The Impacts of Airline Loyalty Programs on Revenue Management Optimization

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SUBMITTED TO THE SYSTEM DESIGN AND MANAGEMENT PROGRAM IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE IN ENGINEERING AND MANAGEMENT

AT THE

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

JUNE 2017

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Submitted to the System Design and Management Program on May 12, 2017, in Partial Fulfillment of the Requirements for the Degree of Master of Science in Engineering and Management

Abstract

Loyalty Programs have evolved over years turning into unique business units, responsible for producing an important source of revenue for airlines. However, despite their contribution to the business, the lack of knowledge on the impacts of giving away rewards to loyal customers may lead to suboptimal decisions, harming bottom line results.

The main objective of this thesis is to develop a methodology to model and measure the net revenue impacts of award passengers as they integrate to current airline revenue management optimization practices. By modeling an award demand using the Passenger Origin Destination Simulation tool, it was possible to understand the impacts on airlines’ main metrics compared to an environment without these passengers, and to define a baseline scenario based on current airline industry data, to analyze the impacts of different RM strategies.

A methodology was proposed to identify and quantify three main effects seen when allowing award passengers into the current RM optimization. The Award Revenue accounts for the economic benefit for the airline of each award passenger. Displaced Revenue is the ticket revenue loss due to the displacement of paid passengers. And, the Sell Up effect measures the change in average paid fare as a result of the introduction of this new demand.

Differences between the real economic benefit to the airline of award passengers and the value that the RM optimizer uses for assigning their availability were introduced to measure the net award revenue impact. Results showed that at award valuations higher than the lowest fare, airlines are able to increase their total revenues due to higher award revenue and lower displaced ticket revenue. This outcome was consistent for all RM Schemes and demand levels examined.

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Acknowledgments

I would like to start thanking Peter Belobaba for letting me be part of this amazing academic experience. His knowledge and guidance were critical for the development of my research and the fulfillment of this thesis. It was certainly a privilege to work and learn from him. I'll always be grateful for the opportunity and funding towards my education at MIT.

To Craig Hopperstad for developing all the capabilities needed in PODS that made possible my research and this thesis.

To all the PODS members for their rich feedback and guidance throughout the PODS meetings.

I would also like to thank our incredible team; Adam Bockelie, Alex Bachwich, Benjamin Sanchez, Matthieu de Vergnes and Mike Wittman. It was a real pleasure working with such bright, supportive and humble people.

Special thanks to my parents for raising us in such beautiful and supportive way. This accomplishment is far from being a personal one. On the contrary, is the result of your unconditional love and all the opportunities that you have given me throughout my whole life. To my sisters, for always taking care of me, supporting me and making us the amazing family that we are.

And finally, to my faithful companion Rosario. Thank you for being there, once again, in this crazy adventure. You bring light to everything that we do and I don't get tired of admiring your joy, wisdom and strength that you give to our (new) family. Gero, thanks for sleeping when I needed the most.
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1. Introduction

For almost 40 years, and after 1978’s airline deregulation, airlines have developed complex systems and strategies to capture as much value as possible to survive in a highly competitive and challenging industry. Efficiency at every dollar going in and out, has been vital to sustain a business throughout different economic cycles. In doing so, airlines have put an important effort in optimizing short-term operational costs as well as in understanding customer behavior to define an intelligent pricing scheme. These strategies seek to maximize margins over current capacity in the short-term. But, due to high uncertainty in the markets and economies, it has been difficult to secure profitability and reduce risk for these results in the long run. The introduction of loyalty programs in particular, have helped airlines to secure market shares over time, by rewarding their customers for being loyal. This long-term strategy has had important benefits for airlines, but at the same time has raised difficulties and challenges when managing it in the short-term as part of the optimization processes of the revenue management teams.

1.1. Revenue Management

Different services exist out there that commit to deliver a specific product in a certain moment of time. Within this group, an interesting type of services are the ones that have a high capital investment and an already sunk cost to deliver their committed product. Airlines, hotels, cinemas, or even a stadium, share this challenge. They commit to give customers a specific service or product at a specific moment in time. And, regardless of how many others bought that same product or service, most of the time they will have to deliver with what was offered.

What these services share, is that all of them are managing a perishable inventory. This kind of inventory, as the word defines it, perishes or won’t be available the next day or hour. A room in a hotel will be there, regardless if that night was occupied or not. A movie showcased in a cinema, will be presented at a specific time regardless of how many people bought a ticket for it. And, same for airline flights, which will take off regardless of how many seats were bought¹.

Under this scenario is where airlines try to maximize revenues, by defining an effective yield management, including both pricing and seat inventory control (Belobaba, 1987).

¹ Without considering commercial cancellations.
subject to different customer and market conditions. This is what revenue management is about. Put in other words, revenue management tries to maximize revenues by defining a set of prices and allocations, trying to match customer’s willingness to pay and understanding customer behavior by defining a set of rules to apply on a flight-by-flight basis.

Airlines have been able to match customers’ willingness to pay to price, by having different prices or fares for a given flight, but at the same time, different products to match customers’ behavior. In addition, understanding levels of demand, competition implications, and macroeconomics, among others, have been crucial to maximize revenues, in a highly competitive and low margin industry.

The revenue management optimization cycle, starts by estimating a demand forecast, one of the most important inputs of the overall optimization process. This forecast takes in consideration past flight behavior, current bookings and prices of every fare class, and future information, such as important events or low and high demand periods. When all these elements are combined, the optimizer determines an optimal solution that will result in fare class allocations for each flight, understanding the trade-offs between yields and load factors. Depending on the revenue management scheme utilized by the airline, this solution can be determined by maximizing revenues on a leg basis or taking into account all path interactions, maximizing the network performance.

Introduced by Belobaba, the Expected Marginal Seat Revenue (EMSR) model maximizes revenues at a leg level by defining optimal fare class allocations on nested fare class inventories (Belobaba, 1987). By assuming independency on each flight-fare class, EMSR assigns allocations for each fare class by comparing the expected marginal revenue of one more seat on a given fare class, with the expected revenue at lower fares. This algorithm considers a demand with a probabilistic distribution, allowing to determine booking limits for each class on the nesting. Despite the significant contribution that this methodology has added to airlines and their yield management, it underperforms when trying to optimize the performance of a network, taking into consideration contribution of connecting revenues and opportunity costs on each leg.

In order to optimize the entire network, an origin-destination approach to airline Revenue Management was developed, enabling the optimization of both local and connecting passengers, maximizing their revenue contribution at a network level. Under this scheme, it has been found that airlines can increase their revenues by 1-2% (Belobaba, Odoni, & Barnhart, 2015). By introducing Bid Price control, airlines are able to estimate the opportunity cost related to displaced passengers that will book a same leg, but will have a higher network contribution due to connecting flights. This approach allows airlines to
optimize at a leg level, but taking into account connecting passengers that will go beyond a given leg, and contribute with higher revenues based on their origin-destination behavior.

But, dealing with this strategy comes with high complexity and an important resource investment. In order to capture the value of revenue management, airlines need to design a holistic solution that addresses all the necessary inputs and outputs of system. Fleet management, staff, demand forecast, price and allocation definition, airport operation, cancellations, delays, among others, are part of the broad and complex decisions that airlines must take every day. Highly complicated IT platforms are fed with different datasets, with the objective of optimizing and orchestrate the network and each of the crucial decisions for each flight to be the most efficient on its operation, taking into account revenues and costs.

Moreover, well-trained people are needed at the core of the strategy. This sophisticated system of systems, and the architecture and integration of all parts are as critical as the design and management of each as a separate unit. Having a structure that deals with the overall strategy, supported on key teams and roles throughout all the process, will be key to succeed in a very competitive landscape, where every dollar counts.

In general, revenue management takes care of the short-term, maximizing revenues over a defined capacity and with current economic situations. But, in order to reduce risk and overcome negative exposures in the long-term, airlines have relied on building durable relationships with customers over time.

1.2. Loyalty Programs in the Airline Industry

In highly competitive markets, designing tactical actions are important to sustain the short-term result of the airline. But, securing market share over time, is key for the long-term profitability and sustainability of the business. With this objective in mind, airlines introduced loyalty programs to retain and build durable relationships with customers by giving them a defined set of benefits if they remain loyal to them.

With the launch of Texas International Airlines’ frequent flyer program in 1979, and rapidly followed by American Airlines’ AAdvantage and United Airlines’ Mileage Plus in 1981 (Rowell, 2010), a whole era of free perks and benefits started. The idea was a simple one; airlines would give customers a free flight after they flew with them a fixed number of trips or miles. From the customer perspective, this new benefit was perceived as a gift,
increasing customer satisfaction. And from the business side, this strategy allowed them to reduce costs by retaining an existing customer rather than acquiring a new one, which can be three to five times more expensive (Jang & Mattila, 2005).

Still, at this point, loyalty programs were seen as a marketing cost or a long-term discount, with little knowledge on the impacts, positive and negative, that this strategy was producing at different revenue and cost stream lines. But, while there was no clear understanding on the monetary impacts, the loyalty system seemed to go in the right direction strengthening the value of the airline and creating a not-estimated potential on frequent flyer program’s currency due to its massive penetration and people’s better understanding.

The important shift and game-changer arrived when airlines realized the high value that currency was gaining for customers. Having access to this new currency was the path to free flights, and airlines were the central bank in charge of issuing it. And, more importantly, the ones to set a price for it.

Airlines and their loyalty programs started to sell their currency to third parties interested in giving it to their customers in a different industry. Co-brandings between airlines and banks were born, and frequent flyer programs were no longer a marketing cost, but a business unit. Now, airlines, through their loyalty programs, opened a new stream of revenue, with particular benefits for the airline and for the partners associated with the frequent flyer.

On the airline side, the loyalty program, as a business unit, has three main cash sources (EY, 2014); spread on points, breakage revenue and negative working capital, due to the time difference between receiving cash from partners and when customers decide to redeem their points. Additionally, frequent flyer programs require a low investment for its operation and can bring stability to earnings, reducing exposure to macroeconomic fluctuations. All of these streams have an important effect on the airline’s bottom line, but, the one that can be more exposed to revenue management decisions, is the spread on points.

The value generation through spread on points, has two main drivers; the price at which the loyalty program sells points to third parties, and the value at which the airline and loyalty program allocate seats for customers to redeem. In this allocation process, and availability definition, most airlines agree on a fixed or variable, points-dependent, payment for each award ticket redeemed. With this valuation or proxy, airlines can determine and assign availability to award fares. In consequence, the first part of the spread on points, will come from the difference between the price that the loyalty program sell those points, and the accountable value of points. This last one, depending on the
accountability model, incorporates all the points sold over time, determining the current value of points.

On the other hand, spread on points due to redemption depends on how efficient the airline is able to allocate seats available for award passengers. This margin will be the difference between the accountable value of points and the redemption cost, given by the cost of purchasing a seat on the airline’s inventory. This cost can vary between routes or fare class but, regardless of its value, it will determine how much value remains on the airline and how much value goes to the frequent flyer program as a business unit. Especially important for spun-off loyalty programs, this value has the power to transfer value from one company to another, having important market repercussions.

Breakage and negative working capital, are another important benefit of point-based loyalty programs. Under certain accountability regulations, frequent flyer programs are allowed to recognize as profit the expired and never-redeemed points. Since all the points in each of the members’ accounts is a debt from the airline to the customers, loyalty programs must account for this liability. But, when points expire, loyalty programs move those points from liability to equity. These expired points, along with the points that will never be redeemed nor expired, is called breakage and accounts for a significant stream of revenue for frequent flyer programs and airlines. In addition, the time difference between the revenue of miles sold and the cost incurred for purchasing seats, gives an accountability benefit, allowing airlines to make capital investment, hedge on currency changes, fuel prices, among others.

Since the redemption of points is vital for a frequent flyer program to generate cash, and for the airline to make tangible the reward of been loyal, the valuation for an award seat plays a key role in defining the allocation. Moreover, this value can easily transfer value from the airline to the frequent flyer program, or vice versa, having significant financial implications.

Loyalty Programs can come in three major flavors; Spin-Offs, Partial Float or separate internal accounts. A spin-off, is a completely separate company from the airline, and is not controlled by the airline. As of 2017, Air Canada’s Aeroplan is the only loyalty program following this strategy, when ACE, Air Canada’s holding company, sold completely Aeroplan. A Partial Float, similar to a spin-off, has the frequent flyer company as a separate company, but partially controlled by the airline holding. Multiplus with LATAM, and Smiles with GOL, are examples of this strategy, where LATAM and GOL have an ownership on their loyalty program of 73% and 57%, respectively. Finally, the most common strategy is to manage the frequent flyer program as an internal but separate
account. The airline has total control on its business model, and therefore can align easily both airline and loyalty program strategies.

But, regardless of the business model and strategy, allocating and defining a value for award seats have been challenging for both revenue management and loyalty program's teams (Brunger W., 2013). This difficulty comes mainly from a different understanding of value and time horizon. Revenue management teams tend to view award travelers as “zero-value” passengers, that will decrease their targeted yield on flights. Moreover, revenue management cares mostly about the short-term revenue maximization, generating a mismatch with mid to long-term value creation of the loyalty program. Even surpassing this challenge, there is still a conflict on deciding the right level of award availability based on objective data.

