Figure 2.3: Time-space network [4]

As an airlines schedule and fleet assignment is made up of different constraints and integer decision variables, most models that are being used by airlines consist of time-space networks. In an early paper by *M. Etschmaier and D. Mathaisel (1984)* it was determined then that in order to produce any meaningful results in terms of scheduling, it was needed to represent the airlines schedule in a considerable amount of detail, thus the need of a time-space network representation [16]. Following this, further research continued towards solving these scheduling problems, albeit with larger sets of data. In a publication by *Rushmeier and Kontogiorgis (1997)*, a more advanced formulation was created for USAir that would solve large scale problems, would avoid any infeasibilities, and represent connection possibilities by accurately representing connection times. This next evolution did prove promising, with results showing solutions being generated in under an hour on average, and savings of $15 million USD (all in 1997). Further research is still dedicated towards improving the way that a time-space network is used and attempting to make it more efficient, in terms of computing efficiency [32]. As time has gone on and research within time-space networks has evolved, most of the basics remain the same. The time-space network is still an effective tool for fleet and schedule planning, however the evolution has been directed towards being able to do more than just initial schedule development. In the paper by *Sherali et al. (2006)*, they reviewed at all current work that has looked at integrating maintenance routing and crew scheduling with the initial solution, integrating forecasts into the model, as well as a dynamic fleet assignment throughout the booking period [35].

Overall there has been a significant amount of research poured into time-space networks and their applications with the airline industry. Current gaps and trends continue to look into making this a more robust system that is not just limited to initial fleet and schedule assignment. Such gaps include looking at how through-flights can be incorporated, looking deeper into maintenance scheduling, and recovery. At the moment, time-space networks seem to be most widely used in the category of dynamic capacity allocation as they have been extensively researched and they do provide great results. This is not to say however that time-space networks should no longer be looked into as continued research can still prove useful in this area. One of the gaps would of course be looking at computational time, is it possible to have this method become faster? If so this would become increasingly appealing as it could become more widespread and more widely used.

2.3.1. Fleet Assignment Model

In the airline industry, one of the biggest applications of the time-space network, is the fleet assignment model (FAM). This is of course a general name for any fleet assignment and is not just limited to time-space networks, but in this section the time-space network version of the FAM will be discussed. This version of the model makes use of linear programming and mathematical optimization to assign different aircraft to particular flights. This has been widely used, with some of the first major publications being written in the last century. It has thus had time to grow and evolve. In some of the first versions there were difficulties, such as with the timing of flights. In the paper by *Subramanian et al., (1994)* [38] complications arose when modeling turn around times for flights. A computerized optimization problem isn't able to determine when an aircraft is ready to depart, they simply only had a standard turn around time but failed to implement taxi times and any of the time in between servicing. This was something that has since been incorporated into most time-space network fleet assignment models. Most research has since evolved to continue expanding the capabilities of the fleet assignment model, with a recent paper by *Kenan et al. (2018)* looking at how uncertainty plays a role in the model. With their use of a stochastic programming model they were able to find promising solutions while accounting for uncertainty in demand [24]. As with most fleet assignment models however, gaps still exist when attempting to account for other problems such as crew scheduling. Future research does appear to be working on integrating these other problems with the initial fleet assignment models.

It is important to note that the use of the fleet assignment model with time space networks have had a significant impact on the industry. With the implementation of this model savings were widely noticed across the airline industry. Notably American Airlines found a 1.4% improvement in their operating margins [1], Delta Air Lines achieved annual savings of $100 million per year [38], and USAir found annual savings of $15 million per year [32].

2.4. Demand Driven Dispatch

Demand driven dispatch, sometimes referred to as DDD or D^3, is a concept introduced by *Berge and Hopperstad (1993)* during their time at Boeing [8]. This is a technique that is used by airlines as a way to dynamically manage their fleet to get the aircraft that is most proper for a certain flight. This means that the schedule is periodically changed in order to match the aircraft with the right amount of seats for the given demand on a particular day for a particular flight [17] or simply match the supply with the demand. The conceptual flow of D^3 is shown in Figure 2.4. There are multiple different strategies for D^3, the strategy that includes its detailed pairing with revenue management will be described fully in chapter 4. Most other methods take a simple approach to revenue management, or either ignore it. Furthermore, in order to properly implement D^3, a few prerequisites were determined. These are listed below [8].

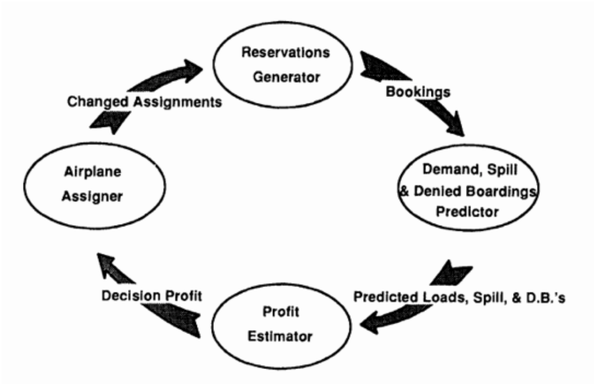

Figure 2.4: D^3 Conceptual Flow [8]

- Aircraft family with two or more planes with different seating capacities
- Computerized yield management systems
- Computerized reservation systems
- Sufficient computing power and algorithm efficiency

As schedules are made in advance and these schedules are sent to other departments such as crew scheduling, it can be quite difficult to update that schedule with a completely new aircraft. The big issue with swapping an aircraft in a route mainly lies with crew planning. Flight crew, especially pilots, are typically only certified to fly one type of aircraft. This then means that they can fly an aircraft within a family of aircraft, for example any aircraft within the Boeing 737 family. For these reasons, D^3 is limited to swapping aircraft only within the same family as any other swap would have to mean a rework of crew scheduling and other big optimization problems [9]. Other requirements such as computerized yield management and reservation systems are needed in order to allow for ease of aircraft change. These systems will make swapping an aircraft seamless in the eyes of a passenger and for a reservation agent. In one of the earlier papers by *Bish et al. (2004)* [9], they looked at D^3 in a simple way. They looked to avoid complicating the network by only looking at routes that are easily 'swappable'. That is which loop consists of a simple round trip flight originating and ending at a common airport with similar time frames so that the swappable aircraft can be easily swapped for a simple loop. Some solutions to solve this problem can be to create a soft constraint in the original FAM to help create more swappable loops [34]. Thus as can be seen, there are certain conditions and aspects that must first be taken into account when looking into D^3 as a technique to optimize capacity for routes.

According to *Bish et al. (2004)* [9], D^3 has three main swapping strategies, these are listed below:

- Limited swapping strategy
- Multiple swapping strategy
- Perfect information swapping strategy

Limited swapping strategy allows for a swapping decision to be made once before departure, typically 4-6 weeks from the day of. This strategy does not allow for a swap to be revisited. Multiple swapping strategy is again made at a specific period before departure (4-6 weeks) but can be revisited multiple periods before departure based on updated demand forecasts. The perfect information swapping strategy is the most ideal strategy, which is why it can also be referred to as the upper bound. This theoretical strategy assumes perfect information on realized demand, thus any potential bad swaps are avoided. As far as is known, this strategy has not yet been implemented in reality. Depending on when the swap is done, it could be possible that the initial fleet assignment and crew scheduling has not yet been done, thus leaving the possibility to swap an aircraft that is outside of the original family.

Some other strategies that do not look at swappable loops, instead look at the possibility of leveraging retiming. In the paper by *Jiang and Barnhart (2009)*, they looked at the retiming of flights. That is, manipulating the departure times of flights and shifting them in a certain time window order to refleet flights [23]. With this strategy, again there are a period of reoptimization points before the day of departure. This shows that a continual reoptimization strategy is not effective and is instead costly. It is simpler and easier to select a time period before departure, or multiple time periods before departure. By shifting the time it is noted that there is the possibility of passengers itineraries becoming infeasible. However, by the creation of these time windows the impact to the customer is limited. Such a model for a retiming D^3 strategy can look like Figure 2.5.

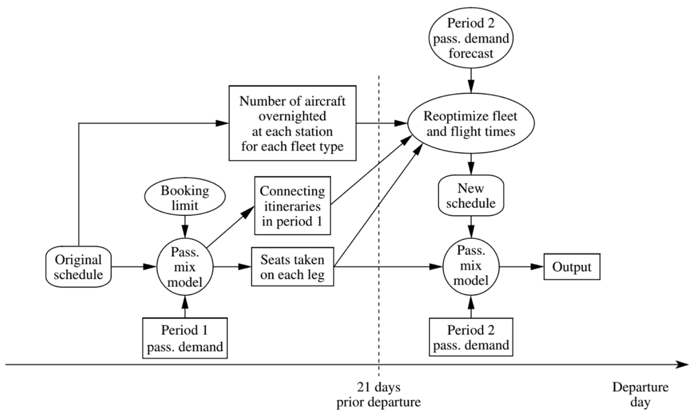

Figure 2.5: D^3 Retiming Conceptual Flow [23]

Overall, with D^3 it is found that there are near consistent improvements of 1-5% in operational profit [34]. It is noted however that D^3 is not as simple as it might sound, with multiple other complications to consider before attempting to implement. These complications mainly come from crew scheduling and maintenance scheduling problems. For research purposes however, it is possible to set aside those advancements until further initial research has been done.

Overall D^3 can be very beneficial depending on the usage case and how it is implemented. With D^3 load factors can be improved, as well as yield and revenue. There still remains gaps, namely those attempting to integrate crew scheduling and maintenance scheduling, however current trends look to improve on the revenue management model that is incorporated, as well as looking to make the programs more computationally efficient.

2.5. Conclusions

Dynamic scheduling can be a useful approach to reallocating certain aircraft types to certain legs. Overall there are multiple different approaches, namely those of either dynamic programming or the use of linear programming to create a time space network optimization model. These two approaches are simply tools to achieve what is needed, which is to optimize which aircraft is assigned to which flight leg. This concept of dynamic fleet scheduling is highlighted in demand driven dispatch. This method, created initially at Boeing [8] looks to use a "rubber" aircraft to more closely match demand with supply. By doing so, it can be ensured that costs are minimized and revenue is maximized. Most work has looked at this problem, however with a simplistic revenue management approach [9]. Even with certain key elements simplified, these versions have still managed to create scenarios in where revenue is improved, with some airlines showing improvements of 1 to 5 % [40]. Current trends look at continuing to find new and effective swapping strategies, and some are also looking at increasing . Some research has looked at including more detailed revenue management models, those are described in chapter 4. Other areas of research have looked at the different ways to expand the research, such as looking at a competitive analysis [18] or using machine learning [41].

3
Revenue Management

Revenue management, commonly referred to as RM and also known as yield management, is the scientific application of analytics and operations research to help a company achieve and manage the most revenue for their product or service. The goal is to sell the right product at the right price to the right customer at the right time. There are many applications for revenue management, but the biggest and most common problem is that of the airline RM application. In the context of this literature study most applications that will be discussed will be based on airline RM problems and solutions. Firstly, a brief history of RM will be given followed by the key areas of what RM is made up of will be explained. Following this the first RM model will be explained and further innovations and the current state of RM will be explained.

3.1. History

RM has its beginnings around 50 years ago with a model created by Littlewood while he worked at BOAC (now British Airways). Shortly after this, American Airlines began using this concept to create a new lower fare class, this was done shortly before deregulation. However, as deregulation happened most carriers began seeing the potential of RM and began integrating it into their business model. Before the introduction of RM most airlines simply focused on controlling overbookings, through time however airlines started to experiment with creating lower fares with more restrictions and mixing these passengers with those higher paying passengers in the same cabin. With this came the introduction of Littlewood, and shortly after having a simple single-leg control, RM advanced to segment control, and then on to origin-destination control and beyond. As the success became noticed, more airlines began looking into RM and creating their own RM departments to help optimize their revenue brought in on each flight [29].

As is seen in Figure 2.1, RM is a continual step that occurs after fleet assignment. This is because there needs to be a known number of seats, or inventory, available to help better plan the pricing. Of course inventory is not the only thing needed for pricing, but a wide range of factors including the details of the specific flight leg that is being taken on [4]. When looking into airline bookings it is important to know that typically leisure travelers book far in advance, while business travelers book closer to the point of departure. From this it is typical that leisure travelers are less flexible in terms of price whereas business passengers are more willing to pay a higher price for their ticket. Having this known plays a key part in RM, mainly having the biggest problem spelled out, how to maximize the revenue for each flight without missing on earning potential from all customers [29]. An example of this trend can be seen in Figure 3.1, where it is seen that bookings and price tend to increase significantly as the day of departure nears. RM from the perspective of the passenger can be seen in Figure 3.2 where they can either get their booking request approved or denied, leading them to a different fare. With advancements in science, including statistics, operations research, and economics, paired with advancements in IT, including greater computing power and advanced programming, RM has been able to advance significantly since the 70's. These advancements have allowed RM to improve to its current state but also allow for future improvements, making the field such an important part of the industry [39]. Large airlines would be at a significant disadvantage if they did not invest in creating a proper department.

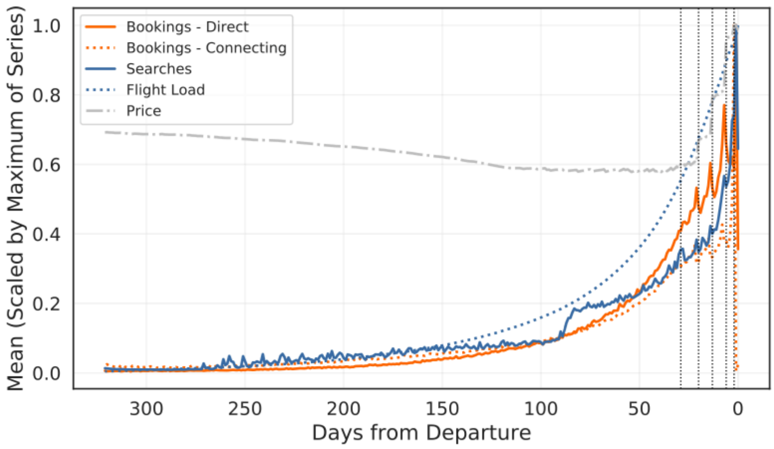

Figure 3.1: Search, bookings, and prices over a full booking horizon [21]

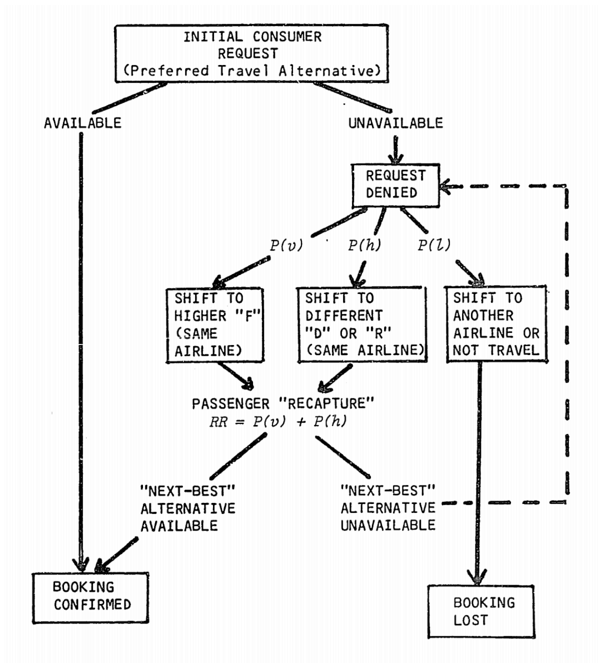

Figure 3.2: Booking process from the customer and airlines perspective [5]

3.2. Key Areas

In a paper by *McGill & Van Ryzin (1999)* where they went over what RM is and its prospects for the future, they listed four key areas that any analyst should be aware of. These areas are forecasting, overbooking, seat inventory control, and pricing [29]. This information will be supplemented with information explained in the book *The Theory and Practice of Revenue Management* by *Talluri and Van Ryzin (2004)* [39]. These topics will be discussed in the following sections.

3.2.1. Forecasting

Forecasting is the way that airlines are able to estimate just how much demand a certain flight will have and by when they will have that demand. Generally based off of historical data that the airline already has, they can use forecasting to help in RM. By knowing how many passengers the flight might have they can first already know what size the aircraft should be, but after this they can also estimate how many high-paying passengers there will be and how many leisure low-paying customers they will have. In addition to this data, they can also estimate how many passengers will cancel their itineraries, how many passengers will be no-shows, that is passengers that buy a ticket but do not show up for a flight thus leaving an empty seat on a flight. This empty seat is important because that is a seat that could have been sold, thus extra revenue [29]. This leads to overbooking which will be explained more in subsection 3.2.2.

There are different models to help estimate forecasting, studies, such as the one by *Shlifer and Vardi (1975)*, which shows that a normal probability distribution gives a good aggregate demand approximation [36]. However it has also been pointed out that the normal distribution becomes increasingly inappropriate at higher levels of disaggregation. Thus most models use a Poisson distribution, as the memoryless property is useful for the dynamic nature of demand [29]. Due to the nature of the data that forecasting uses, there are issues, namely that with censorship. Historical data can only provide information up until booking closes, that is when all the seats have sold or at the day of departure. Therefore, it is possible that there could have been more demand for a particular flight, but this is not known due to inventory being empty. In a thesis by *Sa (1987)* [33] it has been pointed out that regression is a better technique to improve the performance of RM systems. It is unknown what method most airlines use to create their forecasts as a forecast is a key part of RM, but it is assumed that most methods involve a simple smooth moving average of historical data [29]. In a recent paper by *Balaiyan et al. (2019)*, it is shown that current trends in forecasting look at parametric joint forecasting models, mixing demand on O&D markets, booking curves, and seasonality. These models can thus be considered dependent demand models [2].

3.2.2. Overbooking

Overbooking is the process of selling more than there is available. It is actually estimated that 15 % of all seats would be spoiled without some form of overbooking [37]. An example of overbooking limits and reservations can be seen in Figure 3.3. As can be seen, without having overbookings an airline can greatly miss out on extra revenue as they will simply leave with an empty seat.

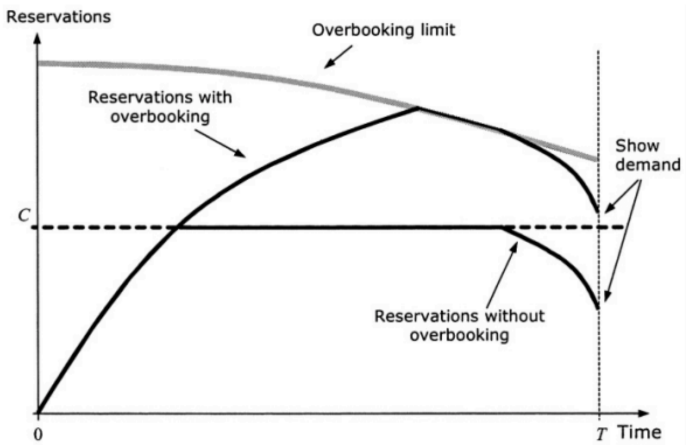

Figure 3.3: Overbooking limits and reservations over a full booking horizon [39]

There are multiple different models that can be made for overbooking, including static, dynamic, and combined capacity-control and overbooking models [39]. Static models are the simplest and take both cancellations and no-shows as the same. These static models simply determine the maximum number of reservations to hold at a given time given estimated cancellations and no-shows from that point on until the day of departure. These include simple binomial models and approximations. Dynamic models account for the dynamic nature of cancellations, arrivals, and the decision making that is needed. Such models include exact approaches and heuristic approaches. The final model is the combined capacity-control and overbooking, these models involve looking at either exact approaches for no-shows and cancellations or class-based approaches for no-shows and cancellations [39].

Current research points towards dynamic optimization program with the objective to determine a booking limit for each time period before flight departure that maximizes revenue for that specific flight [29]. Other papers, such as the one by *Kunnumkal et al. (2012)* [25] look to create a randomized linear programming model to jointly make capacity control and overbooking decisions which has been shown to create tighter upper bounds and higher profits compared to other benchmarks.

3.2.3. Seat Inventory Control

Seat inventory control, or capacity control, is the way in which a single class of service is split into different booking classes. That is, how the same seat can be sold at different price points as well as how and when to control that limit. This is a key element in RM as inventory control helps determine just exactly how much a certain flight can make. This is an element that has been extensively researched going from Littlewood's in 1972 to expected marginal seat revenue (EMSR) around twenty years later. One of the biggest differences between Littlewood's and EMSR is the fact that Littlewood's only deals with two fare-classes whereas EMSR can have multiple fare classes. However, as both are quite significant to RM they will be discussed in detail in subsection 3.4.1 and subsection 3.4.2.

Most early research consisted of focusing only on single-leg seat inventory control where researchers simplified the problem, simplifying assumptions such as sequential booking classes, arrival booking patterns, and single flight legs without considering the network effects [29]. In addition to the early research, there are other papers taking a dynamic programming approach to this problem and others have related this problem to a series of special cases of certain stochastic knapsack problems [29]. Altogether, the single-leg seat inventory control problem has been shown by *Brumelle and McGill (1993)* that under the given assumptions, the inventory control problem is a monotone optimal stopping problem and therefore static control limit policies are optimal over the class of all control policies [10].

The next set of research that was considered for inventory control, was that of segment origin-destination control. Thus looking at a key element that was relaxed in the single-leg control problem. The issue that makes segment and origin-destination control complex arises from volume. There are potentially hundreds of itineraries for a single leg of a flight, and these will have to be mapped into much smaller controllable booking classes [29]. One of the more straightforward solutions to this is to use mathematical programming. These typically solve for a minimum cost network flow problem where passenger demand is deterministic, so the formulation focuses on the effects of the network. An issue that does arise with this solution is the fact that the solutions produced are non-nested allocations. Nested allocation is the containment of different fare classes (of the same hard product) within the highest fare class. This will be further explained in section 3.3. Other solutions use segment control, that is to control bookings at the segment level, allowing for multi-leg revenue so long as an itinerary does not involve connections between two or more flights. Virtual nesting is another example solution, one that was developed to accommodate the number of controllable booking classes. The other solution explained is to use bid-price models. This again uses a linear programming formulation to create a bid-price for an itinerary. With this a booking request for a passenger can be rejected if the bid price exceeds the fare for the itinerary, or accepted otherwise [29].

3.2.4. Pricing

Pricing is the fare management policy of an airline, or simply put, how an airline decides to price different tickets for their flights. The existence of this differential pricing is considered the starting point for RM, as the price of a ticket is what will drive a consumer. Knowing this it is clear that there is a duality between capacity and price, as price is the variable this will determine how many seats can be filled in a certain booking class, if it is too high then the price will have to be driven down as the demand has not yet reached that point. Some other characteristics of pricing include demand being nonstationary, competitive analysis, and stochastic selection. This all plays into pricing as any of these elements can mean that a flight is priced too high, meaning revenue will be lost due to not enough customers, or the flight could be priced too low meaning revenue will be lost [19].

3.3. Booking Limits

Booking limits are a feature of RM that limit the capacity that can be sold at any point in time for any class of service. Booking limits can either be partitioned or nested. A partitioned booking limit simply divides the available capacity into separate fare buckets, one for each fare class that can only be sold within that designated class. This is the simplest form of booking limits, but as such, does not allow an airline to perform as well as it can [39].

Nested booking limits are more complex, but allow for a higher revenue to be achieved. These limits overlap in a hierarchical manner which allow for the higher fare classes to have protection limits as well as access to all of the capacity that is set for the lower fare classes. In this case an analyst can decide to close lower fare classes early even if they might have not filled up, allowing for an airline to maximize its revenue on routes that might have a sudden increase in demand. This visualization can be seen in Figure 3.4. It is important to note as well that these different fare classes are all for one class of service, an example of this can be seen in Figure 3.5, where it can be seen that each class of service (Coach, Business, First) has multiple different fare class codes, each representing a different price for the same hard product. Booking limits and nesting have evolved over time to be an integral part of any RM model.

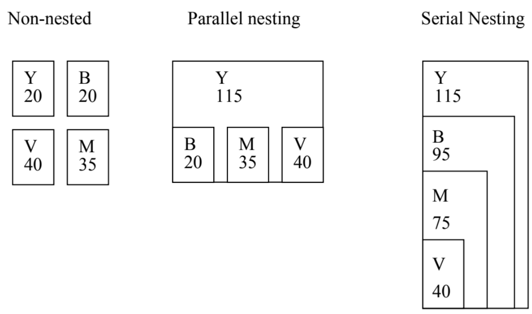

Figure 3.4: Nested booking limits [12]

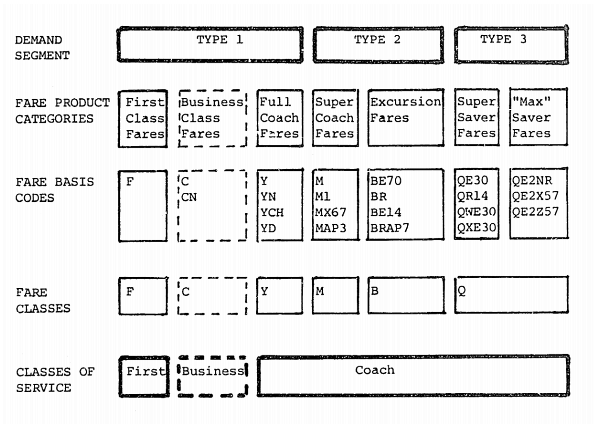

Figure 3.5: Fare Classes[5]

3.4. Modeling

Throughout the history of RM there have been a number of different models and heuristics developed, however there are two major models and heuristics that have created the most impact. The first ever model developed was that by Littlewood, which paved the way for RM [30]. This is the first model described below. Following this, Belobaba developed his Expected Marginal Seat Revenue (EMSR) heuristic, this heuristic still in use today was the next advancement in RM, will be described further below. Lastly, the use of stochastic programming in RM will be described as well as its benefits.

3.4.1. Littlewood's Model

Littlewood's model is the earliest model that was created for quantity-based RM. This static single-resource two class model was developed by Kenneth Littlewood while working at BOAC (now British Airways). As it is an early model there are some assumptions that make this model easy to implement, the biggest simplifications are that there are no cancellations or overbookings [29].

Littlewood's model is a basic model involving inventory theory and marginal analysis. This model is based on simply equating the marginal revenues from both fare classes, once these are equal then the low-yield fare class will close. This can be seen in Equation 3.1

$$(1-P) \leq \frac{r}{R} \tag{3.1}$$

Where r is the low yield fare, R is the high yield fare, and P is the maximum risk that the acceptance of a low yield passenger will result in the subsequent rejection of a high yield passenger [27]. Thus, low yield requests should continue to be accepted until $1-p$ reaches the value of the ratio of the mean revenues from low yield and high yield passengers. If the acceptance of low yield passengers is stopped sooner the higher fare will be offered to the high yield passenger, if the acceptance is stopped later then the lower fare will be offered to the high yield passenger. This equation can also be rewritten as Equation 3.2 with F being a continuous distribution to model the demand and y is the optimal protection limit. This concept can thus be seen as setting booking class protection levels [30].

$$y_1^* = F_1^{-1}\left(1-\frac{r}{R}\right) \tag{3.2}$$

3.4.2. Expected Marginal Seat Revenue

After the introduction of Littlewood's model, there was need for a more robust model, one that would be able to handle more than two classes, this is what Belobaba wanted to achieve with his expected marginal seat revenue (EMSR) model/heuristic. The first version was created in 1989 and labeled EMSRa. This model, originally developed in a doctoral thesis, aimed to create a decision framework that could be applied to multiple nested fare class inventories [5]. Again, the goal with EMSR is to determine how many seats not to sell in lower fare classes so that there can be a possible sale in a higher fare class, thus generating more revenue for the flight. The protection level for the higher fare classes is what is set out to be determined. Previously it was assumed that there is no relationship between demand levels for different fare classes, in EMSRa this is also the case, it is further assumed that a customer denied a fare class request represents a missed booking opportunity [6]. To determine the EMSR of the S_ith seat the following formulation can be used:

$$EMSR(S_i) = f_i \cdot \overline{P}_i(S_i) \tag{3.3}$$

Where the EMSR for the S_ith seat is entirely dependent on $\bar{P}_i(S_i)$, the probability that the S_ith seat made available to class i will be sold and f_i is the fare level [6]. In Figure 3.6 a graphical view of the equation above can be seen. In this BL stands for booking limit, s_2^1 are the seats protected from class 2 and available exclusively to class 1. Visualizing this, it can be seen that the optimal protection limit for s_2^1 is where the EMSR(S_1) curve intersects f_2.