The lack of study, research and knowledge on the impacts of non-revenue passengers on revenue management optimization, makes the availability decision a subjective one. Little expertise on understanding these effects, generates tension between RM teams and loyalty program teams, leading to suboptimal solutions and costly resource involvement.

This expectations mismatch, in addition to the limited knowledge of the impacts of these decisions on the overall revenue management optimization, can lead to different results, impacting both paid and award profitability in unexpected ways.

1.3. Motivation for Research

As presented in this chapter, there has been a collision between the as-is revenue management optimization and the award passenger availability and valuation definition. There is little knowledge of the impact that these passengers have on the paid passengers’ revenue optimization, and therefore a blurry strategy to deal with them. Putting together the short-term and long-term benefits of these two worlds is challenging, but at the same time necessary to define a strategy taking into account all the effects, without destroying value in the intent.

This thesis will focus on understanding the effects of the introduction of award passengers to the revenue management optimization. More specifically, to understand the impacts and behavior of these passengers on the current revenue management optimization, under different revenue management schemes, product definition and their choice process. To identify, classify and estimate these effects, will be the main objective of this
research. But, instead of using historical data or biased assumptions, this research will be based and developed over MIT’s Passenger Origin Destination Simulator, PODS.

PODS, described in later chapters, is a simulation tool that helps to develop different commercial strategies for airlines and understand the impacts on metrics at different levels. The simulator presents an environment with different airlines, each of them optimizing with different specifications, and passengers, arriving to this environment going through a choice model to determine their best option, if any. The capability of understanding not only at a leg level for a specific airline, but to understand the impacts of a certain strategy at a market and network level, is the major benefit of using this tool.

In this sense, different award settings will be tested on PODS with the objective of determining which effects are produced within a specific airline, but also modelling the award passenger choice process when shown both paid and award options.

1.4. Thesis Outline

This thesis is structured in six chapters. This first one introduces the concept of revenue management, loyalty programs and the motivation of this research. Chapter 2 reviews the literature and research already developed in this field, summarizing the key elements for this research as well. Chapter 3 presents the methodology used throughout this thesis, introducing the PODS simulation tool and the award demand generation and RM optimization process implemented in PODS. Chapter 4 shows the performance of different RM Schemes and AP restrictions with this new capability to simulate award demand. And then, Chapter 5 develops a methodology to measure the net award revenue from the airline’s perspective, identifying and quantifying the effects of award passengers in the current revenue management optimization. Finally, Chapter 6 summarizes the findings of this thesis as well as the suggestions for future research.
2. Literature Review

This chapter addresses and summarizes the relevant research and literature available, related to this thesis. A general overview of loyalty programs and how they generate value to airlines is explored. The second section presents the work done on integrating loyalty and a customer-centric strategy with revenue management optimization.

2.1. Loyalty Programs and Value Generation

Loyalty programs, or commonly called frequent flyer programs in the airline industry, have been a common tool for airlines to promote purchase behavior, and to increase willingness to pay, translating into higher revenues for airlines (Reinartz & Kumar, 2002). By increasing repetitiveness and showing higher prices paid than non-members (Meyer-Waarden & Benavent, 2006), loyal customers help airlines to increase profits.

Different strategies have been developed by airlines and their frequent flyer programs to seek loyalty from their customers. But, the most common approach has been to reward purchases by giving points or miles to customers. For a long period, airlines used to give away points based on the distance flown and multipliers depending on the fare paid or tier status. However, most recently, airlines have been shifting to a revenue-based model, where points are accrued just based on the amount the customer paid. Even though multipliers for status or type of fare paid still apply, this new model has been the trend for the last couple of years.

Moreover, customers can boost their points accounts by using the co-branded credit cards affiliated with each program. Typically, banks will issue a specific credit card that will accrue points with every purchase made, regardless of the industry, and with a certain rate calculate points collected. This stream of points, not only helps members to enrich their points’ wallet, but is part of a well-thought plan by airlines to increase their bottom line profit.

Once points are collected and accumulated by members, loyalty programs offer different options to reward their purchase behavior. Discounts, upgrades, free gifts and free air tickets, are part of the offer for redeeming points (Berman, 2006). By allowing customers to redeem for these add-on incentives, members materialize the benefit of being loyal to the airline. At the same time, and depending on their accounting model, airlines reduce their liabilities and are able to recognize revenues for points sold and breakage. This latter...
consists on the points that will never be redeemed as a residue, and the points that expire. Because none of these will be redeemed, airlines are allowed to reduce liability and recognize these points as revenue, when members redeemed or when members accrue points, depending on their accounting model.

This behavior-reward model has become the norm among airlines around the world. With this framework, airlines look to secure market share in time and generate barriers to entry for other competitors in their markets. Changing from one airline to another, will be costly to the customer due to the switching costs involved. These switching costs, as a share of the ticket price, are quite substantial (Carlsson & Lofgren, 2006), and are affected by different factors such as departures, airports, airline itself and the frequent flyer. For example, one airline might have a better departure time for business travelers than its competition, and therefore these passengers will incur on higher switching costs when changing to another airline with worse departure times. Or, when trying to accrue enough miles for a free flight, changing from one airline to the other translates in a loss of miles on the preferred loyalty program, making no improvement on reaching the free-flight goal. Moreover, switching costs are intrinsically related to satisfaction and perceived value, driving loyalty over time (Yang & Peterson, 2004).

In addition, there are studies that discuss the impact of loyalty programs on the willingness to pay of their members when purchasing an air ticket. In fact, loyalty programs members are more likely to purchase the program’s brand and show a higher willingness to pay, whether due to true loyalty or loyalty towards just the reward program (Mathies & Gudergan, 2012). Also, this willingness to pay depends on the type of passenger and its tier level, evolving over time to higher willingness to pay for low and mid tiers (Liu, 2007). These results were proved across all sales channels, even when customers buy lower fares on online channels and higher fares on agencies, due to easiness for searching and more control over buying process (Brunger, 2009).

But, frequent flyer programs not only generate value by developing loyalty over time or by making a business out of their currency, they also are a valuable source of customer information. In this sense, airlines have built entire departments to understand customer behavior and take decisions based on customer intelligence analytics, with segmentations, product differentiation and targeted marketing. And, the information provided by the loyalty program is rich in customer insights, and can drive better segmentation for airlines to work on. With this, loyalty initiatives can focus on customer engagement, providing a consistent brand experience and the smart use of loyalty data to build long-term relationships (Vinod, 2011).
2.2. Loyalty Programs and Revenue Management Integration

As part of highly competitive markets and more accessibility to airlines’ currency, loyalty programs have grown rapidly over the past decades. This not only generates a profitable business for airlines, but also creates a new source of passenger demand to deal with for the Revenue Management department. This complementary demand to the actual paying customer, creates different challenges for the RM team. On the one hand, there is a timing difference between the RM department optimization, and the loyalty program member contribution to the airline. Usually, the RM team manages yield and load factors in the short term, trying to maximize revenues subject to their capacity. Whereas, the contribution of a frequent flyer to the airline, happens in the long run, and therefore it becomes a challenge to understand its contribution on a transactional manner.

On the other hand, there has been a constant debate on the valuation and contribution of frequent flyers from an RM perspective (Brunger W., 2013). Most of the research has focused on the overall contribution of frequent flyer programs and understanding of the macroeconomic impacts of them (Carlsson & Lofgren, 2006), (Vinod, 2011) and (Dorotic, Bijnolm, & Verhoef, 2012). But, very few efforts have been made to understand customer behavior and micro-economics around air tickets redeemed with points. What are the costs involved for both customer and airline? or, what are the impacts on paid fare class mix and revenues? are still questions without an answer.

On the award redemption valuation, there are a couple of papers that touch on this topic. Focused on understanding the price premium of loyalty programs’ members, they incorporate in the availability process definition, the value of the frequent flyer on the short term. These approaches, using MultiNomial Logit (McCaughey & Behrens, 2011) and large linear regressions (Brunger, 2013), define a threshold for availability definition based on the value of the price premium of the different tier levels and the opportunity cost for the award seat. The member will be granted with an award seat if the opportunity cost of the seat is less than the price premium times the value of the tickets required to earn a reward (taking into account breakage of points, purchase programs, among others).

Similarly, some others have tried to incorporate customer lifetime value into the availability equation. By developing a customer-centric availability evaluation, they have developed a framework for capacity control for loyal and occasional customers (Vaeztehrani, Modarres, & Aref, 2015). By integrating long term revenues of loyal customers in the hotel industry, they were able to calculate net revenue losses due to discounts offered and room availability guarantee in the short term. According to Hoff
Revenue management applications that enable non-revenue-based customer-centric strategies offer airline organizations a significantly increased targeting capability making customer recognition programmes more clearly focused on delivering benefits to the most profitable or highest value customers.

With the objective of understanding the benefits of loyalty programs, many studies have focused on understanding the long-term benefits, driving loyalty, frequency and price premium of customers. However, there is not a clear agreement on the impact of loyalty programs on satisfaction and overall profit and airlines’ performance (Vilkaite-Vaitone & Papsiene, 2017; Noone & Mount, 2008), where statistical data analysis has shown that no significant relationships exist between loyalty program, revenue and profit.

Less research has been done on the actual costs that loyalty programs bring to an airline. More specifically, understanding the impacts of allowing non-revenue passengers to access the seat inventory, is still an unknown topic of research. Driven by the perceived value of points and its relationship with revenue management optimization (Basumallick, Ozdaryal, & Madamba-Brown, 2013; Liston-Heyes, 2002), research has focused on understanding the relationship between paid fares and points. By analyzing past behavior of award bookings and available paid fares at the moment of redemption, it was possible to estimate the perceived value of points that customer faced when deciding between paying the air ticket with cash or points. Again, the intention was to define the optimal availability for loyal customers or analyze changes on point accrual policies, based on the past perceived value of points. But, no cost or impact analysis has been done to understand the underlying repercussions of allowing this type of passenger on the overall revenue optimization process.

This thesis provides an assessment of the different impacts that a revenue management strategy faces when allowing award passengers to book for an air ticket. Moreover, it presents a methodology to deal with the costs and benefits that award passengers produce in the revenue management optimization. By understanding effects under different RM optimization schemes, and presenting an award passenger choice process, incorporating passenger disutilities due to perceived value of points, a cost-benefit framework is proposed to incorporate non-revenue passengers in the overall optimization.

2.3. Summary

The objective of this chapter was to present the research and work done related to loyalty programs, their value added and how they have integrated with revenue management
optimization in different levels. At the same time, it discussed the lack of research and studies surrounding the impacts and costs that airlines perceived by accepting non-revenue passengers into their optimization process. Is the aim of this thesis to understand and analyze the impacts of having award passengers as part of the optimization process, by modelling their choice process under different RM schemes and award characteristics, using MIT's PODS simulation tool.
3. Methodology

This chapter aims to present the methods and tools that will enable the analysis and study of this thesis. Most of this research will be developed from the simulations of a system called Passenger Origin-Destination Simulator (PODS). Due to its importance to this thesis, this chapter will present and describe PODS’ architecture, framework and functionalities. The first section presents PODS’ system and its capabilities, followed by a presentation and definition of the network where different models will be run. The third section shows how PODS is adjusted in order to model an award demand with different features. Finally, sections 3.4 and 3.5 present the calibration process for an award demand and its relationship with the current choice process, as well as the methodology used to analyze the outcomes of this new scenario.

3.1. Passenger Origin Destination Simulator (PODS)

The Passenger Origin-Destination Simulator (PODS) is a software that simulates airline networks, considering airline revenue management optimization and its interaction with passengers under a choice process. It is used to test and analyze the performance of different revenue management techniques, such as revenue management optimization models and forecasting methods in particular, in different and controlled simulation environments (Belobaba, 2010). As a system that simulates an airlines-passengers environment, PODS provides a holistic view of the interactions between different stakeholders. It not only allows to analyze a specific airline with a defined revenue management optimizer and forecaster, but also to understand the impacts of different strategies and passenger behavior at a network level.

PODS simulates the booking process of one departure day, with many samples. The first samples are run for airlines to build their booking database, and develop their estimated forecast. By running 600 samples per trial, PODS discards the first 200 to eliminate any initial condition of the system. The other samples are averaged to have robust and statistically significant results. Along a 63-day period, divided in 16 time frames, passengers can book any flight, based on availability and their preferences.

As mentioned before, PODS defines an environment were passengers interact with one or more airlines at the same time. Passengers arrive to the system looking for a specific origin-destination market, and need to decide between different offers with different characteristics, such as airline, path and fare classes available. At the same time, PODS
allows to define the product that each airline will offer on each market. And, based on historical booking behavior and simulation inputs, it is possible to define prices and different attributes or restrictions attached to each airline.

In order to simulate this interaction, PODS has two main components; the Passenger Choice Process and the Revenue Management System. The interaction between these two components is illustrated in Figure 3-1.

![Figure 3-1: PODS Architecture](image)

The Passenger Choice Model’s main objective is to generate passenger demand and model each passenger’s decision process on choosing between one product and another, among different airlines. This model produces passengers that arrive to the system with specific characteristics and travel desires. Once all available options are filtered based on path/class availability, each passenger makes a decision based on his preferences. This booking information is then sent to the airlines and stored in the Revenue Management System.

The Revenue Management System, has three main components. The Revenue Management Seat Allocation Optimizer, the Forecaster and the Historical Booking Database. The Historical Database feeds the Forecaster with historical bookings, and is updated with bookings and cancellations as they occur. Once the Forecaster estimates a
demand, the RM System is able to define the optimal solution for seat allocation. At the same time, the RM Seat Allocation System is the one that interacts with passengers by offering them the available options, based on their behavior, product restrictions and current status of the whole system.

3.1.1. Passenger Choice Process

As illustrated in Figure 3-1, the Passenger Choice Process comprises four main steps; the Demand Generation, Passenger Characteristics, Passenger Choice Set and the Passenger Decision.

The first step of the Passenger Choice Process is to generate demand for air travel in each O-D market. An average total daily demand, for each of the system markets, is split in two types of passengers; leisure and business. Based on airline industry data, PODS inputs assume 60% of the total demand leisure passengers, and 40% business passengers. Random deviations from the mean are generated in order to introduce variability from day to day. Once the level of demand is determined for each type of passenger and market, passengers arrive to the system according to the defined booking curves. These curves, also based on industry behavior, are an input to the system.

Typically, these curves are as illustrated in Figure 3-2, with a determined percentage of passengers arrived per time frame.

![Graph showing Booking Arrival Curves per Passenger Type](image)
As it can be seen, these curves show a clear difference in arrival time to the system. While leisure demand tends to arrive earlier in the booking process, business demand shows a lower advance purchase, arriving later on in the booking window.

At the start of each time frame, the RM system re-optimizes the booking limits, and all booking and cancellations, as well as closed and re-opened classes occur within each time frame. Like the booking curves, the time frames definition is another PODS’ input. Table 3-1 summarizes a frequently used time frame setup, with the days until departure and time frame duration, for each time frame.

<table>
<thead>
<tr>
<th>Time Frame</th>
<th>Days until Departure</th>
<th>Time Frame Duration (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>63</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>56</td>
<td>7</td>
</tr>
<tr>
<td>3</td>
<td>49</td>
<td>7</td>
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<tr>
<td>4</td>
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<td>7</td>
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<tr>
<td>5</td>
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<td>4</td>
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<tr>
<td>6</td>
<td>31</td>
<td>3</td>
</tr>
<tr>
<td>7</td>
<td>28</td>
<td>4</td>
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<tr>
<td>8</td>
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<td>14</td>
<td>4</td>
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<td>12</td>
<td>10</td>
<td>3</td>
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<tr>
<td>13</td>
<td>7</td>
<td>2</td>
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<td>14</td>
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<td>15</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>16</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3-1: Booking Process Time Frames

Once the demand is generated, passenger characteristics are defined based on three features: decision window, willingness to pay and disutility costs due to product attributes and travel options.

The decision window specifies the earliest departure time and the latest arrival time that the passenger is willing to consider as possible. The objective of assigning a decision window for the passenger is to model how tolerant are different types of passengers to different schedule options. Leisure passengers will typically be more flexible, having a
greater decision window, whereas business passengers will have a smaller decision window, since they will probably want to travel at a specific time, with less flexibility.

A maximum willingness to pay is also assigned to the passenger. This value is derived from a price-demand curve for each type of passenger, that determines the demand willing to purchase a specific price-product. This curve is modeled using a base fare and a negative exponential distribution. Differences among passenger types, are reproduced by assigning different base fares as inputs to the distribution curve. With this, business passengers will have a higher willingness to pay than leisure passengers.

Disutility costs are introduced to model passenger preference for different product alternatives. Since airlines offer products with different attributes and restrictions, passengers will face a cost on top of the fare due to the specific attributes of each available product. These disutilities might be affected by options outside the decision window, connecting versus non-stop flights and restrictions of the fare class, like non-refundability, changes or Saturday night stay. In order to model differences between leisure and business passengers, disutilities in PODS are also different for each passenger type. By introducing differences among passengers, PODS simulates the particular sensitivity of each passenger type to product attributes or changes between passenger’s desire and actual booking.

Having defined the disutility costs, the total cost of an option perceived from a customer perspective will be the sum of the air fare plus the disutility costs that the passenger sees on his choice process. PODS will then rank all the possible alternatives, among all airlines, for each passenger by the total cost, subject to RM availability. Finally, the system will assign to the passenger the option with the lowest total cost. Once the decision is made, the passenger makes a booking and the revenue management systems are updated accordingly.

3.1.2. Revenue Management System

In order to define an availability solution in PODS, airlines rely on a Revenue Management System that can operate frequently enough to consider all variables in place. As presented before, the Revenue Management System consists of an RM Seat Allocation Optimizer, a Forecaster and a Historical Booking Database.
PODS has the ability to define different RM Systems for each of the airlines within the network. For the purpose of this thesis, each airline will be assigned to one RM Scheme among these options; EMSR, DAVN, UDP and ProBP.

**Expected Marginal Seat Revenue (EMSRb)**

Originally developed by Belobaba (Belobaba, 1992), EMSRb is a refined model of its former version EMSRa, developed by Belobaba (Belobaba, 1987). In a general idea, EMSRb assigns booking limits and protections to each fare class in a nested structure, by computing the marginal benefit of moving one seat from one class to the other.

EMSRb assumes that the demand for each fare class is independent from the others, and is possible to model it by an independent Gaussian distribution. The mean and standard deviation for each distribution will be estimated by the historical data, and will be used to calculate the distribution of demand for joint classes, combining each fare with all higher classes. Once demand is modeled, protections and booking limits are defined for each fare class as shown in Table 3-2.

<table>
<thead>
<tr>
<th>Fare Class</th>
<th>Booking Limit</th>
<th>Protection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y</td>
<td>60</td>
<td>5</td>
</tr>
<tr>
<td>B</td>
<td>55</td>
<td>6</td>
</tr>
<tr>
<td>H</td>
<td>49</td>
<td>2</td>
</tr>
<tr>
<td>K</td>
<td>47</td>
<td>2</td>
</tr>
<tr>
<td>M</td>
<td>45</td>
<td>5</td>
</tr>
<tr>
<td>L</td>
<td>40</td>
<td>2</td>
</tr>
<tr>
<td>V</td>
<td>38</td>
<td>5</td>
</tr>
<tr>
<td>S</td>
<td>33</td>
<td>4</td>
</tr>
<tr>
<td>N</td>
<td>29</td>
<td>4</td>
</tr>
<tr>
<td>Q</td>
<td>25</td>
<td>5</td>
</tr>
<tr>
<td>O</td>
<td>20</td>
<td>20</td>
</tr>
</tbody>
</table>

*Table 3-2: Fare Class Booking Limits and Protections*
These protections, and therefore booking limits, are given by the EMSR curves for each class. These curves are illustrated in Figure 3-3, and shows the booking limit will be the number of seats at which the EMSR curve of one class is equal to the EMSR curve of the following class.

![EMSR Curves and Booking Limits](image)

As described before, EMSRb maximizes revenue at a leg level, not necessarily network contribution. Even though it takes into consideration connecting passengers, EMSRb will open a leg as part of the overall path only if that class is open, needing each leg to be open independently to have availability on the complete path. Other RM Optimizers will compute the benefit of accepting new passengers but at a network level.

**Displacement Adjusted Virtual Nesting (DAVN)**

While EMSRb determines booking limits on each fare class at a leg level, DAVN is an O-D control mechanism that incorporates differences between O-D itineraries within a fare class (Williamson, 1992). Instead of using fare classes for seat inventory control, DAVN uses virtual buckets where each path-class is mapped to, based on network revenue.
values. The network revenue value, or also called pseudo fares, represent the actual fare of the origin-destination, minus the sum of all displacement costs related to other legs involved in the itinerary. With this, DAVN penalizes for the potential displacement on other connecting legs.

Given each displacement adjusted origin-destination fare (ODF) is determined, they are assigned to a virtual class or virtual bucket based on their estimated network revenue contribution. In order to assign a value to each leg of the itinerary, DAVN subtracts from the total ODF all the down-line leg displacement costs due to connecting demand. The displacement costs, as well as the revenue ranges for virtual inventory buckets, are re-optimized at every time frame using EMSR. The path-class demand forecast used as an input for DAVN is rolled up to a leg-bucket level, to follow the same structure as the optimizer. This computation allows DAVN to manage availability at a leg level, making it similar to EMSRb, maximizing revenue contribution flight by flight.

**Unbucketed Dynamic Programming (UDP)**

As an extension of DAVN, UDP takes DAVN’s network displacement solution and uses it without mapping ODFs to classes or buckets. By using the same leg displacement costs as in DAVN, UDP uses the displacement adjusted path-classes directly to calculate leg DP bidprices based on the remaining leg capacity.

But, instead of having a static solution for each timeframe-flight, UDP introduced dynamic programming to generate dynamism within each timeframe. By taking into account the current booking status and capacity of flights, UDP is able to determine variable booking limits or bid prices that move with each flight status. Bid prices are determined by using a dynamic programming approach at leg level, based on single leg concept (Lautenbacher & Stidham Jr., 1999).

In order to define availability, the DP bidprices are summed up across all legs within the OD itinerary, and if the fare is higher than the sum of DP bidprices, then the OD-path-class is open, otherwise is closed.

**Probabilistic Network Bid Price (ProBP)**

Originally developed by Bratu (Bratu, 1998), ProBP is a nested probabilistic network convergence algorithm. This path-based forecast, estimates the network value contribution of each ODIF on each of the associated legs by incorporating the probabilistic
nature of ODIF demand, as well as taking into account that when a seat is available for
given ODIF, it should be available for ODIFs with higher values.

Based on ODIF data demand forecast, ProBP estimates a critical EMSR operator for each
leg, by accounting for complete nesting of ODIF availabilities as shown in Figure 3-4.

Once critical EMSR values are obtained, ProBP uses them as additive bidprices for local
and connecting path requests, determining availability against the OD fare. Availability
requests are computed by comparing the fare value against the sum of all bidprices at
each leg traversed for connecting flights. If the fare value is greater or equal than the sum
of bidprices, then the OD-path-class is open, otherwise is closed.

**Forecaster**

As illustrated before in Figure 3-1, the RM Seat Allocation Optimizer needs a forecasted
demand as an input. Moreover, depending on the optimizer that an airline is using, the
forecaster should be aligned with the choice by giving the input accordingly. For the
purpose of this thesis, and for the RM Optimizers previously described, forecaster will
come in two flavors in PODS; standard leg-class forecasting and standard path-class
forecasting.
Standard leg-class forecasting will be used as an input for EMSR, and it consists in estimating a demand at leg level for each flight-leg of the network. This forecast will be based on the aggregated leg-class historical database. On the other hand, standard path-class forecasting will serve as an input for DAVN, UDP and ProBP. This method, estimates the demand based on an aggregated historical path-class bookings database. This forecaster gives an estimation of demand by origin-destination-path-class, aligned with the rationale behind each of the O-D control mechanisms.

But, regardless of the forecasted output, each method employs the pick-up forecasting methodology. This methodology forecasts the bookings to come, based on the current bookings and the historical bookings to arrive until departure. The forecasted bookings to come are computed based on the historical database that each airline has, and that are updated after each sample of PODS.

### 3.2. Network U10

Network U10, a network developed for PODS, will serve as the scenario for all simulations for the purpose of this thesis. This network allows four airlines to compete, with different strategies, over a mix of domestic and international markets. Between all airlines, they serve 572 OD markets, 442 flight legs, business and leisure passengers and 44 cities. In addition, each airline has one hub, 10 fare classes and 3 fare structures to define the offer to customers.

#### 3.2.1. Airlines

Network U10 consists of four airlines, each one operating in a hub-and-spoke structure different than the others. Airline’s 1, 2, 3 and 4 networks are illustrated below in Figures 3-5, 3-6, 3-7 and 3-8, respectively. Airline 1 operates to all cities in the network from its hub in MSP, with some other point-to-point connections between some major cities. Airline 2 and 4 have a similar network structure, having hubs in ORD and DFW, respectively, but don’t serve all the cities that are part of the market. And finally, Airline 3 is a smaller low cost carrier (LCC), serving fewer cities than the other carriers from its MCI hub.
Figure 3-5: PODS Airline 1 Network. Source: Belobaba (2013)

Figure 3-6: PODS Airline 2 Network. Source: Belobaba (2013)
3.2.2. Fare Structures

Within Network U10, each airline offers 10 different fare classes for the different O-D markets that they are serving. There are three different fare structures defined in PODS for airlines to offer; Domestic Restricted, Domestic Less Restricted and International Restricted. These structures are summarized in Table 3-3, showing for each product-
class what restrictions apply and how different they are from one product to the other. Typically, airlines define advance purchase, minimum stay, cancellation fees and Saturday night stay, as their restrictions for each class. Table 3-4 introduces these definitions and their relationship with the restrictions that airlines will use in PODS simulations presented in Table 3-3.