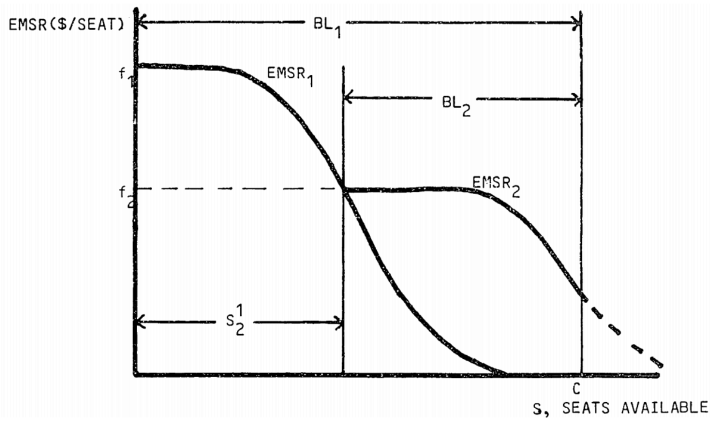

Figure 3.6: 2-Class nested EMSR example [5]

These protection levels are then able to give the booking limit on each fare class j with Equation 3.4:

$$BL_j = C - \sum_{i=1}^{j} S_j^i \tag{3.4}$$

With C equal to capacity. Having the booking levels known, the nested protection level for class j is determined by:

$$NP_j = BL_j - BL_{j+1} \tag{3.5}$$

This then means that the capacity should equal the following:

$$C = \sum_{j=1}^{k} NP_j + BL_k \tag{3.6}$$

One of the issues with EMSRa is that its protection limits are too conservative, thus leaving a large number of low fare bookings unavailable. This led to the development of EMSRb. In a presentation given by Belobaba to an AGIFORS symposium, the EMSRb heuristic was given. This was a modification to generate joint protection levels for higher fare classes. Firstly s_j^n is given as follows:

$$s_j^n = \text{Total seats protected for all classes} n < j \tag{3.7}$$

The aggregated mean demand levels are given as:

$$\overline{X_{1,n}} = \sum_{i=1}^{n} \overline{X_i} \tag{3.8}$$

With the aggregated standard deviation being:

$$\overline{\sigma_n} = \sqrt{\sum_{i=1}^{n} \hat{\sigma_i^2}} \tag{3.9}$$

This leads to the aggregated fare levels for the combined fare classes being:

$$f_{1,n} = \frac{\sum_{i=1}^{n} f_i \overline{x_i}}{\sum_{i=1}^{n} \overline{x_{1,n}}} \tag{3.10}$$

Thus the total protection for all aggregate classes when $i \leq n$, where $n = j-1$ is s_j^n

$$EMSR_n(S_j^n) = \overline{P_n}(s_j^n) \cdot f_n = f_j \tag{3.11}$$

Booking limits for each lower class j are thus given by:

$$BL_i = C - s_j^n \quad \forall j > 1 \tag{3.12}$$

These above equations allow for protection levels, booking levels, and fare levels to be determined for various different fare levels [7] [28].

3.5. Conclusions

Revenue management started off as a way to control inventory and pricing, ensuring that each flight had its revenue maximized and that all potential passengers were captured ranging from leisure travelers to business travelers. Most of the early years in revenue management was spent understanding how it worked, and how it could be used across the networks that airlines had. The advancement of models has also played a large role in understanding booking limits and protection levels. These different levels helped ensure that certain fare classes would not be sold out by the time a flight was nearing its capacity. Current research is aimed towards continuing to transform revenue management. Such trends include dynamic pricing, using machine learning, and incorporating ancillary pricing into revenue management [11].

4

Combining Dynamic Capacity Allocation with Revenue Management

Dynamic scheduling, as was described earlier, is the process of continually updating and evolving a schedule for an airlines network. Revenue management is the science of optimizing the mix of fares sold to help maximize the revenue for a particular flight. These two processes alone are very powerful and can help either save an airline money, or increase revenue. Therefore both look to help an airline increase its profit. In this section we thus explore the existing literature that has researched and tested the possibilities of combining both dynamic capacity allocation with revenue management. The current status of this work will also be analyzed, followed by the gaps in the research and what can be researched next.

4.1. Integration

There are two models that are key for the integration of dynamic capacity allocation and revenue management. The first would be that of the fleet assignment model, the one that assigns a fleet to a specific route. In the case of demand driven dispatch, it is possible that an initial fleet assignment model is made therefore for this case the FAM can be simplified. Simplifying can be done by eliminating different types of constraints that are no longer needed [18]. The other part of integration is of course with revenue management, as this process is an ongoing process done up until the point of departure, there is not much simplification that can be made. There is however a choice of models that can be used, ranging from EMSRb to displacement adjusted virtual nesting (DAVN) to probabilistic bid price control (ProBP). These models are in reality up to the airline and what is currently in use, but for research purposes all can be analyzed to see which combination yields the best results. These models should contain an advanced forecasting tool to accurately provide results [14]. In addition to this, it should be noted that an airline should have a fleet family to fully realize the integration of dynamic scheduling and revenue management. Having a fleet family, such as the Boeing 737 or A320, allows for flexibility in capacity without sacrificing pilot commonality.

The basic structure of this integrated model begins firstly with an airline schedule, with the fleet assignment model already completed. This ensures that the route network has an aircraft with a given capacity assigned. Following this stage is the opening of the booking period. Using an RM model, booking limits are set and the demand forecast is updated as bookings roll in and time advances. With an updated demand forecast it then becomes possible to revisit the fleet assignment model, the fleet assignment model can be ran again with an updated forecast and an aircraft swap can be made if it is found to be beneficial. This process can be repeated up until the end of the booking horizon until the flight has closed. An example of this flow can be seen in Figure 4.1.

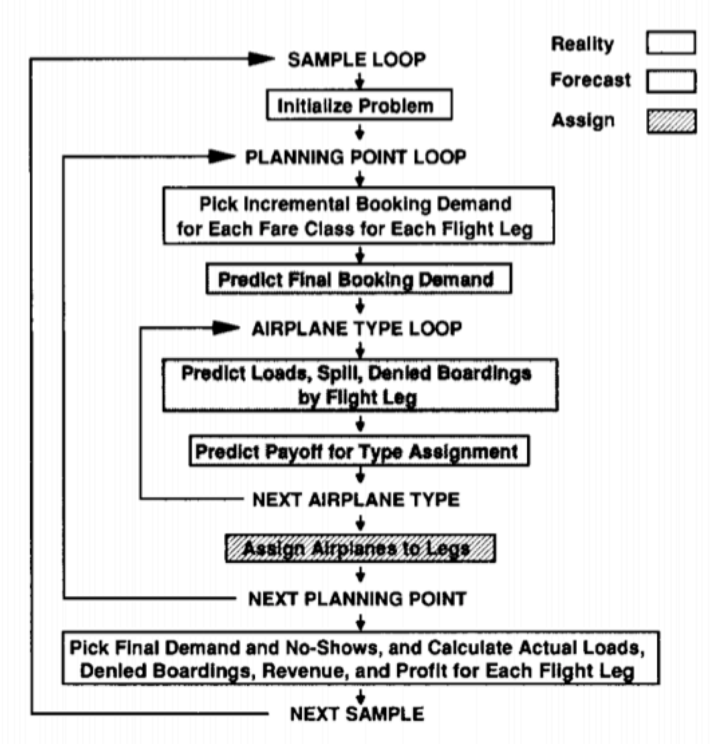

Figure 4.1: Integrated D^3 & RM conceptual flow [8]

4.2. Methodologies

When it comes to combining dynamic scheduling and revenue management, there are different strategies that can be implemented. As these strategies are different they each bring different results as well as different constraints and impracticalities. Some of these methodologies have already been worked on, their results will be discussed below.

4.2.1. Delayed Fleet Type Assignment

One of the first formulations that was developed for D^3 and RM was that of a delayed fleet assignment. This combined D^3 and EMSRb to see what effects this would have on an airlines revenue. This algorithm, created by *Cots (1999)* [14], proposed a postponement of the solution of the FAM until one of the flight legs registered at least one spilled passenger from any fare class. The issue that was noticed however is that without an initial aircraft there are no booking limits set, therefore protection levels can not be created which can lead to an unoptimal solution. The solution is then to use two virtual capacities. These will be set at either the minimum number of seats, representing the smallest aircraft in a family, or it can be set at the maximum number of seats, representing the largest aircraft of the family. The main benefit of using this strategy is that an airline can avoid solving the FAM multiple times, thus saving time and money when creating an airline schedule, as the FAM is typically a large problem.

This problem creates two possible objective functions, either total spill minimization, or revenue maximization. To simplify the analysis of all the possible different sub-algorithms, a constraint was introduced that ensures that if a flight has already reached a certain amount of bookings that exceed the minimum number of seats, that flight can not be assigned that aircraft, this is to avoid spillage. A base case was created in the thesis of *Cots (1999)* [14] to give a baseline for results. This base case removes the chance of a swap, thus treating it as a regular schedule without the implementation of D^3. This base case made use of EMSRb for its RM portion of the model. The other cases looked at implementing both the maximum virtual capacity, and the minimum virtual capacity with either maximizing revenue or minimizing spill.

The results from the 500 simulation runs of the thesis of *Cots (1999)* [14] are shown in Table 4.1.

Table 4.1: Results from delayed fleet type for 500 simulation runs

	Base Case	Max Revenue Min Capacity	Max Revenue Max Capacity	Min Spill Min Capacity	Min Spill Max Capacity
Total Demand (Avg Passengers)	223.40	224.78	226.02	224.73	226.02
Total Revenue ($)	27897.53	28033.89	28087.40	28023.83	28087.40

These results show that demand driven dispatch does provide benefits in terms of both increasing demand and increasing revenue. This simulation only included two different flights, but even with it is seen that revenue can be a few percentage points. It does show that the best performing cases were that where maximum capacity was used for the initial virtual capacity, but it is noted that this strategy does have an inherent risk, namely in that spillage is more likely to happen in this scenario as you begin with the highest capacity for both flights, when in reality you do not have the inventory needed.

4.2.2. Bookings Based Swapping

In the thesis of *Fry (2015)* [18], an intuitive solution was proposed, this methodology consisted of looking at flights and ranking then by their estimated bookings at departure. In this thesis, the effects of competition were also analyzed. Cases where only one airline used D^3 as well as where both used D^3. This thesis thus gives further research into the effects of competition as well as dynamic capacity allocation with an advanced RM model. In this initial strategy, swaps are based on the current amount of bookings at the time of the swap. This way the flights that are estimated to have the highest amount of bookings could be assigned the larger aircraft. It is pointed that this method might not be optimal, but it is intuitive and simple, therefore provides a good option to see if any improvements can be had with D^3. This solution works by using D^3 at various different booking periods. At the different booking periods the bookings that have been received will be used, as well as updated forecasts to determine how many estimated bookings are still to come. These two numbers are then summed to find the total bookings estimated at departure. This model uses an EMSRb based RM system to help determine future forecasts and protection levels, however this method can use any RM system.

It was determined, that in a competitive setting when one airline uses D^3 and the other doesn't, that airline will experience an increase in total revenue while the other will experience a decrease. However, when both airlines implement D^3, both airlines will experience an increase in revenue, but at a significantly lower rate, creating a Nash Equilibrium [18]. This creates a case where bookings based swapping can be useful, but may not prove to be the best implementation method.

4.2.3. Network Optimization

Another methodology proposed by *Fry (2015)* [18] was to use a network optimization model that is used for the fleet assignment to help drive D^3 and RM. The network optimizer that is used in this case is a minimum cost flow problem. Where each aircraft is modeled as a left node and each pair of flight legs are modeled as a right node. This can be seen in Figure 4.2.

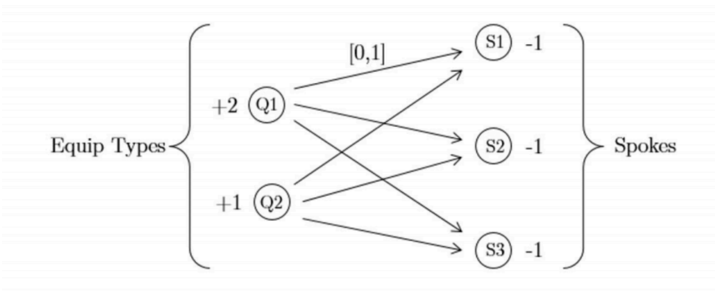

Figure 4.2: Minimum cost flow [18]

The way that this is then optimized is by looking at the incremental revenue to come (RTC), as formulated in Equation 4.1. Where $Inc_R TC_{Q2}$ is incremental revenue to come for aircraft type Q2.

$$IncRTC_{Q2} = RTC_{Q2} - RTC_{Q1} \quad \text{given original assignment is Q1} \tag{4.1}$$

With the associated cost value being constructed in a similar manor using BHC as the aircraft operating cost, and $IncBHC_{Q2}$ being the incremental aircraft operating cost of aircraft type Q2.

$$IncBHC_{Q2} = BHC_{Q2} - BHC_{Q1} \quad \text{given original assignment is Q1} \tag{4.2}$$

This then leads to the following objective function in Equation 4.3.

$$\text{Minimize} \quad z(x) = \sum_{(i,j)\in A} -1(x_{ij}(IncRTC_{ij} - IncBHC_{ij})) \tag{4.3}$$

With the decision variable being $x_{ij}, (i, j) \in A$ and the constraints being as follows:

$$\sum_{j\in N} x_{ij} = b_i \quad \text{for each i} \in \text{N} \tag{4.4}$$

$$\sum_{i\in N} x_{ij} = 1 \quad \text{for each j} \in \text{N} \tag{4.5}$$

$$x_{ij} = 0 \quad or \quad 1 \tag{4.6}$$

These constraints ensure that the fleet assignment solution must assign exactly as many of each type of aircraft that exist in the fleet. The other constraint ensures that only one aircraft is assigned to each flight leg pair. The last constraint is a binary constraint ensuring that no half-aircraft are assigned at any point. With this model it should be the case that any flight leg pair should never have a reassignment where capacity is less than the current bookings in hand at the point of reassignment. In the thesis by *Fry (2015)* [18], both EMSRb and DAVN are used for the RM portions of the model.

Following this model strategy, similar results from the earlier bookings based swapping are had. This is the case when either using EMSRb or DAVN.

4.3. Conclusions

Reviewing the work that has been done up to this point shows that while there has been progress, there is still more work that should be done to further investigate the full potential of combining demand driven dispatch and revenue management. Work up until this point has been at a low level, investigating overall how a detailed RM approach can benefit as well as how different strategies behave. These have showed results, and each iteration continues to improve. These were results given both by *Fry (2015)* [18] and *Cots (1999)* [14]. In addition, the thesis of *Fry (2015)* showed how two competing airlines, each implementing a version of D^3, behaved and how their results varied due to the fact. Thus, current trends continue to research how a detailed revenue management system can benefit D^3, seeing just how much extra revenue and profit can be had. Gaps in this field are mainly in strategies. There is still a multitude of different strategies, including that of timing. When and how many times swapping is done is still an area of interest and should continue to be investigated. How many times swapping is done, as well as when the swaps are performed can all play a factor into just how many bookings arrive, and how much revenue can be generated. Forecasting is another area that can still be looked into, seeing if a forecast should be updated periodically or if the original forecast is acceptable.

5

Problem Description

In this section the problem description and the framework will be clearly stated. This will provide the certain foundation for the remainder of the thesis project. The research problem and questions that were originally stated in chapter 1 have been supported with the literature that was reviewed in the previous chapters. With these questions supported, they will be further described and defined, along with any assumptions and simplifications that will be made.

5.1. Definitions

The problem that has been pitched throughout this literature study, and will be the basis of this upcoming thesis project, is one that has had some research done, but where there are still more questions to answer. Most of this problem has been categorized under the topic, demand driven dispatch, or D^3, however has also sometimes been categorized under demand driven refleeting. The terms **dispatch** and **refleeting** refer to the same thing, this is the process of dispatching new aircraft (or refleeting) to a specific flight leg. Demand driven refers to the fact that demand is the key element that is deciding whether a flight leg receives a new aircraft type.

Other terms, such as **dynamic**, refer to the constantly changing nature of the problem. This problem looks at demand as it evolves throughout time, thus making demand dynamic and not static. This thus makes the problem more complex as demand should be reevaluated at periodic steps, whereas currently demand is taken from historical data and that information is used to make all necessary decisions.

When considering a **network**, for an airline, this is global space that they will fly in and out of. This will consist of a set of **nodes** and **arcs**, where each node is an airport and each arc is the link between the two airports. Networks typically consist of two different types, these are the hub and spoke network, or a point to point network. The hub and spoke model uses one (or more) fixed bases where an airline will fly in and out of. Most passengers using this system will originate from one node, transition thru the hub node, and continue to their final destination node. The alternative is the point to point network, where an airline will fly directly from the origin node to the destination node that the customer desires.

5.2. Assumptions

As this problem is quite complex, there are a number of simplifications and assumptions that need to be made in order to reduce this problem into a more manageable size given the time constraints.

Initial assumptions and simplifications involve ignoring the crew scheduling problem as well as maintenance scheduling. These problems are quite large by themselves, and by introducing these problems into the main question, the problem can become too complex. This can produce noisy results, leaving the desired question to be unanswered.

Other assumptions and simplifications involve the model that will be developed. Such simplifications concerning the revenue management portion of the model involve creating a simplified version of an RM model. This simplified version will help the project focus more on the integration, rather than detailed specifics. These simplifications involve ignoring overbookings, and creating a simplified forecasting model.

The remained of the RM portion of the model will involve ensuring that it sets booking limits and seat protection levels. This model will be EMSR based, as this is a widely used model and is a very significant model with numerous amounts of research proving its capabilities.

Regarding the dynamic capacity allocation portion of the model, a time-space network will be used to help optimize the fleet. This linear programming model will be used to help formulate a fleet assignment model that will be used to redispatch aircraft after an original assignment.

Finally, when looking at the system that this model will be built around, it has been identified that a hub and spoke model will prove to be the most useful. This is one of the most used network models, so this will prove to be of greater use for future research or if an airline decides to implement this system.

6
Conclusion

The assignment that has been proposed at the beginning of this paper is that of dynamically allocating an airlines fleet with the use of an optimal revenue management system. This is a problem that has not had much research on together, yet does have a lot of work separately. It is therefore a great topic to continue further research on and further collect data on just how beneficial this joint model can prove to be.

Throughout this literature study, various existing models, techniques, and solutions were analyzed that answered pieces of the combined question. Firstly, in chapter 2, the history and existing models and methods for dynamic fleet allocation was analyzed. It was seen that fleet planning is typically the first part of planning for an airline, as this step helps other planning aspects of the airline, such as crew scheduling and revenue management. Dynamic programming was reviewed as an effective solution to this problem, albeit not necessarily widely used. This then led towards time-space networks and how they work, it was seen that the time space network was the basis for the fleet assignment model (FAM), which is how most airlines create their schedule. This model could also be combined with the passenger mix model (PMM), to create the itinerary-based fleet assignment model (IFAM). This solution, typically solved by a column generation algorithm allows for the creation of an airlines schedule as well as ensures that a passengers itinerary is complete [3]. While this model can be used for the combined problem, it is unsure how useful it would be due to how large the problem can get. This then led towards the investigation of demand driven dispatch, or D^3. This is one of the current practices that is most like dynamic fleet allocation. This method, developed by Boeing, looks at using a "rubber" aircraft, that is a family of aircraft that have different sizes but share a common rating [8]. The benefit of this method is that problems that might typically arise if a schedule is constantly redrawn, are mostly eliminated. This method looks to be the most promising basis for future study of dynamic fleet allocation.

In chapter 3, an analysis of revenue management was given. This included a brief overview of the history of revenue management, showing how it has progressed from a simple yield management technique in the 70s, progressing towards Littlewood's revolutionary model and onto Belobaba's expected marginal seat revenue (EMSR) model. EMSR proved to be very successful, being one of the most implemented models at most airlines. This simple model allowed for the creation of multiple different fare classes, allowing for cheaper fares to become available thus increasing the revenue for airlines. This model has then continued to evolve and has been introduced into different itinerary based booking systems, including displacement adjusted virtual nesting, and network probabilistic bid price control. These models are the current leading standard and will make for a great basis for future research.

Lastly, in chapter 4, the combination of dynamic scheduling and revenue management was looked at. This analyzed the current state of research, and looked deeper into the previously discussed demand driven dispatch. As it was mentioned, D^3 is a method that looks to dynamically reallocate the fleet of an airline to different routes. Most work on this has taken revenue management from either a simple perspective, or has not integrated it. In this section, there were two main papers that did integrate revenue management fully with D^3. These papers looked at various different strategies at just how to implement D^3. All of these strategies proved to be successful in their efforts of increasing revenue and profit [18] [14], however it is noted that there are still areas that can still be investigates, and that there can be other strategies that might increase revenue even further. These gaps in the research will serve as a starting point for future research in this topic, and will look to have the same percentage increase in revenue or will look to have a higher increase. These gaps have been identified throughout this study as being uncertainty in which swapping strategy truly is the most optimal, what timing strategy is the most optimal, and how should the RM forecast behave in terms of integration. Other opportunities have been identified as aiming to improve upon the computational speed that can be achieved. It is hoped that this research can improve upon computational efficiency.

7 Research Proposal

This chapter presents a research proposal for the topic that has been studied in this literature study. This will be the project planning, which will give a timeline in which the research is expected to flow as well as the expectations of the project and what is expected to happen throughout the major checkpoints.

7.1. Project Planning

To answer the question and sub-questions that have been proposed at the beginning of this paper in chapter 1, a gantt chart has been created (Figure 7.1). This gantt chart is a timeline that has the different elements of the thesis project as well as their estimated duration.

The first of these tasks is that of research and data collection. This task is estimated to take around two weeks of full time effort to complete. The first part of this task is dedicated to obtaining a clear view on the setup of the project and the different models that will need to be created. This will involve drafting different elements of the fleet assignment and revenue management models. Following this, the data collection will be done. This data collection will gather all the necessary data that needs to be used for the case study. Such data involves flights from a specific airline as well as fleet type information. This will help ensure accuracy in testing.

The following task is dedicated to the development of the revenue management model. This model is estimated to take five weeks to complete. This will be a model developed in python using EMSR principles to help accurately determine booking and protection levels. This will also be paired with a forecasting model that will take demand information to develop an accurate forecast that will feed into the main RM model.

Following this is the fleet assignment model development. This model will take an estimated two weeks to complete. This model, based on a time-space network will use linear programming and a commercial solver to work as intended and help deliver the best results.

With the main models developed, approximately one week will be spent on testing and debugging these models to help ensure full functionality.

Following this, an initial case study will be developed, this will last approximately one week. The results from this case study will be used in the midterm review to show the progress that has been made up to that point, and will allow the supervisors to determine what needs to be improved, what needs to be changed, and what should be simplified.

With the midterm having been completed, approximately one week will be spent incorporating the feedback that was given. Following this, four weeks will be spent working on the integration of the two separate RM and fleet assignment models. This will then lead to the final case studies which should take approximately one week. This then leave verification and validation, which is estimated to take approximately two week. This is then culminated with the draft thesis writing which will take an estimated four weeks, with the greenlight meeting taking place shortly before the final submission.

With the feedback being delivered for the draft, approximately two weeks will be spent implementing this feedback and assuring that the thesis is ready for final submission. The final two weeks of the project will be spent preparing for the final defense and thesis presentation.