<table>
<thead>
<tr>
<th>Restriction</th>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advance Purchase</td>
<td>AP</td>
<td>Minimum days before departure that the class will be available.</td>
</tr>
<tr>
<td>Minimum Stay</td>
<td>MIN</td>
<td>Minimum days that passenger needs to stay in destination.</td>
</tr>
<tr>
<td>Cancellation Fee</td>
<td>CXL</td>
<td>If cancellation fees apply due to cancellation of ticket.</td>
</tr>
<tr>
<td>Saturday Night Stay</td>
<td>SAT</td>
<td>If class requires a Saturday night stay to be available.</td>
</tr>
</tbody>
</table>

Table 3-3: Fare Structures and Restrictions

<table>
<thead>
<tr>
<th>FC</th>
<th>AP</th>
<th>MIN</th>
<th>CXL</th>
<th>SAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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<td>0</td>
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<td>4</td>
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<td>10</td>
<td>21</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3-4: Restrictions definitions
When comparing the restrictions among the different products, it can be seen that the Domestic Restricted and Domestic Less Restricted have the same AP restriction structure, but differ on the MIN, SAT and CXL. The Domestic Restricted from fare class 5 to 10, requires a minimum stay, whereas classes 1 to 4, do not. In addition, almost all fare classes have a cancellation fee, except for classes 1 and 5. And, only classes 9 and 10 require a Saturday night.

On the other hand, Domestic Less Restricted does not have minimum stay restrictions for any of its classes, nor Saturday night requirement. On top of AP restrictions, all classes have cancellation fees, except for class 1.

The International Restricted product, has a similar restriction structure as the Domestic Restricted. It has advance purchase, cancellation fees and maximum stay, structured in a way such that lowest fare is more restricted than the higher classes.

### 3.3. Award Choice Process Implementation in PODS

As reviewed in Chapter 2, most of the award passenger research has targeted the valuation of frequent flyers and/or how to incorporate this valuation into the RM optimization process. And, as highlighted, there is almost no study on how these passengers affect the RM optimization process. Modeling an Award Choice Process in PODS, will help to understand the impacts of these passengers under different scenarios and characteristics.

So far, and as illustrated in Figure 3-1, PODS is able to generate demand with defined characteristics that will evaluate the options made available based on the RM Seat Allocation optimization of the different airlines in the network. In order to implement an Award Choice Process, it is necessary to model both supply and demand for the Award Product. The option of having access to a points-based fare will be simulated as one class at the bottom of the fare structure with a defined RM value and only available to a portion of the total demand. On the one hand, airlines need to allocate award seats and define an availability based on the value that those seats represent for the airline. And, on the other hand, passengers will now have the option to access this new product, making necessary to model how passengers will consider this new alternative in addition to the current alternatives.
3.3.1. Award Class RM Input

Whenever there is an availability request from the passenger to the RM Seat Allocation Optimizer, each optimizer, depending on the RM Scheme, will determine whether that fare class is open or not. This result depends on the current RM availability for each airline, and on the price or value assigned to each fare class. By introducing an 11th class, under the lowest class (10), each airline will now be able to assign a specific availability for award bookings only. At the same time, a new parameter is introduced for each airline to assign a value to this new class in its RM Optimizer.

The Award Class RM Input is a value that represents the value of the award class for the RM system to determine availability for this new fare class. The parameter implemented in PODS is based on the lowest fare, class 10, meaning that it takes the lowest fare and multiplies it by the Award Class RM Input in order to define a value for the award class.

Table 3-5 shows how the new award class is introduced to the fare structure. In this example, the Award Class RM Input is 50%, so the value for the RM system for the award class is 50% of the lowest class (10), which is equal to $108.

<table>
<thead>
<tr>
<th>FC</th>
<th>Fare</th>
<th>AP</th>
<th>MIN</th>
<th>CXL</th>
<th>SAT</th>
</tr>
</thead>
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<td>0</td>
<td>0</td>
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<td>0</td>
</tr>
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<td>7</td>
<td>363</td>
<td>14</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>345</td>
<td>14</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>256</td>
<td>14</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>216</td>
<td>21</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

| 11 (new) | 108 | 21 | 1   | 1   | 1   |

Table 3-5: Example of Award Class RM Value at 50%. 

39
At the same time, the new award class copies class 10’s restrictions for baseline tests. Since the value of the award class is lower than the lowest paid fare class, it makes sense that at least this new class should acquire the same restrictions as of class 10. This will represent the base case to run different tests, and also the baseline scenario to compare against to when making changes and adjustments to test other environments.

As mentioned before, the Award Class RM Input is how the RM optimizer values the award class for assigning availability to it. Since there are multiple benefits when a customer redeems their points for a seat, the Award Class RM Input will simulate the value that each airline decides to assign to this benefit. In practice, by moving this value the RM optimizer will assign less or more availability to the award class, being a lever to control award availability. The accounting or economic value afterwards, is not intended to be simulated.

3.3.2. Award Class Eligibility

Up to this point, the RM Optimizer is able to define a certain availability for the award class based on the value that the airline or frequent flyer program assigns to it. The next step in order to incorporate this new product into the current passenger choice process is to determine what portion of the demand, already generated, is eligible to have access to this class.

The Award Class Eligibility parameter is the probability that a leisure passenger is eligible to book an award class on a given airline. Eligible will mean that the passenger has enough points on the airline and is willing to spend them. For each leisure passenger that arrives to the network looking for a specific ODIF, PODS will determine if the passenger is award eligible on each airline with the probability defined by the Award Class Eligibility parameter.

Figure 3-9 illustrates how the Award Class Eligibility Probability defines in which airline the award class will be considered for each leisure passenger. The example considers a 5% probability and acts on each airline, having equal probability for the passenger to be award eligible on each of them. Once the process determines on which airline the passenger is award eligible, the RM Optimizer determines if the award class is open in addition to the other fare classes for the ODIF requested.
When combining both parameters, it is possible to integrate the award demand and availability into the current choice process. Whenever a leisure passenger is generated, the Award Class Eligibility Probability will determine if he is award eligible on each airline of the network. Then, the RM Optimizer, based on the Award Class RM Input, will resolve if the award class is open for the ODIF requested, and the passenger will evaluate all possible options considering both award and paid fare classes.

Once all open options, award and paid, are determined, the passenger will compute the total disutility for him. This disutility consists of the fare of the class open, plus all the disutility costs regarding cancellation fees, ticket refundability or Saturday night stay.
PODS models fare disutilities in the baseline, including award, based on four disutility parameters. As shown in Table 3-6, each disutility will be given by a combination of the disutility parameters and if that disutility is active or not for that fare class. The total disutility will be given by the following equation,

\[
\text{Disutility Fare}_i = \text{Fare}_i + \text{base}_\text{fare} \sum_j \text{disutility}_\text{parameter}_j \times \text{disutility}_\text{active}_{ij}
\]

where base_fare is a PODS network parameter equal to the lowest fare. In consequence, the total disutility for the passenger will be the fare that is available plus the base_fare times the sum of the disutility parameters active for the specific fare.

As it can be seen, the fare for the award class (11) is 0. This means that the passenger will view the award class a zero-value class. But, disutilities will still apply. In the next chapter, this will be an assumption that will be removed by testing different values for the award disutility.
3.4. Baseline Calibration and Definition

With the development and parameters defined in the previous section, PODS is now able to generate an award demand, as well as assign award class availability on any flight on each of the airlines in the network. In this section, different values for these parameters will be tested and simulated in order to calibrate the model and define a baseline scenario to analyze sensitivity on other PODS parameters.

3.4.1. Experiments and PODS Setup

The calibration process starts by defining a scenario in which to run different experiments. In this case, network U10 will be the network where four different airlines will have the option to offer an award class. Airline 1, 2 and 4 will use DAVN, and Airline 3 will be using EMSRb as their RM Systems, and all airlines will have an award class as fare class 11.

The nine experiments to test, are presented in Table 3-7. As can be seen, there are three values for the Award Class Eligibility Probability and three value for the RM Award Class Input. Once these scenarios are run, the output will be compared to industry level for award bookings. By asking experts in the field, mainly from the PODS Consortium at MIT, the target percentage of award bookings over total bookings, should be within the 5-8% range.
3.4.2. Calibration results

Once all scenarios are run, different metrics can be shown to understand their behavior with award passengers now able to access the seat inventory. At this point, only total metrics, at a network level, will be analyzed to see which set of parameters models these new passengers in the best way possible.

When analyzing total Load Factor (LF), which is the total bookings, including award bookings, divided by the total capacity, it can be seen that as the Award Class Eligibility increases, LF increases. The same happens when the RM Award Input increases, with Airline 1 increasing its total LF. Figures 3-10, 3-11 and 3-12 show the impact of changing the Award Class Eligibility Probability and RM Award Input for Airline 1. The “base” represents a base scenario where there is no award class demand, nor award class availability.
The same analysis can be done, but now looking at Ticket Revenue on Airline 1. Ticket Revenue is considering only Paid Revenue up to this point, and not incorporating the economic benefit of having award passengers on flights yet.
Figures 3-13, 3-14 and 3-15 show how Ticket Revenue change as both the Award Class Eligibility Probability and RM Award Input change. The result is completely opposite to the LF variation, where Ticket Revenue decrease as the Award Class Eligibility Probability increases, and also decrease as the RM Award Input increases.
As mentioned before, one of the key metrics that will help to calibrate the model is the percentage of award bookings over total bookings, paid and award. In order to simulate a realistic scenario, this value should be within the 5-8% range, as discussed with the airline members of the PODS Consortium.

Figure 3-16 shows the percentage of award bookings using 50% for the RM Award Input and a 5% of Award Class Eligibility Probability, for all airlines. This value, measured by the share of award passengers trip over total bookings, is within the 5-8% range that should be to be comparable with industry levels.

![Figure 3-16: %Award bookings for pax_trip for all airlines (%)](image)

Finally, and to analyze how availability is behaving along timeframes in the simulation process, the percentage of the requested times where the award class is open is illustrated on Figure 3-17. At the same time is compared to the lowest fare to understand the relationship between these two metrics, since the availability definition for the award class is based on the lowest fare (class 10).
When the award class has a 50% of RM Award Input and a 5% of Award Eligibility Probability, the percentage of closed fare for the award class ranges from 42.7% up to 50.5%. As bookings and flights fill up, this value decreases when closer to departure. Both classes, award and 10, are totally closed by timeframe 8, which represents the advance purchase restriction of 21 days that both classes have, as presented in Table 3-5. This analysis also helps to understand the behavior and to discard outliers that might be present due to this new class introduction.

3.4.3. Baseline scenario definition

After analyzing the impacts and sensitiveness of the Award Eligibility Probability parameter and the RM Award Input, the baseline scenario to perform further research is summarized in Table 3-8. The two parameters will be equal for all airlines at a network level, and therefore no modelling differences will be introduced by airlines. The results for the baseline scenario for Total LF, percentage of Award bookings, Ticket Revenue and Yield, are presented for Airline 1 only, which will be the Airline used to compare results under different setups in the next chapters.
To understand and clarify the definitions of each of the metrics defined in Table 3-8, Table 3-9 summarizes the metrics, their equations and their considerations.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Equation</th>
<th>Consideration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Load Factor</td>
<td>$\frac{\text{award RPMs + paid RPMs}}{\text{ASM}}$</td>
<td>Considers both award and paid RPMs.</td>
</tr>
<tr>
<td>% award bookings</td>
<td>$\frac{\text{award bookings}}{\text{Total bookings}}$</td>
<td>Award bookings over Total bookings.</td>
</tr>
<tr>
<td>Ticket Revenue</td>
<td>$\frac{\sum \text{paid revenue}}{\text{Total RPMs}}$</td>
<td>Sum of paid revenue only.</td>
</tr>
<tr>
<td>Total Yield</td>
<td>$\frac{\text{Ticket Revenue}}{\text{Total RPMs}}$</td>
<td>Ticket Revenue (paid only) over Total RPMs (award and paid).</td>
</tr>
</tbody>
</table>

Table 3-9: Metrics definitions and considerations

### 3.5. Summary

This chapter presented the methodology and tools that will be used in the next sections of this thesis. The Passenger Origin Destination Simulator (PODS) was described, going deeper into the Passenger Choice Model and the different Revenue Management Schemes of the Revenue Management System. In addition, the network that PODS will simulate on for the purpose of this study was outlined, describing the different features of airlines and fare structures. Finally, the Award Choice Process in PODS was presented, understanding the impact of the parameters to assign availability and generate passenger demand. A baseline scenario was finally presented to perform the upcoming simulations.
4. Award Class under different RM Schemes and AP restrictions

This chapter examines the impacts of the award class performs under different RM Schemes and advance purchase restrictions. Moreover, it analyzes the impacts on both paid and award passengers and the overall outcome for the main metrics once the award class is introduced to the optimization process. First, the RM Schemes and advance purchase restrictions to test are described. In sections 4.2 and 4.3, the results of the simulations are presented for the RM Scheme and advance purchase, respectively. Finally, a summary presents the main findings of the experiments.