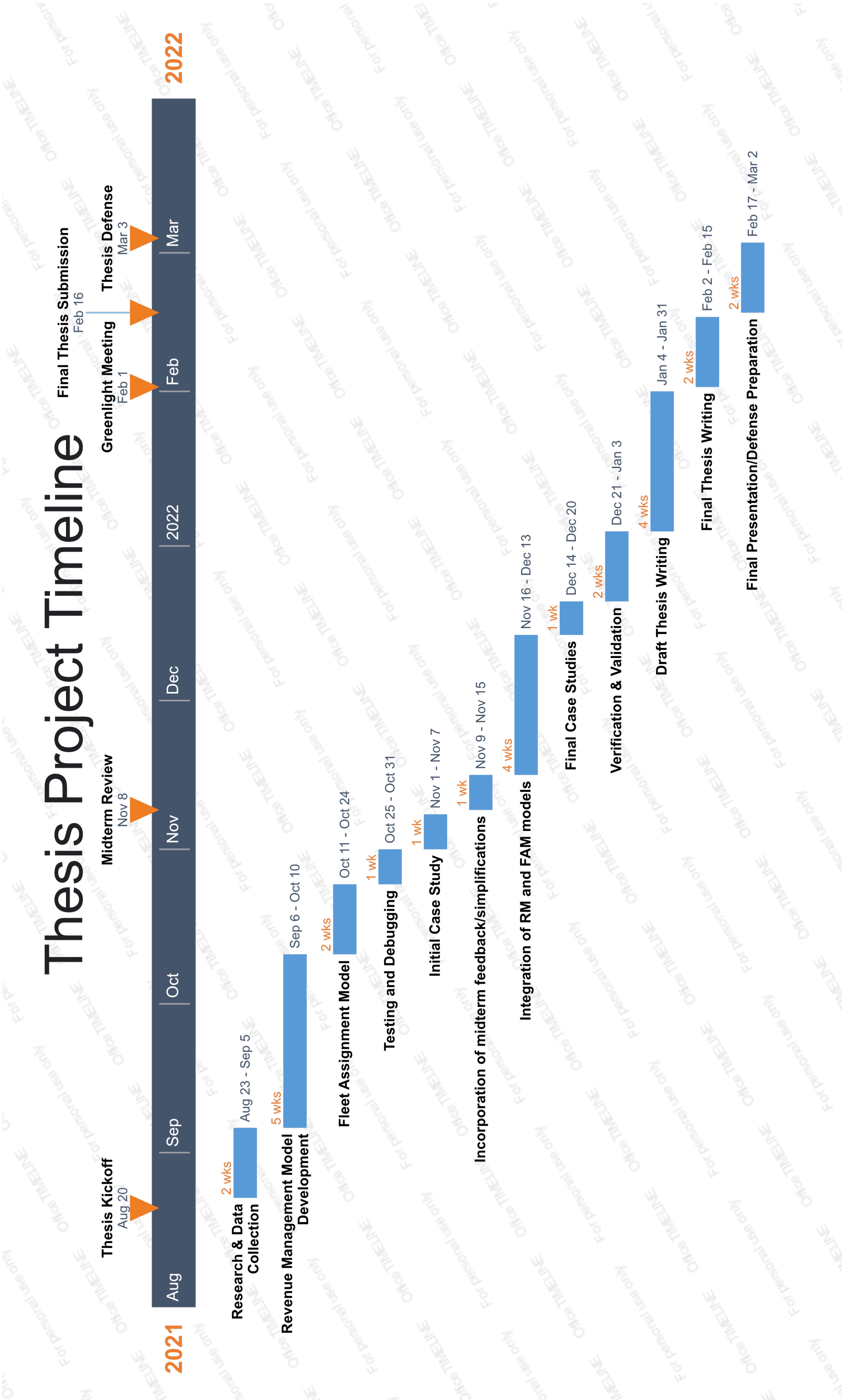

Figure 7.1: Thesis Project Gantt Chart

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III

Supporting work

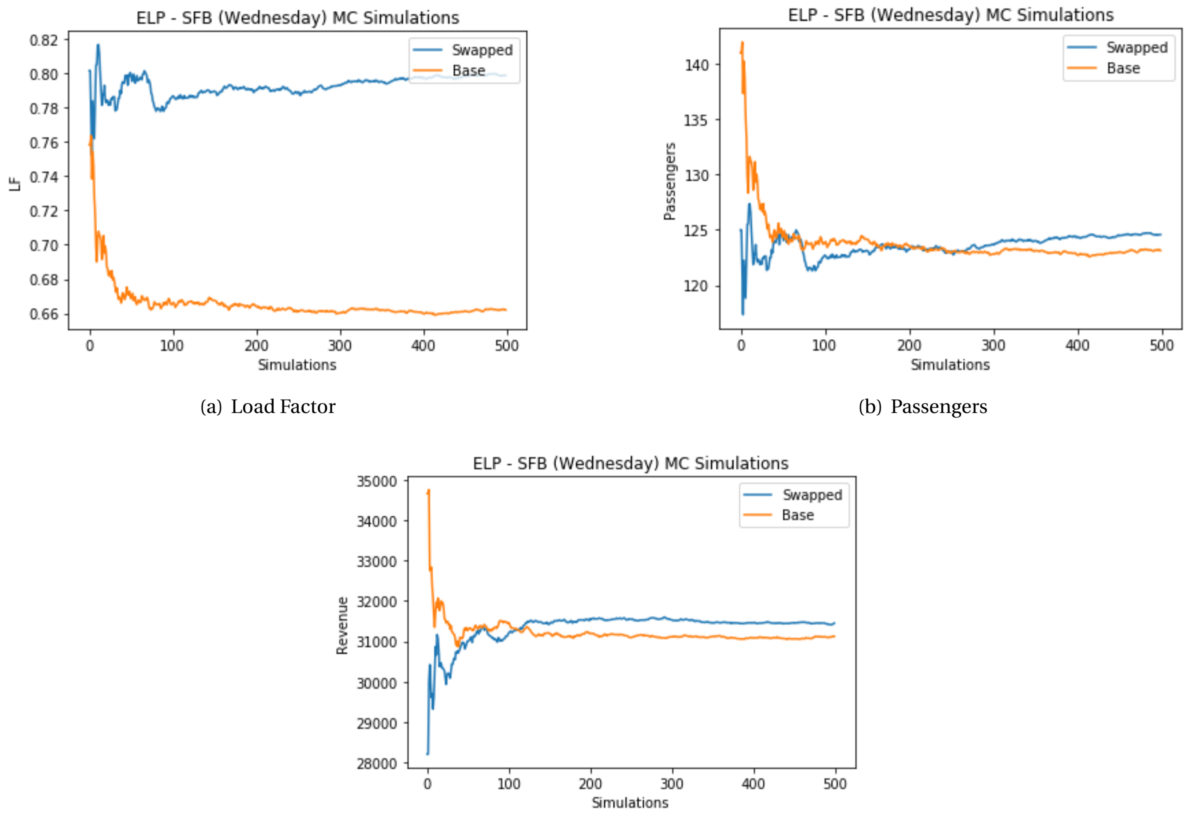
1
Results

In this section a more detailed analysis and overview of the results that were obtained will be discussed. In addition to a more detailed discussion, additional case studies that were evaluated will also be presented in this section. These case studies were created to help find additional information into how timing plays a factor in swapping capacity between flights. The goal of these additional case studies is to help find which timing strategies are best and which under-perform.

1.1. Simulation Convergence

Before being able to process any results, there needs to be assurance that the the data being used will provide accurate and consistent results. Given that randomness was introduced to help reduce any noise, this brought up the need to introduce Monte Carlo simulations. This simulation along with randomness will help show that while each scenario may behave slightly differently, there will still be a final expected value.

To help highlight convergence, a random selection of a certain flight on a certain day of week was taken. This shows that for each simulation taken, the values will converge as the simulations increase and the rolling average is taken. As this research looked at swapping flights, two different scenarios are plotted against each other. The orange line will highlight the case of the baseline scenario, that is where no swaps were done and the model simply built demand over a flight until its final departure date. What is being plotted is the final results, that is how the flight finished at the end of its booking window. The other scenario that is introduced is that where the flight was swapped with another aircraft gauge. This shows the effect of swapping, whether negative or positive. By introducing a swap, the aim with these plots are to show how consistent swapping can be and how there is a final expected value.



(a) Load Factor

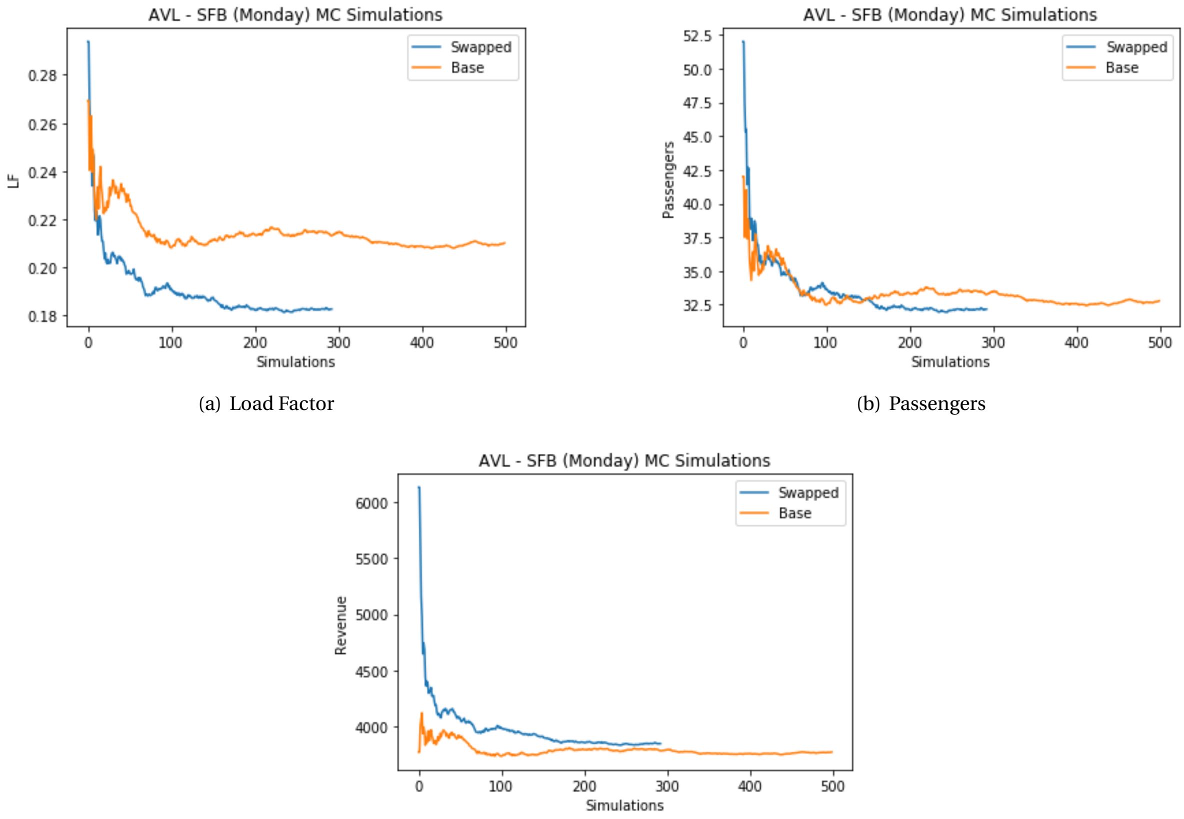
(b) Passengers

(c) Revenue

Figure 1.1: Distribution of all flights that were swapped compared to the baseline with full simulation runs

As can be seen in the above figures, there is complete convergence and well before the end of the simulations one can already see the final expected value. This shows that the data and the randomness that is being used can be used with confidence. These results will help assure that each flight that is modeled and simulated will provide a solid result and can be used in aggregate to help give final guidance as to how the methodology works.

It is important to note that the above scenario considers the case that the flight is swapped in every possible simulation. This is good to have, however given that randomness was used in each simulation, this means that not every flight is going to behave the same in every simulation. There are cases where certain flights are going to perform strongly, no matter the circumstances, such as in the case above. This is good to have, as these results can be expected consistently. However, as not every flight is going to behave the same, and some flights will be weak in some simulations and strong in others, this means that a flight might not be swapped in every possible simulation. These results should not be discarded as they still provide insight into how a flight with softer demand might perform. Or simply how a flight might perform on a weak demand time period. Therefore, it is of interest to see if these flights will still converge even if they are not swapped at each possible simulation. The following plots below will highlight flights that were swapped at just over half of the possible simulations, or just 300 of the possible 500 simulations.



(a) Load Factor

(b) Passengers

(c) Revenue

Figure 1.2: Distribution of all flights that were swapped compared to the baseline with swapped incomplete simulation runs

Reviewing the figures above, it can be seen that even though this particular flight was not swapped for each possible simulation, the results do converge and a final expected value can be obtained. Additionally, it can be seen that convergence can begin as early as 200 simulation runs, or 20 % of the possible total simulations that were ran. This shows that even though certain flights might not have consistent strong demand, in the cases where they are swapped, their final results are consistent and these flights can be used for final analysis to help drive the case of the methodology even further.

1.2. Additional Case Studies

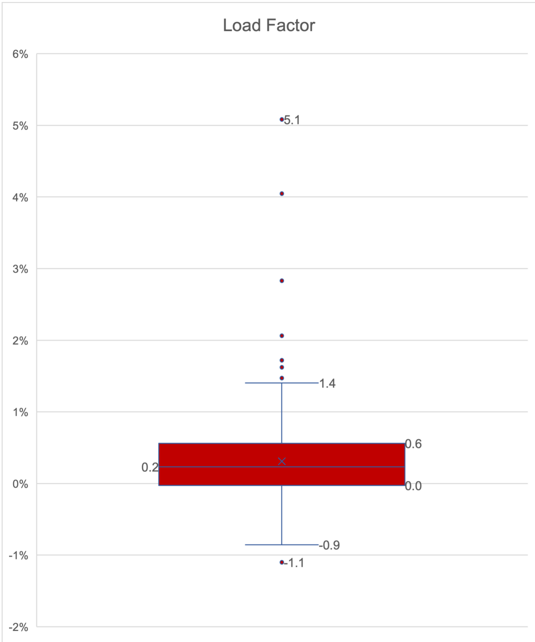
In addition to the case studies that were detailed in the scientific paper given in Part I, additional case studies were developed to help further determine the optimal timing strategy for this methodology. A simplified view of this methodology was given in Part I and a detailed view of this methodology framework can be seen in Appendix A.

The additional case studies that were developed use the advanced decision making logic that was developed using the random forest model and are further described below:

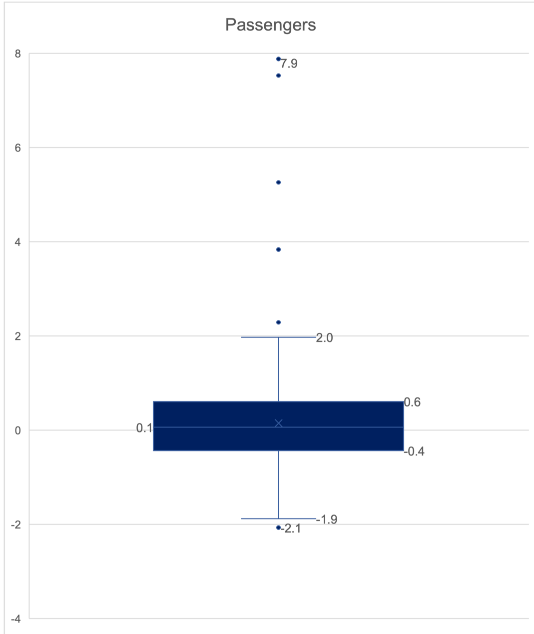
Weekly Monitoring

This case study will use the same models as previously used with the incorporation of the random forest decision making logic. The difference with this case study is that the swapping intervals are changed and this case study will analyze swapping flights once a week for the duration of the booking window. This window is again restricted as it is ensured that a rotation must have an average load factor of 25 % before swapping can begin, and that swapping will stop as soon as the flight is approximately two weeks away from departure. In this scenario a flight is ultimately left with a maximum of approximately 35 swaps throughout its booking window.

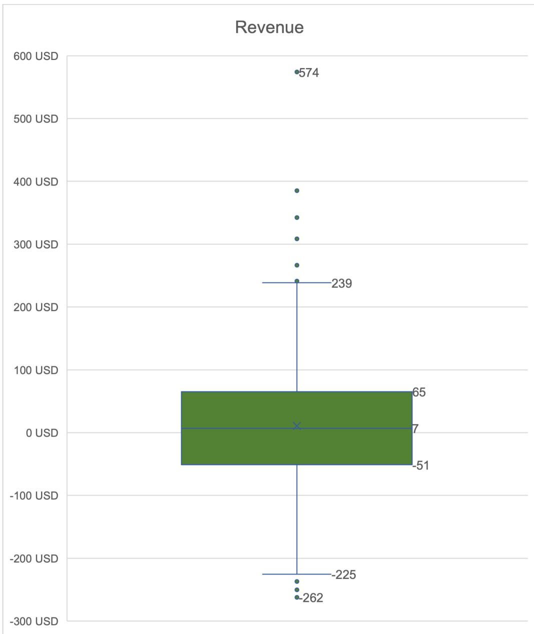
Box plots that highlight the spread of results for only flights that were swapped are given below.