4.1. RM Schemes and AP Tests

As presented in Chapter 3, four RM Schemes will be used in this thesis to test and understand the behavior of changes on the award class simulation. These are EMSRb, DAVN, UDP and ProBP, where the first is a leg-based optimizer, whereas the other three are path-based optimizers. More than understanding the impacts of applying one of these schemes, the goal of this analysis is to understand how these schemes perform with an award class.

The experiments that will be tested are summarized in Table 4-1.
For the first experiment, Airline 1 will change its RM Scheme with all else equal. Airline 2, 3 and 4, will be using DAVN, EMSRb and DAVN, respectively. In terms of fare structure, this test will be conducted copying class 10's restrictions for the award class. These restrictions, described on Chapter 3, consider a non-refundability fee, Saturday night stay, minimum stay and advance purchase (AP). In this case, the AP for the award class will be 21 days, same as class 10.

The second experiment will be varying the AP restriction for the award class. In this scenario, Airline 1 will use DAVN as its RM Scheme and only the AP restriction on the award class will change. All other restrictions for the award class will be the same as class 10.

In both cases, the simulations are in Network U10 and with load factors ranging from 83 to 85%, which is defined as Medium Demand in PODS.

### 4.2. RM Schemes Results

After the simulations under different RM Schemes were performed, considering an 11th class for the award class, PODS generates different output information to analyze. This analysis will focus on network-level data, without detailing what happens at a leg level. This is mainly to interpret the overall impacts of introducing an award class to the RM optimization controls.
Ticket Revenue is one of the main metrics to analyze. In this case, Ticket Revenue only considers revenue from paid tickets, and it does not consider revenues or benefits of award passengers. This assumption will be relaxed in Chapter 5. Figure 4-1 shows the changes in Ticket Revenue for different RM Schemes, when an award class is introduced. Changes are shown over an EMSRb base for Airline 1.

As expected with OD-control optimizers, all of them perform better than EMSRb due to optimization at a network level and not at a leg level. But, when an award class is introduced, ProBP shows the highest Ticket Revenue, with a +0.66% change over EMSRb. UDP and DAVN also increase Ticket Revenue, with a +0.53% and +0.22% gain over EMSRb base, respectively.

![Figure 4-1: Ticket Revenue for different RM schemes with an Award Class (M$)](image)

But, to understand what drives the change in Ticket Revenue, it is important to analyze what happens with both passengers and average fare. Figure 4-2 shows the change in award and paid passengers over EMSRb. UDP is the most permissive RM Scheme with award passengers, with the highest nominal award bookings, reaching a 7.01% share of total bookings. On the other hand, DAVN and ProBP decrease the number of award bookings from the EMSR base, also dropping the share of award bookings down to 6.50% and 5.85%, respectively.
Even though UDP allows the highest number of total passengers, driven by a higher contribution of award passengers, it reduces the paid passengers by -0.19%. This results in a 1.37pp drop for paid passengers share, compared to EMSRb. On the contrary, ProBP increases paid passengers compared to EMSRb, boosting Ticket Revenue, as shown in Figure 4-1.

One of the reasons that helps UDP to increase the number of award passengers compared to the other RM Schemes, is the Poisson assumption used to calculate bid prices. The low variance of the Poisson distribution results in lower bid prices in early booking periods, which gives higher availability to the award class, even at a low fare value.

Based on this result, UDP shows the highest Total Load Factor, reaching 84.44%. The Total Load Factor considers both paid and award RPMs, and since the supply has remained equal, this result is driven by an increase in paid and award passengers, and route mix. Figure 4-3 summarizes this result for all RM Schemes tested.
As a result, Total Yield drops by 0.2% for UDP since there is less Ticket Revenue and more total passengers carried. It is important to note that, Total Yield is measured without considering award revenues or benefits, but award passengers are counted as part of the RPMs for this metric. At the same time, DAVN and ProBP increase Total Yield driven by an increase in Ticket Revenues, and a decrease of Total Load Factor, compared to EMSRb. These changes are presented in Figure 4-4.
Up to this point, the benefit or revenue of each award passenger that is booked has not been taking into consideration for the analysis. Only award passengers, and award RPMs, have been affecting the metrics previously presented. In order to understand what happens when the award revenue is introduced, this benefit will be assumed as the same as the RM Optimizer is currently using to value award class. This means that if the Award RM Input Parameter is 50%, and the lowest fare is $100, the award revenue per ticket will be assumed as $50. Since the lowest fare is different for each OD-product, the award revenue per ticket will move accordingly.

Figure 4-5 shows both award and paid revenue for each RM Scheme. Now that the award revenue is introduced, UDP shows the highest Total Revenue, increasing by 1.0% Total Revenues over EMSRb. DAVN and ProBP follow Figure 4-1 tendency by adding on top of paid revenues the award revenue. As a result, DAVN gains 0.5% Total Revenue over EMSRb, and ProBP does the same, increasing Total Revenues by 0.7% over EMSRb. This result is aligned with the passengers result summarized in Figure 4-2, showing that UDP has a higher share of award passengers, and therefore now, when award revenues are incorporated, Total Revenues are higher under this RM Scheme.

Another way to analyze what is happening at a more detailed level, is to analyze Award Load Factor vs Paid Load Factor at a leg level. With this analysis, it can be seen how award bookings are distributed over the total seats available and paid load factor level on individual flight legs in the network. Figure 4-6 shows the Award Load Factor for each Paid Load Factor level, for all RM Schemes, at each level. On the horizontal axis, legs...
are grouped by Paid Load Factor, from 50% up to 100%, by 10pp increments. On the y axis, the Award Load Factor is shown for each Paid Load Factor group level.

The results show that the Award Load Factor increase at low level Paid Load Factor, and decrease at high level Load Factor. This result is not surprising since the award class will have more room for award bookings with less paid passengers booking in those flights.

At the same time, it can be seen how UDP shows a higher Award Load Factor for almost all Paid Load Factor levels. On the contrary, ProBP presents the lowest Award Load Factor for almost all Paid Load Factor levels, resulting in the lowest Award Load Factor.

In the next chapter, it will be analyzed how this distribution of Award Load Factor over Paid Load Factor, impacts the displaced paid revenues. Up to this point, having more award bookings on low level load factors, might be better in terms of paid passengers’ displacement. The hypothesis is that at low Paid Load Factor levels, the displacement of award bookings should be lower than at high Paid Load Factors.

<table>
<thead>
<tr>
<th>Award LF (%)</th>
<th>EMSR</th>
<th>DAVN</th>
<th>ProBP</th>
<th>UDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;0.5</td>
<td>12.1%</td>
<td>10.5%</td>
<td>9.9%</td>
<td>11.7%</td>
</tr>
<tr>
<td>0.5-0.6</td>
<td>13.7%</td>
<td>11.9%</td>
<td>7.1%</td>
<td>11.3%</td>
</tr>
<tr>
<td>0.6-0.7</td>
<td>11.3%</td>
<td>8.3%</td>
<td>6.9%</td>
<td>7.3%</td>
</tr>
<tr>
<td>0.7-0.8</td>
<td>13.7%</td>
<td>6.1%</td>
<td>6.9%</td>
<td>8.0%</td>
</tr>
<tr>
<td>0.8-0.9</td>
<td>11.3%</td>
<td>4.3%</td>
<td>4.1%</td>
<td>6.1%</td>
</tr>
<tr>
<td>0.9-1</td>
<td>12.1%</td>
<td>5.4%</td>
<td>3.3%</td>
<td>0.8%</td>
</tr>
</tbody>
</table>

* Figure 4-6: Flight Leg Award Load Factor by Paid LF for each RM Scheme (%)
The second analysis that was described in section 4.1, considers changing the advance purchase (AP) restriction for the award class at a given RM Scheme, that in this case will be DAVN. In the baseline, the award class is copying all fare restrictions of class 10, assigning a 21 AP restriction for it. In this section, only the award class AP will be changed to 14, 7 and 0.

The Ticket Revenue Result summarizes all the underlying effects, and shows the direction of the impact when decreasing the award AP restriction. As mentioned previously, Ticket Revenue only includes revenue from paid bookings, and award revenue is not considered. As presented in Figure 4-7, Ticket Revenue decreases when the Award AP restriction decreases. This result not only suggests that there are less paid bookings, but more importantly, that the award AP is quite effective at 21 days. In this sense, the AP restriction at 21 days is helping to segment the demand, regardless of the availability that the optimizer assigns to it after the 21 days of AP. When this restriction is relaxed, the RM optimizer still gives availability, and therefore more award bookings can be accepted.

When considering award revenues, based on the RM Award Input, the percent change in revenues is still negative for all AP less than 21 days. This result is shown in Figure 4-8,
where, as the AP goes down, Total Revenue goes down, reaching a -0.5% change when the Award AP is 0. Even when introducing the gain in award revenue due to higher availability, this revenue cannot compensate the loss on paid revenue.

![Figure 4-8: Paid and Award Revenue distribution for different AP restrictions for Award Class (M$)](image)

But, due to this higher award availability, the increase in award passengers surpass the loss in paid passengers, resulting in higher Total Passengers transported, as shown in Figure 4-9. This result is true for all AP scenarios, and the Total Passengers increase as the Award AP decreases, showing a +0.5% change on Total Passengers for 0 AP.
As a consequence, Total Load Factor, considering both award and paid passengers, increases as the Award AP decreases, presented in Figure 4-10. There is a total gain of 0.42pp in the Total Load Factor when the Award AP is 0, reaching a Total Load Factor of 84.13%. However, since Ticket revenue, only accounting for paid revenue, decreases and Total RPMs increase, the Total Yield decreases as the Award AP goes down. This effect is summarized in Figure 4-11.
Yield, which only accounts for paid revenues, but takes into consideration both award and paid RPMs, decreases from 0.1206 cUSD to 0.1188 cUSD, dropping by 1.5% from 21 days to 0 days of AP. This result is not surprising since, Ticket Revenue decreases as more award passengers book flights with a lower AP. And, at the same time, Total RPMs, considering award and paid bookings increases as shown in Figure 4-10 when analyzing the Total Load Factor. For all scenarios, supply, meaning ASMs, remains equal, therefore the change in Total Load Factor only is affected by Total RPMs.

4.4. Summary

This chapter analyzed the effect of the award class under different RM Schemes and changes in the AP restriction for the award class. More specifically, the impacts on Total Revenue, Load Factor, Passengers and Yield, were analyzed to understand the variations in each scenario.

When analyzing RM Schemes, UDP showed the best Total Revenue performance, increasing both Award and Paid Revenue over an EMSR base. Even though DAVN and
ProBP also showed an increase in Total Revenue, both increasing Paid and Award Revenue, UDP was the one showing a higher change. This was mainly due to a larger increase of Award Passengers and a small negative change in Paid Passengers, compared to the other Schemes.

The variation of the Award AP restriction proved that the lower the Award AP, the lower the Total Revenues. In this case, when decreasing the AP from 21 days down to 0 days, Total Revenues, the sum of Paid and Award, decreased by 0.5%. Despite the gains in Award Revenue due to higher availability, this increment could not compensate for the loss in Paid Revenue.
5. Measuring Net Award Revenue

This Chapter describes a new methodology to understand the impacts of Award Passengers on the current revenue management optimization. By introducing an Award Disutility in the choice process, it is possible to incorporate the passenger rationale behind the decision of whether using their points or pay for the air ticket. Once the baseline scenario is defined in section 5.2, several experiments are run in order to analyze sensitivity over key metrics. Section 5.3 defines the base scenario and experiments to be performed relative to this base. Section 5.4 defines the effects and the methodology to measure various impacts when analyzing each of the experiments. Finally, section 5.5 studies the relationships between the award valuation and availability, and how this difference impacts the overall optimization.

5.1. Award Disutility

As described on Chapter 3, PODS models disutilities for each class based on the following equation,

\[
\text{Disutility Fare}_i = \text{Fare}_i + \text{base\_fare} \sum_j \text{disutility\_parameter}_j \times \text{disutility\_active}_{ij}
\]

where \( \text{Fare}_i \) is the value of fare \( i \), \( \text{base\_fare} \) is a network parameter equal to the lowest fare, \( \text{disutility\_parameter}_j \) is the disutility parameter for restriction \( R_j \) and \( \text{disutility\_active}_{ij} \) determines whether the restriction \( R_j \) applies or not to class \( i \).

But, as mentioned before, since the award fare is modeled as a “zero-value” fare, the total disutility for the award class is always less than all of the paid fare classes, which might not reflect passenger choice preferences in reality. Depending on the route, days before departure, restrictions, the price of the award in points, and others, the disutility of using points for redeeming an award ticket can be lower, equal or higher than the available paid fares.

In order to model the disutility related to the award class, a new restriction, \( R5 \), was introduced to the fare structure. This restriction is only applicable for the award class, where its disutility parameter definition will be part of a new calibration to ensure that the percentage of awards bookings remains at the levels seen in the industry.
Table 5-1 shows the new fare structure scheme, where the new restriction R5 only applies on the award class and its value is not determined yet. An important note is that the award class remains as a “zero-value” fare, where all disutilities come from the restrictions and R5, which models the disutility of using points instead of paying with money the fare value.

<table>
<thead>
<tr>
<th>FC</th>
<th>FARE</th>
<th>AP</th>
<th>R1</th>
<th>R2</th>
<th>R3</th>
<th>R4</th>
<th>R5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>669</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>447</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>394</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>341</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>302</td>
<td>7</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>264</td>
<td>7</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>234</td>
<td>14</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>204</td>
<td>14</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>185</td>
<td>14</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>166</td>
<td>21</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>0</td>
<td>21</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

This change in the fare structure scheme allows us to model a more realistic behavior when passengers perform their choice process and assign a disutility to the value of their points. If R5 takes the value of zero, all other restrictions will apply but the passenger will assign no disutility to use their points. If R5 is equal to one, and assuming no change to the baseline fare structure scheme, then the passenger is indifferent between the award class and the lowest fare.

In the next section, a sensitivity analysis will be performed in order to define a baseline scenario to run further experiments, understanding the impacts of changing the R5 value on key metrics.
5.2. Sensitivity Analysis of Award Disutility Parameter

The Award Disutility now allows us to model in an enhanced manner the choice process for award demand. But, the introduction of this new parameter affects the current baseline defined in Chapter 3, where the percentage of award bookings was only dependent on the Award RM Input and the Award Eligibility Parameter.

With the goal of understanding the impact that the Award Disutility parameter has on the key metrics, a calibration is run evaluating five different scenarios. R5 will take the value of 0, 0.5, 1, 1.5 and 2. Impacts will be examined on revenues, bookings, paid average fare and class composition.

Figure 5-1 shows the impacts of increasing the Award Disutility parameter on both Ticket Revenue and Award Revenue, where Award Revenue is measured as the award passengers at the Award RM Input value. This assumption will be changed in the next sections. As can be seen in the figure, from 0 to 0.5 there is almost no change to both sources of revenue, gaining only 0.1% on Total Revenue. When the Award Disutility parameter takes the value of 1, Award Revenues decrease by almost 2/3 and Ticket Revenues are increased by almost 3%. When increasing even more the Award Disutility parameter, Award Revenue is almost zero, and Ticket Revenues are increased, resulting on a 2.1% and 2.2% increase, when setting the Award Disutility parameter on 1.5 and 2, respectively.
These results are driven by changes in award and paid passengers, as well as the ticket average fare. Figure 5-2 shows how award passengers decrease and paid passengers increase as the Award Disutility parameter goes up. Again, there is almost no change between 0 and 0.5 for both passenger types. But, when the Award Disutility level is 1, Award Passengers are reduced to 2.1% of total bookings, and diminished almost completely when R5 is 1.5 and 2. In addition, total passengers are reduced for all R5 values except from zero, with no complete replacement between paid and award passengers.

As described in section 5.1, this disutility helps to take into account the value or “internalized cost” that the passenger assigns when using points to redeem an award ticket, including the value of points, restrictions, accrual rate, among others. Therefore, when the disutility of using points is high, i.e., R5 taking values higher than 1, passengers typically would prefer to buy the ticket rather than using points. And, as a result, the airline carries less award passengers, resulting in less Award Revenue.
The paid average fare decreases as the Award Disutility level increases, as shown in Figure 5-3. With almost no change between 0 and 0.5, the paid average fare decreases only 0.1%. But, for higher R5 values, the paid average fare decreases from 1.7% down to 2.5%, when the Award Disutility parameter takes the value of 2.
This negative change on the paid average fare is due to a different mix of paid classes, when the award class is reduced in terms of its bookings. As Figure 5-4 shows, class 10 increases its share by almost 4pp when the Award Disutility parameter goes from 0 to 2. On the other hand, higher classes see almost no change, and in consequence the paid average fare goes down as the R5 value goes up.

Since the award availability definition is based on a value lower than the lowest fare, FC10, award bookings tend to displace FC10 bookings mostly. And, as the Award Disutility increases, fewer award bookings increase FC10 share of bookings, since they are no longer displaced. This reduction in award bookings leads to more FC10 bookings and therefore a reduction in the paid average fare.
In general, an increment on the Award Disutility level translates into a reduction of award passengers and an increment of the paid passengers. For values over 1 for R5, award bookings are reduced almost completely since at high award disutility levels award tickets become less attractive compared to paid tickets, and passengers prefer to pay instead of using their points for the ticket. At the same time, lower classes see a positive change, gaining passengers and share among all other classes, driven by the reduction of award passengers. And, as a consequence, these changes on class mix decrease the paid average fare.

5.3. Baseline Definition and Experiments

Before running different experiments over relevant variables, a new baseline must be defined. This baseline should be closer to reality in terms of the typical restrictions for award fares that can be seen in the airline industry, but also should meet the typical levels of award bookings that are accommodated by airlines.
5.3.1. Baseline Definition

Based on feedback gathered from airline revenue management experts at the PODS Consortium meetings, and based on data from the US airline industry, it was decided to test four main parameters to determine the new baseline. These parameters are the advanced purchase (AP) for the award class, the Saturday Night Stay (SAT) restriction for the award class, the award disutility level (R5) and the Award Eligibility. The Award RM Value will be set at 50% and not tested for the baseline definition. This parameter will be tested as part of the experiments, later on this chapter. Table 5-2 summarizes the possible values that each parameter takes for each scenario tested.

| SAT Stay | on | off | on | off | off | off | off | off | off | off |
| AP | 21 | 21 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7 |
| Award Disutility | 0.5 | 0.5 | 0.5 | 0.5 | 0.6 | 0.7 | 0.8 | 1.0 | 1.0 | 1.0 |
| Award Eligibility | 5% | 5% | 5% | 5% | 5% | 5% | 7% | 8% | 9% | 10% |
| Award RM Value | 50% | 50% | 50% | 50% | 50% | 50% | 50% | 50% | 50% | 50% |

Table 5-2: Possible baseline scenarios

The SAT restriction for the award has been removed by many US and international carriers. Then, it makes sense to build a baseline scenario without this restriction. In addition, most of the US carriers allow passengers to redeem their lowest award fare up to 7 days in advance. This parameter will be also tested on how sensitive it is to be reduced from 21 days. The Award Disutility level is also an important variable to calibrate, and for the calibration process it will be tested with values ranging from 0.5 up to 1.0. As described before, when this parameter takes the value of 1.0, award eligible passengers are indifferent between the lowest paid fare and the award fare. Finally, the Award Eligibility will be tested with values between 5 and 10%, helping to increase award bookings when other parameters diminish this number.
As mentioned before, the most important metric for calibration purpose is the percentage of award bookings over the total bookings. This metric will be the major guideline to define which scenario should be the baseline scenario, which, based on what can be seen in the US airline industry, should be within the 5-7% range.

Figure 5-5 shows the percentage of award bookings for all 11 scenarios tested.

As expected, when removing the SAT restriction for award bookings, the % of award bookings increase, all else equal. This result can be seen when comparing scenarios 2 and 4, compared to 1 and 3, respectively. The gain in award bookings is 0.16 and 0.17pp for both scenarios.

The AP reduction has a higher impact, increasing the percentage of award bookings by up to 1.23pp for scenario 4. An AP sensitivity analysis was done in more detail in Chapter 4, following the same results as for this test.

Based on the experiments done in the previous section, the Award Disutility level has a negative impact on the percentage of Award Bookings. The increase in the disutility level, decreases the share of award bookings from 7.70% at 0.5, down to 5.78% at 1.0.

Finally, the Award Eligibility has a high impact on award bookings, increasing this metric from 5.78% to 8.20%, when the eligibility parameter goes from 5 to 10%.
As highlighted in green, the chosen baseline scenario is scenario 8. This scenario has no Saturday Night Stay restriction for the award class, a 7 days AP, a disutility parameter of 1.0, making it equally indifferent from the lowest paid fare, a 7% of award eligibility and 50% for the Award RM Value.

The selection of this scenario was mainly driven by having a more realistic scenario for the award value proposition seen across US airlines. Both AP and SAT restrictions are commonly seen among US carriers as similar to the one of scenario 8. In terms of the award disutility, having a similar disutility with the lowest paid fare is something that make sense when both classes are available and that usually make frequent flyer travelers indifferent to choose from. Lastly, the Award Eligibility parameter was used to calibrate to a percentage of award bookings closer to 6%, meeting the typical US carrier levels.

5.3.2. Experiments

So far, most of the experiments have tested the impacts at a network level for Total Revenue, Total Load Factor, Bookings, Yield and class mix. But, one of the important assumptions so far has been that the RM value for determining availability for the award class is equal to the revenue that the airline receives when one of these passengers books an air ticket. This is not necessarily true, since the real benefit to the airline of miles or points redemption depends on a large series of factors, and therefore the value for assigning availability might be defined by other strategic or tactical variables.

In order to incorporate this behavior in the model, the Award RM Value ratio is defined as the following equation,

\[
Award\ RM\ Value\ ratio = \frac{Award\ Valuation}{Award\ RM\ Input\ Value}
\]

where the Award Valuation is the real value or benefit that the airline receives for the redemption of the ticket, and the Award RM Input Value is the value that the RM Optimizer receives for assigning availability to the award class. As mentioned before, up to this point, this ratio has been 1 for all analyses. And, in the next experiments, this ratio will vary depending on each scenario.
The goal of each experiment will be to compute the net impact of award passengers, when, for a fixed Award Valuation, the Award RM Input Value varies. More specifically, experiments will be held such that the Award RM Value ratio can take three possible values: 0.5, 1 and 1.5. That is, the airline RM system can be fed with an Award RM value that is 50%, 100% or 150% of the “actual” award booking value to the airline. This “actual” value corresponds to the economic benefit of reducing points from liability and recognized them as profit. As discussed in previous chapters, the specific value is driven by the price at which points are sold to third parties, expiration policies and accounting methodology. The goal of this analysis does not focus on determining these values, but to define reference values to analyze impacts and serve as a benchmark.

The experiments configuration is summarized in Table 5-3, where the percentages are based on the lowest fare. In this sense, for example, configuration number 2 will have an “actual” Award Valuation of 75% of the lowest fare, and the experiment will test what happens when the availability is defined with an Award RM Input Value of 38%, 75% and 113%.

<table>
<thead>
<tr>
<th>Award Valuation</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>50%</td>
<td>25%</td>
<td>38%</td>
<td>50%</td>
<td>63%</td>
<td>75%</td>
</tr>
<tr>
<td>Award RM Input Value</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
<td>125%</td>
<td>150%</td>
</tr>
<tr>
<td>75%</td>
<td>113%</td>
<td>150%</td>
<td>188%</td>
<td>225%</td>
<td></td>
</tr>
</tbody>
</table>

*Table 5-3: Experiments configuration, percentages based on lowest fare*

These numbers were defined in such a way that the Award RM Value ratio takes the value of 0.5, 1 and 1.5, as mentioned before. These values are shown in Table 5-4 for each configuration.
Moreover, and based on the baseline defined in Section 5.3.1, these configurations will be tested under different RM Schemes and demand levels. Airline 1 will be using EMSR, DAVN and UDP, while all the other three airlines will keep their RM Method of the baseline (see section 3.4.1). In addition, a scenario with higher demand will be tested when Airline 1 uses UDP. This scenario at high demand, will increase load factors 3-4pp from an 83-85% base. These experiments and configurations are summarized in Table 5-5.
In summary, for each RM Scheme-Demand Level setting, there will be five different configurations to test, and, in each configuration, three different Award RM Value ratio will drive the net impact of award passengers.

5.4. Understanding Award Passenger Impacts

To analyze the net impacts that award passengers generate, it is necessary to define a methodology which takes into account the different sources of impact on Total Revenue. This section details the different effects, and how they relate to each other to produce an overall net effect.

All effects will be compared to a baseline with no award passengers, varying only the RM Scheme, depending on the experiment. For example, when running the DAVN at medium demand experiments, the baseline will be a DAVN run for Airline 1, without award passengers, only paid ones.

5.4.1. Award Passenger Impact Ratio

With the introduction of an Award Class, where Award Passengers book flights, there are changes produced in the paid fare classes. These changes not only affect the lowest fare class, as it might be thought since the award class has lower availability than this fare, but it affects bookings in all paid classes. Figure 5-6 illustrates how the new award bookings decrease the bookings in almost all paid classes compared to the baseline, for a 25% of Award RM Input Value example. Among the reasons why this happens is that with this new source of demand with low availability, flights fill up quicker and therefore the RM optimizer save space for higher classes to increase revenue. Another reason is that the award class can actually compete with higher classes if restrictions allow it. One example is if the AP is relaxed, then if the class has availability it can go beyond FC10 or FC9, and reduce the bookings directly of other classes.
This change in award versus paid bookings can be summarized with a ratio that tells how many paid bookings are gained or lost when one award booking is introduced to flight or network, compared to the baseline. The following equation defines the Award Passenger Impact Ratio ($\alpha$),

\[
\text{Award Passenger Impact Ratio (} \alpha \text{)} = \frac{\sum \Delta \text{Paid Passengers}_i}{\Delta \text{Award Passengers}}
\]

where $\Delta \text{Paid Passengers}_i$ denotes the change in paid passengers for class $i$ against the baseline, and $\Delta \text{Award Passengers}$ is the change in Award Passengers.