(a) Load Factor



(b) Passengers



(c) Revenue

Figure 1.3: Distribution of all flights that were swapped compared to the baseline

When analyzing this scenario, it is again seen that the negative tail end is minimized which is a desired aspect. Comparing these results to the continuous daily scenario given in Part I it is seen that the negative tail end does begin to dip lower than was previously seen. This indicates that from this point forward diminishing results may begin to follow. Looking at the positive end, we do see similar results with anticipated large positive gains. In this scenario we see that for most KPIs over 50 % of the results resulted in a positive gain.

Looking holistically at all swapped flights compared against their baseline, it is seen that there is an average load factor increase of 0.20 %, an average passenger increase of 0.3 passengers, and an average revenue increase of 25 USD per flight. These results, particularly revenue, is quite less than the previous scenario. This average revenue increase per flight would translate to approximately 7,500 USD additional revenue per week. This is still a great value to accomplish, but at approximately 80 % less than the daily swapping scenario, which begins to highlight how this scenario and following scenarios may not be desired when it comes to full implementation by an operator.

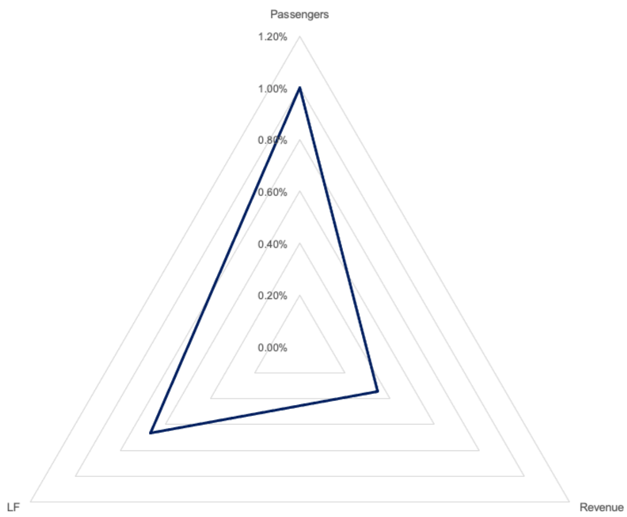


Figure 1.4: Radar Plot

This above radar plot again highlights the impressive passenger growth that has been experienced by the capabilities produced by the swapping model. The negatives that are starting to be noticed however is that the revenue increased has decreased significantly. This is also evident by the significant average decrease from 100 USD per flight in the daily monitoring case study to the now 25 USD per flight. Although these values are still positive and there are no losses, the decrease is a significant value and does not show strength in decreasing the timeline between swaps. The other KPI of LF does show some resilience as it is has not pulled back as much as revenue.

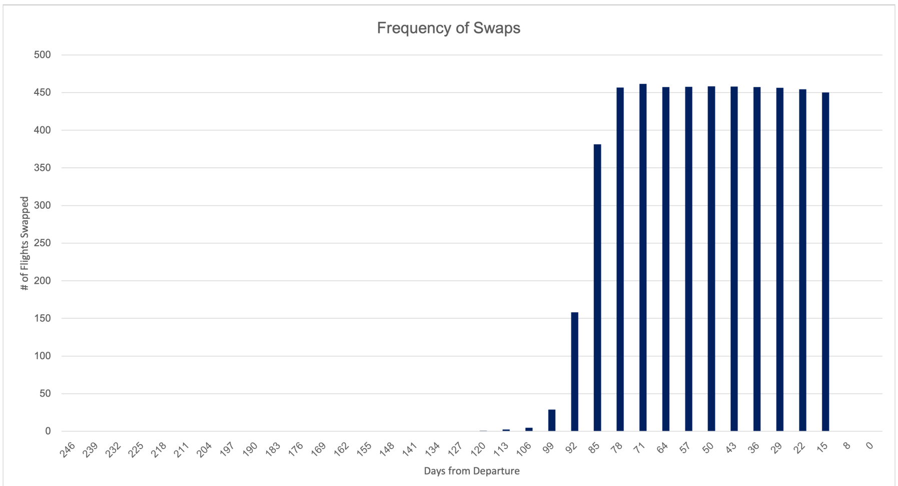


Figure 1.5: Density of Swapping Decisions

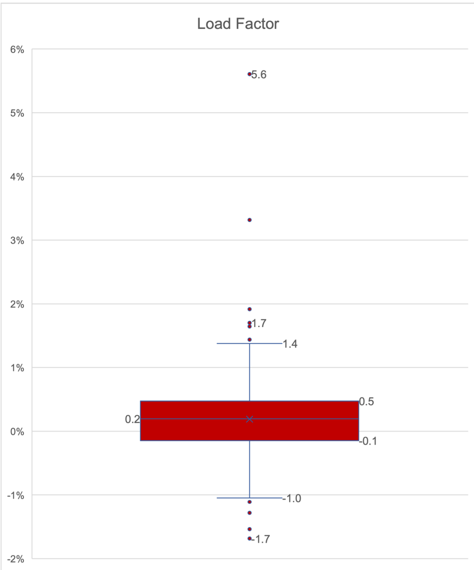
Looking at the swapping density above, it can be seen that again swapping begins at 113 days from departure and will ramp up over the next few swapping opportunities until it has reached its peak at 78 days from departure. At this point, most flights that need to be swapped have fully matured and have reached the point of swap eligibility. This peak continues until 15 days from departure which is when the operational closure takes effect.

When looking at any delays incurred, it was seen that over 75 % of the flights that were swapped faced zero delay or any change to their originally scheduled times. This helps reduce the overall average delay incurred down to just 1 and a half minutes. Shifting the focus to the 25 % of flights that did take on a delay, it is seen that the average delay is just over 6 and a half minutes, which is a minor time change and can still be considered on time. However, looking at the largest delay incurred, it is seen that the delay is very close to the stop gap set. This is a delay of just under 42 minutes.

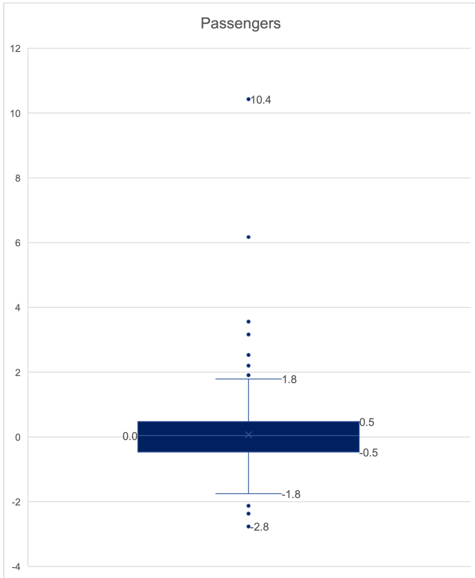
Biweekly Monitoring

This additional case study will have the same restrictions and models as the previously described case study, but will instead look at performing swaps biweekly, or every two weeks. This leaves approximately 18 possible swapping points for each flight.

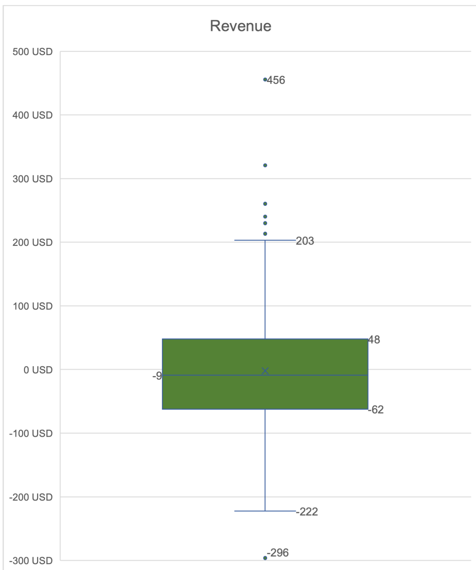
Below is the spread of results that highlight increases and decreases compared to the baseline.



(a) Load Factor



(b) Passengers



(c) Revenue

Figure 1.6: Distribution of all flights that were swapped compared to the baseline

Looking at all the swapped flights compared to their baseline, we see that there continues to be positive results, although the gains have continued to become more minor. In this scenario we see that still for all KPIs at least 50 % of the results have produced a positive result and a positive gain.

Continuing to analyze the overall trend for all swapped flights, we see that there is an average increase of just 0.04 % load factor per flight, an average increase of just 0.2 passengers per flight, and an average increase of just 5 USD per flight. These results are significantly less than the the daily and weekly scenario, which indicates that the decreased amount of time spent swapping returns increasingly diminishing values. To translate the average revenue increase per flight into a weekly value, it is estimated to drive an additional 1,800 USD per week. This is approximately 95 % less than in the daily scenario, or 75 % less than the weekly scenario.

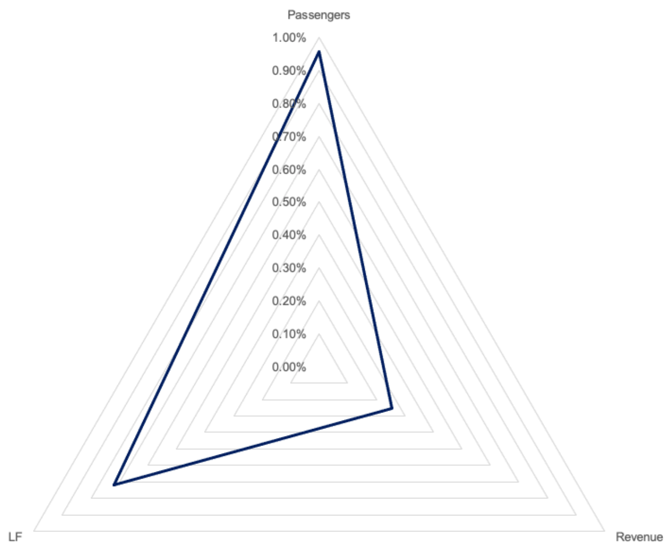


Figure 1.7: Radar Plot

As is again continued, revenue continues to show poor performance. Passenger and LF increases are still showing strong improvement, which indicates that these KPIs do not need much more attention. Instead, the attention should be shifted to revenue to help ensure that the revenue per flight is able to increase at a rate as strong as the other KPIs.

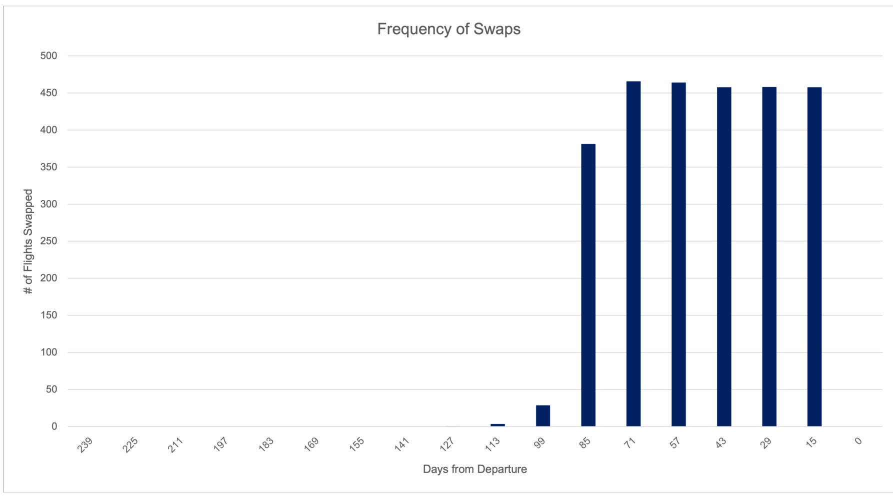


Figure 1.8: Density of Swapping Decisions

In the above figure the density of the swapping decisions can be seen for this scenario. As the amount of opportunities decreases, the amount of swapping possibilities also decreases. The point at which swaps first begin to take place is at 113 days from departure and this ramps up quickly. Once at 71 days from departure the peak is reached and this peak is maintained until the closure for the operational window at 15 days. There is a small decline, but on average 450 flights will be swapped at the various swapping opportunities between 71 and 15 days from departure.

When analyzing the delays, it is seen that 83 % of the flights that were swapped incurred zero delays. This fact brings the average delay down to 1 minute and 15 seconds. Looking at the flights that did notice a delay, it is seen that the average is just under 7 and a half minutes, this delay is still considered on-time. Shifting to the other end, it is seen that the largest delay was close to the stop limit that was set (45 minutes), at just under 42 minutes. This delay is large, but given that there would be a minimum two week notice, any impact that might have been had would be softened by such a large notice prior to the flights departure.

Additional Case Study Conclusions

Having reviewed the additional case studies that were generated, final conclusions can be drawn as to how different swapping timeline scenarios perform. Ultimately, it is noted that by decreasing the amount of time between a swap, the results decrease significantly. This indicates that the best scenario is the case where a flight is given the ability to swap with other aircraft every day. It is noted that this may not always occur, and should not always occur, but having the ability to reevaluate a decision every day will help drive the best possible results.

Regardless of which timing scenario performs best, it is important to highlight that every scenario tested did return positive increases when compared to the baseline scenario. Revenue, load factor, and the amount of passengers transported increased in each scenario that was evaluated, indicating a well created methodology. To highlight these results even further, detailed tables are given in Appendix B which show the top and bottom flights that were swapped for each scenario evaluated. These results are further split into top and bottom performers for each KPI evaluated.

1.3. Flight Modeling

The final area of interest that is left to be seen about how the methodology performs, is to follow a flight throughout its booking window. In this section a flight that is swapped at least once is analyzed and each KPI is measured to see how swapping ultimately affected the performance of the flight.