5.4.2. Displaced Fare

As mentioned before, award passengers not only generate a change in the lowest fare, but they generate changes in all of the above classes. Therefore, the Displaced Fare is the weighted average fare, of all paid fares, but weighted based on the change in bookings due to award bookings, compared to the baseline. This Displaced Fare is defined as follows,
Displaced Fare (DF) = \sum f_{basei} \cdot w_i

w_i = \frac{\Delta \text{Paid Passengers}_i}{\sum \Delta \text{Paid Passengers}_i}

where \(f_{basei}\) is the fare value of class i for the base case, and \(\Delta \text{Paid Passengers}_i\) is the change in paid passengers for class i, against the baseline. See example in section 5.4.5.

5.4.3. Displaced Paid Revenue

Now that the Award Passenger Impact Ratio and the Displaced Fare are defined, it is possible to compute the Displaced Paid Revenue due to the introduction of Award Passengers. The Displaced Paid Revenue is defined as follows,

\[
\text{Displaced Paid Revenue} = \Delta \text{Award Passengers} \cdot \alpha \cdot DF
\]

where \(\Delta \text{Award Passengers}\) is the change in Award Passengers, \(\alpha\) is the Award Passenger Impact Ratio and \(DF\) is the Displaced Paid Fare. This way of breaking down this effect allows us to understand the three causes behind the displaced revenues: impact of award passengers (\(\Delta \text{Award Passengers}\)), how incremental are these passengers (\(\alpha\)) and which fares were displaced (\(DF\)). See example in section 5.4.5.

5.4.4. Paid Sell Up

The Paid Sell Up represents the change in Ticket Revenue, due to the change in Paid Average Fare, compared to the baseline. The introduction of new award passengers change the paid class mix, and therefore the paid average fare. This change, times the new passengers, is the Paid Sell Up effect, defined as the following equation,
\[ \text{Paid Sell Up} = \sum P_{ax_i} \cdot \Delta \text{Avg Fare}_i \]

where \( P_{ax_i} \) denotes the passengers in class \( i \), and \( \Delta \text{Avg Fare}_i \) is the absolute change in average fare for class \( i \), compared to the baseline. In summary, the paid sell up takes into account the change in average fare for each class compared to the baseline, at the new level of paid passengers. This helps us to understand whether the new award passengers lead to an increase in the paid average fare. See example in section 5.4.5.

### 5.4.5. Award Net Effect

Finally, and putting all definitions together, it is possible to measure the net effect of award passengers. This effect will be the sum of the Total Award Valuation, the Displaced Paid Revenue and the Paid Sell-Up effect.

The Award Net Effect is then defined as follows,

\[ \text{Award Net Effect} = \text{Award Benefit} + \text{Displaced Paid Revenue} + \text{Paid Sell Up} \]

where the \textit{Award Benefit} is the Award Valuation of all Award Passengers, the \textit{Displaced Paid Revenue} is the sum of all displaced paid revenues and the \textit{Paid Sell Up} is the sum of all changes in paid average fare.

An example of these effects can be seen on Figure 5-7, where all effects defined above are taken into account to build an award scenario. In this example, the Award Revenue is a positive $42,416 effect, computed as a result of 471 award passengers at $90 fare, given an Award RM value of 25%, as shown in Table 5-6.
Figure 5-7: Award Effects over a scenario without award passengers

Table 5-6: Award Revenue Calculation

<table>
<thead>
<tr>
<th>CLASS</th>
<th>PAX</th>
<th>AVG_FARE</th>
<th>REV</th>
<th>AWARD @25% &amp; 0.5 ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>57</td>
<td>1,087</td>
<td>62,337</td>
<td>57</td>
</tr>
<tr>
<td>2</td>
<td>508</td>
<td>588</td>
<td>299,079</td>
<td>508</td>
</tr>
<tr>
<td>3</td>
<td>621</td>
<td>583</td>
<td>361,793</td>
<td>619</td>
</tr>
<tr>
<td>4</td>
<td>713</td>
<td>500</td>
<td>356,285</td>
<td>700</td>
</tr>
<tr>
<td>5</td>
<td>327</td>
<td>390</td>
<td>127,523</td>
<td>317</td>
</tr>
<tr>
<td>6</td>
<td>701</td>
<td>375</td>
<td>263,169</td>
<td>682</td>
</tr>
<tr>
<td>7</td>
<td>227</td>
<td>371</td>
<td>84,337</td>
<td>217</td>
</tr>
<tr>
<td>8</td>
<td>929</td>
<td>352</td>
<td>327,225</td>
<td>866</td>
</tr>
<tr>
<td>9</td>
<td>1,280</td>
<td>260</td>
<td>332,862</td>
<td>1,199</td>
</tr>
<tr>
<td>10</td>
<td>3,966</td>
<td>198</td>
<td>784,035</td>
<td>3,756</td>
</tr>
<tr>
<td>11</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>471</td>
</tr>
<tr>
<td>TOTAL</td>
<td>9,330</td>
<td>321</td>
<td>2,998,645</td>
<td>9,392</td>
</tr>
</tbody>
</table>

The Displaced Revenue, as shown in Figure 5-7 and Table 5-7, has a negative impact of $104,475, due to the changes in paid passengers in column B and the valuation of those passengers at the base average fare in column A.
Finally, the Sell Up accounts for a positive impact of $22,627, as shown in Figure 5-7 and Table 5-8. This effect comprises the change in average fare for each paid class in column B, and the new passengers carried in column A.

These three effects have an overall impact of -1.4% compared to the base revenue, resulting in a final $2,956,213 Total Revenue. This means that if award passengers are given availability based on 25% of lowest fare Award RM Value, it impacts negatively Airline 1 by -$42,432. And, even though there is a benefit of carrying these passengers...
of $42,416, the displaced revenue is much higher than this revenue, making it a negative overall impact in this example.

5.5. Measuring Net Award Revenue

This section presents the results for EMSR and DAVN at Medium Demand, as well as the comparison between Medium and High Demand for UDP. In all three cases, results are analyzed for Airline 1.

5.5.1. EMSR at Medium Demand

As described in section 5.3, the first experiment considers Airline 1 using EMSR and Medium Demand level for passengers. With this level of demand, load factors aim 83-85%, depending on the route and airline.

After running all 15 different experiments, for all different Award Valuations and Award RM Value ratios, the first metric to analyze is the Total Revenue percent variation. Figure 5-8 summarizes all 15 variations against the base scenario without award passengers.

As shown below, when the Award Valuation moves from 50% of Fare Class 10 (FC10) up to 150% of FC10, Total Revenue impacts increase from ~2% to ~2%. At 100% of FC10 Award Valuation there is a breakeven point, with a near 0% of variation against the base. Scenarios with lower valuation show a negative Total Revenue percent impact, whereas scenarios with higher valuation show positive impacts.
In addition, the Total Revenue percent impacts tend to be more sensitive to Award Valuation than to the Award RM Value ratio. Specifically, around the 100% of FC10 Award Valuation, there is little change in Total Revenue when changing the Award RM Value ratio. This can be interpreted as that for a given Award Valuation, there less change in giving 50% more or less availability to the Award Class, than the impact of having a 50% more or less valuation for each award passenger. In this sense, for a given valuation, changes of 50% on the award availability have less impact because the availability definition is still close to the lowest fare and does not interfere directly with upper classes. As it is going to be analyzed, this also explains why the Displaced Revenues are steadier than the Award Revenue.

Another way to analyze the same behavior is to pick scenarios with same Award RM Values. For example, at 100% of FC10 Award Valuation and 0.5 Award RM Value ratio, the Award RM Value is 50% of FC10. This is same value for the 50% of FC10 Award valuation but with 1.0 of Award RM Value ratio. In these two cases, the Total Revenue percent is -0.15% for the first case, and -1.85% for the second. This -1.70pp difference cannot be found in any other scenario, when changing the Award RM Value ratio, for a given Award Valuation. This difference tends to be consistent from one scenario to the other, where the Total Revenue percent is more sensitive to Award Valuation than to changes to the Award RM Value, through the Award RM Value ratio.
To understand what is happening on each case, a more detailed analysis was done, following the methodology described in section 5.4. Figures 5-9 and 5-10 show the effects of Award Revenue, Displaced Revenue and Sell Up for Award Valuations at 50%, 100% and 150% of FC10.

As shown in Figure 5-9, of the three effects, Displaced Revenue tends to be the dominant effect, followed by the Award Revenue and then the Sell Up. Even though the Displaced Revenue represents most of the Total Revenue percent variation, is a steadier effect, without changing much between scenarios since most of the tradeoff between award passengers and paid passengers happens in FC10, as analyzed in Figure 5-13. On the other hand, Award Revenue increases at a higher pace as the Award RM Value ratio increases because the change in award passengers is more sensitive to changes in this ratio and when increasing the Award Valuation. This behavior is shown in Figure 5-12, where award passengers vary significantly when both Award Valuation and Award RM Value increase. Finally, the Sell Up represents a small portion of the overall effect, and
decreases as the Award Valuation and Award RM Value ratio increase. This change in Sell Up is also driven by the change in paid class mix, as shown in Figure 5-13 where, as these variables increase, there is less change in average fare by class, decreasing the total sell up.

A similar behavior can be seen for the case with 150% of FC10 Valuation in Figure 5-10. An increase on Award Valuation translates into higher Award Revenues, and lower Displaced Revenues (negative). At the same time, when increasing the Award RM Value ratio, Award Revenues increase and Displaced Revenues decrease (negative). But, as analyzed in Figure 5-9, Award Revenues increase at a higher pace than the decrease of Displaced Revenues, translating into higher Total Revenue percent variations.

![Figure 5-10: Effects Comparison between 100% and 150% Award Valuation](image)

The differences in growth rate for the Award Revenue and Displaced Revenue can be understood in a more graphical manner as presented in Figure 5-11. In this chart, each bar represents the Total Award Effect, and its breakdown on each of the three effects. On
the horizontal axis, the Award Valuation increases and, for each valuation, the Award RM Value ratio increases.

As shown with the arrows, the Award Revenue increase at a higher pace with Award Valuation and Award RM Value ratio, than the other effects. At the same time, the Displaced Revenue decrease but at a lower rate, compared to the Award Revenue. Within each Award Valuation, the Displaced Revenues see more sensitivity than the Award Revenues, dominating the overall result for a given valuation.

When the Award Valuation is at 125% of FC10 and with an Award RM Value ratio of 0.5, the effect on Total Revenues start to be positive driven by higher contributions of the Award Revenue and Sell Up. From that point on, the effect on Total Revenues are positive, mainly driven by higher Award Revenues. As described before, the Sell Up plays a minor role compared to the other effects, but it represents a high portion of the total effect.

![Figure 5-11: Award Net Effects for EMSR (k$)](image)

To understand the differences between these changes for Award Revenue and Displaced Revenue, Figures 5-12 and 5-13 show the award passengers and class passenger share,
respectively. Award passengers show a positive tendency with increasing Award Valuation and Award RM Value ratio. As expected the Award RM Value ratio drives the award passengers increment by increasing its availability. This value is more sensitive at 0.5 than at 1.0 or 1.5, but having less impact for higher values.

The Displaced Revenue is mostly driven by the change in the paid passengers’ mix. As shown in Figure 5-13, most of the tradeoff between award passengers and paid passengers is between class 10 and the award class. Higher class see almost no change, and classes between 4 to 9, see a minor negative change. These changes account for a steadier behavior on the Displaced Revenues, since the change in paid classes affects almost only class 10 and little the higher classes.

![Figure 5-12: Award Passengers for EMSR (pax)](image-url)
5.5.2. DAVN at Medium Demand Results

The same experiment was performed with DAVN and Medium Demand, where the results follow the same behavior as with EMSR, but with different variations. As shown in Figure 5-14, the Total Revenue percent variation ranges from -2.26% at 50% of FC10 Award Valuation and 1.5 Award RM Value ratio, up to 3.01% for 150% of FC10 Award Valuation and Award RM Value ratio. Impacts are negative for Award Valuations below 100% of FC10, and are positive for Award Valuations above 100% of FC10. Similarly, to EMSR, at 100% of FC10 Award Valuation there is a breakeven point for Total Revenue percent variation, with low differences among Award RM Value ratios.