The following figure looks at the flights performance in terms of both capacity and passenger growth throughout the booking curve from the moment it is put on sale until the day it departs.

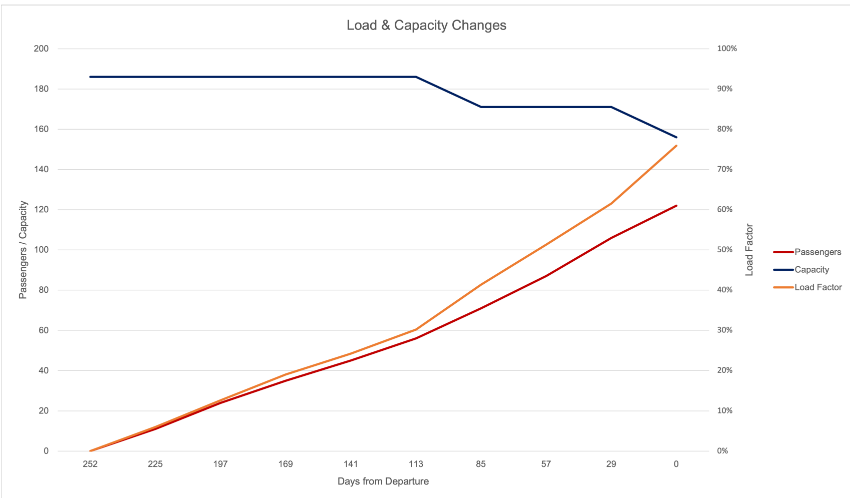


Figure 1.9: Passengers throughout the booking curve

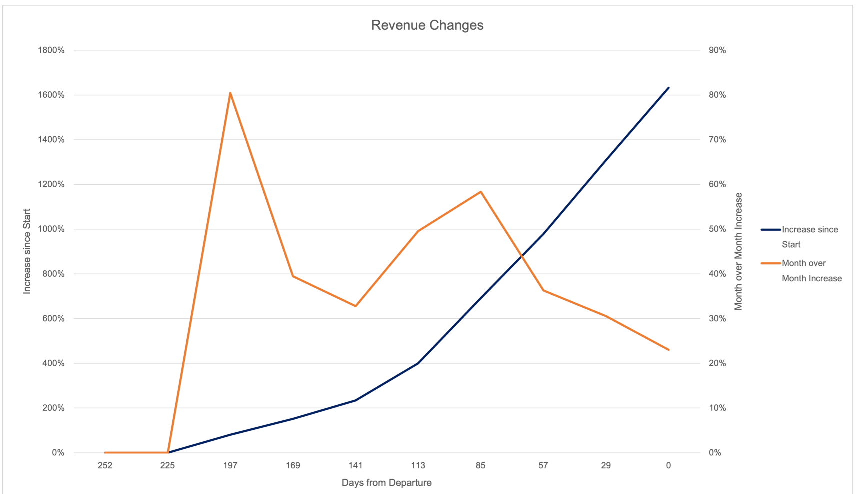


Figure 1.10: Revenue throughout the booking curve

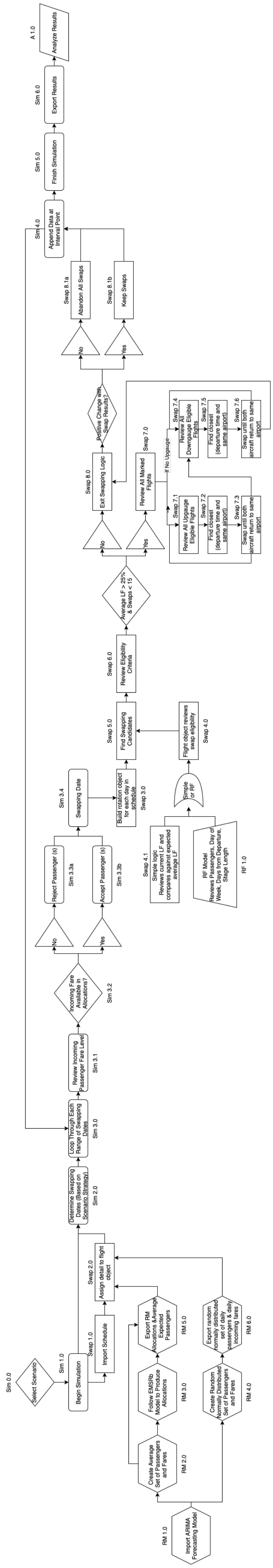
As is shown in Figure 1.9, the swapping algorithm noticed twice throughout the booking curve of this flight that the original assigned capacity was set too high. Thus, accordingly the algorithm found a flight to swap aircraft with and was able to assign this particular flight a lower capacity. This flight began with a 186 capacity aircraft, and in each simulation was able to be ultimately lowered closer to the 156 capacity aircraft. This ultimately helped increase the load factor as well as the amount of passengers allowed as a different set of allocations were created for each flight allowing a different passengers to be accepted. Shifting towards revenue, it is seen that most of the change in revenue achieved within the first two months of the booking curve and does slow down afterwards. Revenue does look to increase around the same time as the swap, however this could also be attributed to general booking noise and not necessarily as a direct result of the swap action.

Overall, it is seen that the swaps are done when necessary and with a swap being done, this will translate directly and immediately into increases for each KPI measured. This shows that the methodology does what is asked of it, and helps return positive increases as was initially expected in the original research question.

IV

Appendices

A
Detailed Methodology Flowchart



Sim 0.0
Select Scenario
Sim 1.0
Begin Simulation
Swap 1.0
Import Schedule
Swap 2.0
Assign detail to flight object
RM 1.0
Import ARIMA Forecasting Model
RM 2.0
Create Average Set of Passengers and Fares
RM 3.0
Follow EMSRb Model to Produce Allocations
RM 5.0
Export RM Allocations & Average Expected Passengers
RM 4.0
Create Random Normally Distributed Set of Passengers and Fares
RM 6.0
Export random normally distributed set of daily passengers & daily incoming fares
Sim 2.0
Determine Swapping Dates (Based on Scenario Strategy)
Sim 3.0
Loop Through Each Range of Swapping Dates
Sim 3.1
Review Incoming Passenger Fare Level
Sim 3.2
Incoming Fare Available in Allocations?
No
Yes
Sim 3.3a
Reject Passenger (s)
Sim 3.3b
Accept Passenger (s)
Sim 3.4
Swapping Date
Swap 3.0
Build rotation object for each day in schedule
Swap 4.1
Simple logic Reviews current LF and compares against expected average LF
RF 1.0
RF Model Reviews Passengers, Day of Week, Days from Departure, Stage Length
Simple or RF
Swap 4.0
Flight object reviews swap eligibility
Swap 5.0
Find Swapping Candidates
Swap 6.0
Review Eligibility Criteria
Average LF > 25% & Swaps < 15
No
Yes
Swap 7.0
Review All Marked Flights
If No Upgauge
Swap 7.1
Review All Upgauge Eligible Flights
Swap 7.2
Find closest (departure time and same airport)
Swap 7.3
Swap until both aircraft return to same airport
Swap 7.4
Review All Downgauge Eligible Flights
Swap 7.5
Find closest (departure time and same airport)
Swap 7.6
Swap until both aircraft return to same airport
Swap 8.0
Exit Swapping Logic
Positive Change with Swap Results?
No
Yes
Swap 8.1a
Abandon All Swaps
Swap 8.1b
Keep Swaps
Sim 4.0
Append Data at Interval Point
Sim 5.0
Finish Simulation
Sim 6.0
Export Results
A 1.0
Analyze Results

B

Detailed Results

Flight (Day of Week)	Swaps	Original Capacity	Average Final Capacity	**LF** % Increase	Passenger % Increase	Revenue % Increase
Top:						
SFB - SGF (Wednesday)	3	186	161	21	19	6
SFB - PIA (Wednesday)	3	177	161	10	3	1
SFB - LEX (Wednesday)	3	177	159	11	-1	-1
Bottom:						
MSY - CVG (Thursday)	1	186	180	1	-2	0
SFB - USA (Sunday)	3	156	178	-13	-1	0
XNA - SFB (Saturday)	2	177	167	10	3	0

Table B.1: Best (Worst) performing flights in terms of LF for all swapped flights - Simple Rule

Flight (Day of Week)	Swaps	Original Capacity	Average Final Capacity	LF % Increase	**Passenger % Increase**	Revenue % Increase
Top:						
PIE - CVG (Saturday)	2	177	182	-3	-4	-1
CVG - PIE (Wednesday)	1	186	180	13	9	5
ELP - SFB (Wednesday)	2	186	170	13	6	1
Bottom:						
MSY - CVG (Thursday)	1	186	180	1	-2	0
SFB - USA (Saturday)	2	156	170	-12	2	1
XNA - SFB (Saturday)	2	177	167	10	3	0

Table B.2: Best (Worst) performing flights in terms of passengers for all swapped flights - Simple Rule

Flight (Day of Week)	Swaps	Original Capacity	Average Final Capacity	LF % Increase	Passenger % Increase	**Revenue % Increase**
Top:						
SFB - MFE (Sunday)	2	186	161	13	-2	-1
SFB - ELP (Wednesday)	2	186	170	14	7	1
XNA - SFB (Saturday)	2	177	167	10	3	0
Bottom:						
GSP - SFB (Tuesday)	3	156	173	-10	-1	-1
SFB - USA (Wednesday)	2	156	181	-12	2	1
SFB - GSP (Tuesday)	3	156	173	-9	1	1

Table B.3: Best (Worst) performing flights in terms of revenue for all swapped flights - Simple Rule

Flight (Day of Week)	Swaps	Original Capacity	Average Final Capacity	**LF Increase**	LF % Increase	Passenger % Increase	Revenue % Increase
Top:							
SFB - SGF (Wednesday)	3	186	161	11	21	19	6
SFB - SJU (Wednesday)	3	186	158	10	18	0	0
CHA - SFB (Tuesday)	3	186	158	10	11	3	2
Bottom:							
FWA - SFB (Tuesday)	2	156	184	-8	-15	0	0
SFB - TRI (Tuesday)	3	156	184	-8	-15	0	0
TRI - SFB (Tuesday)	3	156	184	-8	-15	0	0

Table B.4: Largest difference between swapped LF and baseline LF - Simple Rule

Flight (Day of Week)	Swaps	Original Capacity	Average Final Capacity	LF % Increase	**Passenger Increase**	Passenger % Increase	Revenue % Increase
Top:							
CVG - PIE (Wednesday)	1	186	180	13	10	9	5
CVG - ORF (Monday)	2	186	179	14	10	10	6
CVG - SFB (Wednesday)	1	177	183	7	9	11	6
Bottom:							
SFB - MLI (Sunday)	1	180	157	7	-7	-7	-3
SFB - MEM (Monday)	2	186	168	4	-7	-7	-2
SFB - BLV (Sunday)	1	177	157	2	-10	-3	-1

Table B.5: Largest difference between swapped passengers and baseline passengers - Simple Rule

Flight (Day of Week)	Swaps	Original Capacity	Average Final Capacity	LF % Increase	Passenger % Increase	**Revenue Increase (USD)**	Revenue % Increase
Top:							
CVG - EWR (Monday)	2	177	184	14	18	600	9
CVG - ORF (Monday)	2	186	179	14	10	550	6
CVG - PIE (Wednesday)	2	186	180	13	9	500	5
Bottom:							
SFB - BLV (Sunday)	1	177	157	2	-3	-850	-1
SFB - LIT (Sunday)	1	186	162	2	-11	-900	-4
SFB - MLI (Sunday)	1	180	157	7	-7	-950	-3

Table B.6: Largest difference between swapped revenue and baseline revenue - Simple Rule

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	**LF % Increase**	Passenger % Increase	Revenue % Increase
Top:						
ELP - SFB (Wednesday)	16	186	171	12	6	2
SFB - LEX (Wednesday)	11	177	168	5	-1	0
SFB - LIT (Thursday)	1	186	156	20	1	0
Bottom:						
RFD - SFB (Sunday)	15	156	167	-5	1	0
XNA - SFB (Saturday)	15	177	156	12	-1	1
AVL - SFB (Monday)	1	156	176	-12	-1	2

Table B.7: Best (Worst) performing flights in terms of LF for all swapped flights - Daily Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	**Passenger % Increase**	Revenue % Increase
Top:						
ELP - SFB (Wednesday)	16	186	171	12	6	2
SFB - PIA (Wednesday)	16	177	177	0	4	1
SFB - SGF (Wednesday)	16	186	186	5	19	6
Bottom:						
SFB - USA (Sunday)	14	156	160	2	3	1
XNA - SFB (Saturday)	15	177	156	12	-1	1
AVL - SFB (Monday)	1	156	176	12	-1	2

Table B.8: Best (Worst) performing flights in terms of passengers for all swapped flights - Daily Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	Passenger % Increase	**Revenue % Increase**
Top:						
SFB - MFE (Sunday)	8	186	159	20	2	2
SFB - ELP (Wednesday)	16	186	171	12	7	1
XNA - SFB (Saturday)	15	177	156	12	-1	1
Bottom:						
SFB - USA (Wednesday)	15	156	156	1	1	0
AVL - SFB (Monday)	1	156	176	-12	-1	2
SFB - GSP (Tuesday)	16	156	156	1	1	1

Table B.9: Best (Worst) performing flights in terms of revenue for all swapped flights - Daily Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	**LF Increase**	LF % Increase	Passenger % Increase	Revenue % Increase
Top:							
SFB - LIT (Thursday)	1	186	156	12	20	1	0
ELM - SFB (Saturday)	3	186	157	11	20	1	0
MFE - SFB (Sunday)	8	186	159	10	19	1	1
Bottom:							
SFB - LCK (Tuesday)	8	156	186	-8	-17	-1	-1
ATW - SFB (Thursday)	15	156	186	-8	-16	0	1
SFB - ATW (Thursday)	15	156	186	-8	-15	1	1

Table B.10: Largest differences between swapped flight LF and baseline flight LF - Daily Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	**Passenger Increase**	Passenger % Increase	Revenue % Increase
Top:							
SFB - CHA (Sunday)	8	156	158	11	9	12	4
CVG - EWR (Friday)	1	177	186	2	7	7	3
SDF - SFB (Tuesday)	16	156	156	10	6	10	3
Bottom:							
ABE - SFB (Tuesday)	16	186	186	-1	-2	-1	-1
SFB - ROA (Tuesday)	1	177	156	11	-2	-2	-1
SFB - DAY (Sunday)	1	177	156	13	-2	5	3

Table B.11: Largest differences between swapped flight passengers and baseline flight passengers - Daily Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	Passenger % Increase	**Revenue Increase (USD)**	Revenue % Increase
Top:							
SHV - SFB (Thursday)	10	156	156	5	5	850	3
SFB - MFE (Sunday)	8	186	159	20	2	800	2
SFB - CHA (Sunday)	8	156	158	11	12	500	4
Bottom:							
PBG - SFB (Friday)	15	156	162	-3	0	-150	-1
ABE - SFB (Tuesday)	16	186	186	-1	-1	-150	-1
SFB - SJU (Wednesday)	15	186	183	1	-1	-250	-1

Table B.12: Largest differences between swapped flight revenue and baseline flight revenue - Daily Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	**LF % Increase**	Passenger % Increase	Revenue % Increase
Top:						
SFB - PIA (Wednesday)	12	177	167	7	3	0
ELP - SFB (Wednesday)	11	186	172	12	6	2
SFB - LEX (Wednesday)	8	177	163	9	0	0
Bottom:						
RFD - SFB (Sunday)	11	156	167	-5	1	0
SFB - USA (Sunday)	11	156	174	-8	2	0
XNA - SFB (Saturday)	10	177	172	5	1	0

Table B.13: Best (Worst) performing flights in terms of LF for all swapped flights - Weekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	**Passenger % Increase**	Revenue % Increase
Top:						
ELP - SFB (Wednesday)	11	186	172	12	6	2
SFB - PIA (Wednesday)	12	177	167	7	3	0
SFB - SGF (Wednesday)	12	186	172	13	18	6
Bottom:						
RFD - SFB (Sunday)	11	156	167	-5	1	0
SFB - USA (Sunday)	11	156	174	-8	2	0
XNA - SFB (Saturday)	10	177	172	5	1	0

Table B.14: Best (Worst) performing flights in terms of passengers for all swapped flights - Weekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	Passenger % Increase	**Revenue % Increase**
Top:						
SFB - MFE (Sunday)	6	186	164	15	1	0
SFB - ELP (Wednesday)	11	186	172	10	5	2
XNA - SFB (Saturday)	10	177	172	5	1	0
Bottom:						
GSP - SFB (Tuesday)	11	156	171	-9	-1	0
SFB - USA (Wednesday)	10	156	167	-4	2	0
SFB - GSP (Tuesday)	11	156	171	-7	1	2

Table B.15: Best (Worst) performing flights in terms of revenue for all swapped flights - Weekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	**LF Increase**	LF % Increase	Passenger % Increase	Revenue % Increase
Top:							
SFB - LIT (Thursday)	1	186	157	11	19	0	-1
ELM - SFB (Saturday)	2	186	156	11	20	1	0
SFB - ELM (Saturday)	2	186	156	10	20	1	1
Bottom:							
CLE - SFB (Sunday)	8	156	176	-6	-11	0	-1
PBG - SFB (Friday)	11	156	178	-6	-12	0	-1
LCK - SFB (Saturday)	2	156	184	-8	-16	-1	0

Table B.16: Largest differences between swapped flight LF and baseline flight LF - Weekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	**Passenger Increase**	Passenger % Increase	Revenue % Increase
Top:							
SFB - CHA (Sunday)	6	156	159	8	8	10	4
CVG - EWR (Friday)	1	177	186	2	8	8	3
CVG - SAV (Sunday)	1	177	186	3	5	8	2
Bottom:							
SFB - CHA (Thursday)	11	156	172	-11	-2	-2	-2
PBG - SFB (Wednesday)	11	177	162	6	-2	6	0
MEM - SFB (Monday)	11	186	171	7	-2	3	0

Table B.17: Largest differences between swapped flight revenue and baseline flight revenue - Weekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	Passenger % Increase	**Revenue Increase (USD)**	Revenue % Increase
Top:							
SFB - CHA (Sunday)	6	156	159	8	10	550	4
SFB - MFE (Tuesday)	11	156	171	-6	2	400	1
SFB - ELP (Wednesday)	11	186	172	10	5	350	2
Bottom:							
OMA - SFB (Tuesday)	2	156	156	-1	-1	-250	-1
ICT - SFB (Saturday)	10	156	166	-7	-1	-250	-1
PBG - SFB (Wednesday)	11	177	166	6	6	-250	0

Table B.18: Largest differences between swapped flight revenue and baseline flight revenue - Weekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	**LF % Increase**	Passenger % Increase	Revenue % Increase
Top:						
ELP - SFB (Wednesday)	6	186	170	12	6	1
SFB - LEX (Wednesday)	5	177	166	8	0	0
SFB - PIA (Wednesday)	6	177	173	3	4	2
Bottom:						
SFB - ABE (Saturday)	5	156	169	-8	0	0
RFD - SFB (Sunday)	5	156	166	-6	-1	-1
XNA - SFB (Saturday)	5	177	159	8	-3	0

Table B.19: Best (Worst) performing flights in terms of LF for all swapped flights - Biweekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	**Passenger % Increase**	Revenue % Increase
Top:						
ELP - SFB (Wednesday)	6	186	170	12	6	1
SFB - PIA (Wednesday)	6	177	173	3	4	2
SFB - SGF (Wednesday)	6	186	180	7	17	5
Bottom:						
RFD - SFB (Sunday)	5	156	166	-6	-1	-1
SFB - USA (Sunday)	6	156	158	-1	0	-1
XNA - SFB (Saturday)	5	177	159	8	-3	0

Table B.20: Best (Worst) performing flights in terms of passengers for all swapped flights - Biweekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	Passenger % Increase	**Revenue % Increase**
Top:						
SFB - MFE (Sunday)	3	186	156	20	1	0
SFB - ELP (Wednesday)	6	186	170	11	5	1
XNA - SFB (Saturday)	5	177	159	8	-3	0
Bottom:						
GSP - SFB (Tuesday)	6	156	167	-7	-1	-1
SFB - USA (Wednesday)	5	156	160	-2	0	0
SFB - GSP (Tuesday)	6	156	167	-5	1	1

Table B.21: Best (Worst) performing flights in terms of revenue for all swapped flights - Biweekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	**LF Increase**	LF % Increase	Passenger % Increase	Revenue % Increase
Top:							
ELM - SFB (Saturday)	2	186	156	11	20	1	0
MFE - SFB (Sunday)	2	186	157	10	18	0	0
SFB - LIT (Thursday)	1	186	157	10	17	0	0
Bottom:							
ATW - SFB (Thursday)	5	156	181	-7	-15	-2	0
ICT - SFB (Saturday)	5	156	175	-8	-13	-2	0
LCK - SFB (Saturday)	2	156	186	-9	-17	-1	0

Table B.22: Largest differences between swapped flight LF and baseline flight LF - Biweekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	**Passenger Increase**	Passenger % Increase	Revenue % Increase
Top:							
CVG - EWR (Friday)	1	177	186	5	10	11	5
CVG - SAV (Sunday)	1	177	186	4	6	10	1
CVG - VPS (Saturday)	1	177	186	-2	4	-1	0
Bottom:							
XNA - SFB (Saturday)	5	177	159	8	-2	-3	0
SFB - DAY (Sunday)	1	177	158	11	-2	5	2
ICT - SFB (Saturday)	5	156	175	-13	-3	-2	0

Table B.23: Largest differences between swapped flight passengers and baseline flight passengers - Biweekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	Passenger % Increase	**Revenue Increase (USD)**	Revenue % Increase
Top:							
CVG - EWR (Friday)	1	177	186	5	11	450	5
VPS - CVG (Saturday)	1	177	186	-2	-1	300	0
SFB - MKE (Friday)	5	156	162	-1	2	250	1
Bottom:							
PIA - SFB (Wednesday)	4	177	164	8	3	-200	0
SFB - FSD (Tuesday)	1	156	171	-9	-1	-200	-1
MFE - SFB (Tuesday)	6	156	167	-5	0	-300	0

Table B.24: Largest differences between swapped flight revenue and baseline flight revenue - Biweekly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	**LF % Increase**	Passenger % Increase	Revenue % Increase
Top:						
SFB - PIA (Wednesday)	3	177	157	14	4	2
SFB - SGF (Wednesday)	3	186	157	24	20	6
SFB - LEX (Wednesday)	3	177	157	13	0	1
Bottom:						
SFB - ABE (Saturday)	2	156	174	-10	0	-1
SFB - USA (Sunday)	3	156	184	-16	-1	0
XNA - SFB (Saturday)	2	177	182	3	5	2

Table B.25: Best (Worst) performing flights in terms of LF for all swapped flights - Monthly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	**Passenger % Increase**	Revenue % Increase
Top:						
ELP - SFB (Wednesday)	2	186	186	13	7	1
SFB - PIA (Wednesday)	3	177	177	14	4	2
SFB - SGF (Wednesday)	3	186	186	24	19	6
Bottom:						
RFD - SFB (Sunday)	2	156	166	-3	3	0
SFB - USA (Sunday)	3	156	184	-16	-1	0
XNA - SFB (Saturday)	2	177	182	3	5	2

Table B.26: Best (Worst) performing flights in terms of passengers for all swapped flights - Monthly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	Passenger % Increase	**Revenue % Increase**
Top:						
SFB - MFE (Sunday)	1	186	166	14	1	0
SFB - ELP (Wednesday)	2	186	170	12	6	1
XNA - SFB (Saturday)	2	177	182	3	5	2
Bottom:						
GSP - SFB (Tuesday)	3	156	176	-11	0	0
SFB - USA (Wednesday)	2	156	181	-12	1	0
SFB - GSP (Tuesday)	3	156	176	-10	1	1

Table B.27: Best (Worst) performing flights in terms of revenue for all swapped flights - Monthly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	**LF Increase**	LF % Increase	Passenger % Increase	Revenue % Increase
Top:							
SFB - SGF (Wednesday)	3	186	157	13	24	19	6
SFB - LIT (Thursday)	1	186	156	11	19	0	-1
SGF - SFB (Wednesday)	3	186	157	11	14	10	4
Bottom:							
LEX - SFB (Sunday)	1	156	186	-8	-15	1	2
SFB - LEX (Sunday)	1	156	186	-9	-17	-1	0
SFB - CHA (Thursday)	3	156	182	-9	-16	-2	-1

Table B.28: Largest differences between swapped flight LF and baseline flight LF - Monthly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	**Passenger Increase**	Passenger % Increase	Revenue % Increase
Top:							
CVG - VPS (Saturday)	1	177	186	7	11	8	3
CVG - SAV (Sunday)	1	177	186	8	9	14	3
VPS - CVG (Saturday)	1	177	186	5	8	5	1
Bottom:							
SFB - RFD (Sunday)	2	156	166	-8	-2	-3	1
SFB - LIT (Tuesday)	3	177	163	7	-2	4	1
USA - SFB (Saturday)	1	156	177	-15	-2	-3	-1

Table B.29: Largest differences between swapped flight passengers and baseline flight passengers - Monthly Swapping

Flight (Day of Week)	Swaps	Original Capacity	Final Capacity	LF % Increase	Passenger % Increase	**Revenue Increase (USD)**	Revenue % Increase
Top:							
CVG - VPS (Saturday)	1	177	186	7	8	750	3
VPS - CVG (Saturday)	1	177	186	5	5	700	1
XNA - SFB (Saturday)	2	177	182	3	5	450	2
Bottom:							
SFB - RFD (Sunday)	2	156	166	-8	-3	-250	1
PBG - SFB (Friday)	3	156	177	-11	0	-300	-1
SFB - MLI (Sunday)	1	180	156	15	-1	-350	-1

Table B.30: Largest differences between swapped flight revenue and baseline flight revenue - Monthly Swapping

C

IATA	City	State
CVG	Cincinnati	Ohio
PIE	St. Petersburg	Florida
SFB	Orlando	Florida
LAS	Las Vegas	Nevada
ABE	Allentown	Pennsylvania
ATW	Appleton	Wisconsin
AVL	Asheville	North Carolina
BLV	MidAmerica St. Louis	Missouri
CHA	Chattanooga	Tennessee
CLE	Cleveland	Ohio
DAY	Dayton	Ohio
ELM	Elmira	New York
ELP	El Paso	Texas
EWR	Newark	New Jersey
FSD	Sioux Falls	South Dakota
FWA	Fort Wayne	Indiana
GSP	Greenville - Spartanburg	South Carolina
ICT	Wichita	Kansas
LCK	Columbus	Ohio
LEX	Lexington	Kentucky
LIT	Little Rock	Arkansas
MEM	Memphis	Tennessee
MFE	McAllen	Texas
MKE	Milwaukee	Wisconsin
MLI	Moline	Iowa
MSY	New Orleans	Louisiana
OMA	Omaha	Nebraska
ORF	Norfolk	Virginia
PBG	Plattsburg	New York
PIA	Pioria	Illinois
RFD	Rockford	Illinois
ROA	Roanoke	Virginia
SAV	Savannah	Georgia
SDF	Louisville	Kentucky
SGF	Springfield	Missouri
SHV	Shreveport	Louisiana
SJU	San Juan	Puerto Rico
TRI	Tri-Cities	Tennessee
USA	Charlotte	North Carolina
VPS	Destin	Florida
XNA	Northwest Arkansas	Arkansas

Table C.1: IATA Airport Codes

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