In general, Total Revenue is more sensitive to Award Valuation than to the Award RM Value ratio. This behavior can be clearly seen for 100% of FC10 Award Valuation, where the change in Award RM Value ratio does not produce major changes in the Total Revenue percent variation. As the Award Valuation decrease or increase from 100% of FC10 the Award RM Value ratio generates higher changes in Total Revenue. At 50% and 150% of FC10 Award Valuation, there is an almost ~0.70pp difference between Award RM Value ratio scenarios.
Figure 5-14: Total Revenue %Var for different Award Valuations and Award RM Value ratios for DAVN (%)

The impacts of the effects on Total Revenue can be analyzed in Figures 5-15 and 5-16, for different Award Valuations and Award RM Value ratios. As expected, the Award RM Value ratio has a positive effect on Award Revenue, due to its increasing availability for award passengers. But, at the same time, it has a negative effect on Displaced Revenue, displacing more paid passengers and therefore losing part of that revenue stream. The same happens with Sell Up, where more award passengers lead to a lower change in paid average fare, decreasing the Sell Up effect. This is mainly due to lower changes in average fare by class, as suggested by Figure 5-18, since award passengers are increasing with both parameters.

In addition, the Award Valuation has a positive effect on the Award Net Revenue effect, since it increases Award Revenue at a higher pace than the decrease of Displaced Revenue. This effect can be clearly seen in Figure 5-16 when changing from 100% of FC10 Award Valuation to 150% of FC10 Award Valuation. For the same Award RM Value ratio, Award Revenues increase by ~70%, whereas Displaced Revenues decrease by ~7%. This difference of growth leads to higher Total Revenue percent variations, reaching positive results at Award Valuations higher or equal to 100% of FC10.
Figure 5-15: Effects Comparison between 50% and 100% Award Valuation for DAVN
Figure 5-16: Effects Comparison between 100% and 150% Award Valuation for DAVN

Figure 5-17 compares all effects for the different scenarios run. As highlighted with the arrows, Award Revenues increase with both Award Valuation and Award RM Value ratio, at a regular rate.

On the other hand, Displaced Revenues decrease with increasing Award Valuation, but it is the Award RM Value ratio that drives this behavior. As discussed previously, this is mainly because the Award RM Value ratio controls award availability, and therefore when this value increases, more award passengers are allowed and more paid passengers are displaced. This value is more sensitive to Award Availability than to Award Valuation, that is why it grows at a more irregular rate over Award Valuation than Award Revenues.

Finally, Sell Up represents a minor effect compared to the other two, but compared to the Award Net Effect, it is not negligible. In some cases, sell up is responsible for turning Total Revenue positive or negative, and with high Award Valuations turns to be negative because the change in paid average fare by class is less, driven by low changes in paid passengers share by class, as presented in Figure 5-18.
As analyzed with EMSR, the reason behind the steadier behavior of Displaced Revenues is the change in paid passengers by class. Once award passengers are introduced, FC10 tends to assume most of the loss, by trading its passengers with award passengers. This can be seen in Figure 5-18, where also higher classes don't see too much change, with a minor tendency to decrease share from classes four through nine. This trade-off between FC10 and the award class is responsible for having a steadier behavior on the Displaced Revenues, since most of the passengers lost are from FC10. Furthermore, this serves as evidence that these RM schemes perform well in managing and limiting award bookings, given their valuations on each scenario.
5.5.3. UDP Medium vs High Demand Results

A final experiment was performed, analyzing the impact of the demand level over the three different effects over Total Revenues. In this particular case, UDP was chosen as the RM Scheme, and Medium and High Demand as the level demands. As described before, Medium and High Demand is a parameter available in PODS to manage the volume of passenger arrivals, and therefore impacting loads on all airlines. Typically, a Medium Demand level has a load factor between 83 to 85%, whereas a High Demand level will increase load factors up to 86-89%.

Figure 5-19 shows the Total Revenue percent variation for different Award Valuations, Award RM Value ratios and for Medium and High Demand. Even though both levels of demand follow the same behavior in the change in Total Revenue, there are some specific characteristics for each level of demand.

First of all, both levels of demand have the same behavior when increasing the Award Valuation and Award RM Value ratio. They also share having a breakeven point at 100% of FC10 Award Valuation, where Total Revenues almost do not vary, even though at High Demand there are some negative results for Award RM Value ratios 1.0 and 1.5.
For award valuations below 100% of FC10, both demand levels see negative Total Revenue percent variations. But, at High Demand variations are higher (less negative) that at Medium Demand. At the same time, the Award RM Value ratio seems to have higher impact on Total Revenue variations for High Demand than for Medium Demand. This makes the variation more sensitive to the ratio than to Award Valuation for High Demand, whereas at Medium Demand the Award Valuation leads to higher impact on Total Revenue. This might suggest that, since flights are more filled up at high demand, changes in award availability can have a higher impact on Total Revenues by displacing more paid passengers later on the booking window.

At Award Valuations, higher than 100% of FC10, even though that at both demand levels there is positive variation, there is not a clear relationship between the two types of demand and the impact of Award Valuation and Award RM Value ratio. In some cases, High Demand leads to higher Total Revenue percent variations, and in some others Medium Demand performs better. Something that remains similar is the sensitiveness of the Total Revenue percent variation to both Award parameters. The Award RM Value ratio seems to play a more important role than Award Valuation on Total Revenue, leading to greater changes in the Award Net Effect.

Figure 5-19: Total Revenue %Var for different Award Valuations and Award RM Value ratios for UDP at High and Medium Demand (%)
In order to understand how the three different effects analyzed before drive these results, a comparison at 50% of FC10 Award Valuation is shown in Figure 5-20. The first noticeable difference is that at high demand, the Award Revenue is reduced 30-50%. This make sense since the availability for the award class is less than the lowest fare, at higher demand these classes have less availability, waiting to fill up higher classes.

At the same time, with higher demand, Displaced Revenues are reduced by 25-50%. As analyzed before, the main trade off occurs between FC10 and the award class, and therefore the Displaced Average Fare is similar at Medium Demand. In consequence, the reduction in Displaced Revenue is mainly due to less Award Passengers in the class mix, when demand is high.

Finally, the Sell Up sees a reduction at Award RM Value ratio of 0.5 and 1.0, but an increase for 1.5. This change in growth has to do with what classes are competing directly with award passengers. When the Award RM Value ratio takes the value of 1.5 and Award Valuation is 150% of FC10, the award class has almost the same availability of FC4-5.
This jump in availability decreases paid bookings at higher classes, decreasing the paid average fare, and therefore decreasing the sell up effect.

At 150% of FC10 Award Valuation, Total Revenue percent variations are positive for both Medium and High Demand, as well as for all three Award RM Value ratios. In this case, Award Revenues do not behave like they do at 50% of FC10 Award Valuation. The Award RM Value ratio play a different role for 0.5, 1.0 and 1.50. At 0.5, Award Revenue is reduced in 30% for High Demand, whereas for 1.0 and 1.5 this revenue is increased by 11% and 17%, respectively. This has to do with the availability that the award class has for different Award RM Values. At 0.5, it falls below FC10, and for high demand that means less availability. But, for 1.0 and 1.5 availability for the award class is 150% of FC10 and 225% of FC10, respectively, having more availability and increasing Award Revenue.
Displaced Revenues follow the same behavior. With more award passengers, more paid passengers are displaced in higher classes, and therefore both the Displaced Average Fare and the loss in paid passengers increase. The difference between this case and the 50% of FC10 one though, is that Award Revenues overpass Displaced Revenues, having a positive Award Net Effect.

The behavior of Displaced Revenues across Award Valuations and Award RM Value ratios is shown in Figure 5-22. It can be clearly seen that at High Demand, Displaced Revenue decrease for Award Valuations equal or lower than 100% of FC10. And whenever the Award RM Value is lower than the FC10 availability, for higher Award Valuations, Displaced Revenue is also lower at High Demand. For all other cases, at High Demand, Displaced Revenues increase due to the higher availability for the award class. As mentioned before, due to higher load factors at high demand, when the award class has higher availability than FC10 it competes directly with classes that have a higher share of the paid mix. Therefore, with higher availability, the award passengers displace paid passengers with high value, increasing the displaced revenues.

Figure 5-22: Displaced Revenue comparison for UDP, High Demand vs Medium Demand (k$)
5.6. Summary

This chapter presented a new methodology to measure the effect of allowing award passengers to book flights that were only available for paid passengers before. By introducing an award disutility in the booking process, and restrictions for the award class based on industry references, it was possible to model a demand aligned with industry booking levels for award passengers.

A set of 60 experiments were defined and run to test award behavior under different RM Schemes, Award Valuations, Award RM Values and demand levels. EMSR, DAVN and UDP were the RM Schemes chosen for these experiments, were the first two were run at Medium Demand, and UDP was used to understand the differences between Medium and High Demand. In each experiment, Award Valuations ranging from 50% of FC10 up to 150% of FC10 were tested, and for each valuation, three different Award RM Value ratios were defined to test different availability levels for the award class.

The results were consistent to show that at Award Valuations lower than 100% of FC10, Total Revenue percent variations were negative, whereas at valuations higher than 100% of FC10, Total Revenue percent variations were positive, for all RM Schemes, at both medium and high demand. This result has to do with the differences of growth rate between Award Revenue and Displaced Revenue. At Award Valuations lower than 100% FC10, Award Valuation cannot compensate Displaced Revenue. This can be thought of as that for each new award passenger, there is almost one paid passenger displaced but with higher individual value due to its fare. On the contrary, for Award Valuations higher than 100% of FC10, the value of each award passenger surpassed the displaced paid passenger generated, and therefore the Total Revenue change is positive. The 100% of FC10 Award Valuation scenario turned to be a breakeven point for most cases, where Total Revenue variation was almost zero, regardless of the Award RM Value ratio implemented.

In general, Award Revenue resulted to be positively related with Award Valuation and Award RM Value ratio, due to its higher valuation per passenger and availability control over award passengers. A similar behavior was then observed with Displaced Revenue, where, with more award passengers, the more the paid passengers displaced, and therefore the more ticket revenue lost. But, Displaced Revenue decrease (more negative) at a lower rate than the Award Revenue increment seen. This was mainly due to the tradeoff between FC10 paid passengers and award passengers, having a steadier Displaced Average Fare, regardless of the Award Valuation. Changes in higher classes
were only seen when Award Valuation was 150% of FC10 and the Award RM Value ratio was 1.5, having high availability and competing directly with higher classes.

Sell Up, represented a minor effect across all experiments, compared to the other two. This was mainly due to low changes in the paid average fare, since most of the change in paid class mix, was seen between FC10 and the award class. But, compared to the Net Award Effect, it is not an effect to despise. In several cases, it was the sell up effect the one responsible for turning one case from negative to positive.

Despite the specific differences of Total Revenue variations, as well as each specific effect on the Net Award Effect, results were consistent in showing the drivers and sensitivity of each effect with Award Valuation and Award RM Value ratio. Been able to understand the complete picture of what is happening with ticket revenue by giving access to award passengers, allows to first measure and then take action where needed.
6. Conclusion

Loyalty programs have evolved over time, becoming an important business unit for airlines. They not only help to secure revenue and market share over time by retaining customers with different types of rewards and status, but they have managed to create another stream of revenue. By selling their own currency to third parties, loyalty programs have built a whole new business, making it now a common strategy to diversify risk and increase cash. There are even cases where these business units have transitioned from being internal accounts to partial or full spin-offs, having market cap valuations greater than the airline itself.

But, despite being an important revenue stream, revenue management and commercial teams struggle to define the availability level for air award tickets. Since there is little knowledge on the impacts of these “non-revenue” passengers on revenue management optimization, the decision of award seat availability and its impacts tends to be mostly judgmental. A lack of understanding of these effects generates tension between airline RM teams and Frequent Flyer Program teams, leading to suboptimal solutions and costly resource involvement. This expectations mismatch, in addition to the limited knowledge of the impacts of these decisions on the overall revenue management optimization, can lead to different results, impacting both paid and award profitability in unexpected ways.

With the objective of reducing this gap, this thesis analyzed the impacts of the introduction of award passengers to the current revenue management optimization. It identified, classified and measured these effects, by presenting a methodology to clearly quantify the effects and understand the impacts under different RM Schemes, demand levels and fare structures. All analyses were performed using the PODS simulation tool, which helps to model revenue management strategies for airlines and understand impacts on metrics at different levels of aggregation.

In order to model this new source of demand, a gradual implementation was done in PODS to represent the behavior of these passengers. This process was completed in three major steps. The first one introduced the Award Eligibility Parameter and the Award RM Value input, which control the demand eligibility for award bookings and award availability through the RM optimizer of each airline, respectively. Step two analyzed and defined the rules and restrictions for the award class, defining a baseline based on what can be seen in the airline industry for award product definition. And finally, an award disutility parameter was introduced to model how passengers value their points, integrating all possible sources of value, like accrual rate, earn to burn relationship and expiry policy, among others.
The first set of experiments tested how airlines performed with this new demand. More specifically, four RM Schemes (EMSR, DAVN, ProBP and UDP), and four advance purchase levels for the award class (21, 14, 7 and 0 days) were modeled and tested. Table 6-1 summarizes the findings for the RM Scheme tests, where UDP showed the highest growth in Total Revenue, Award Revenue, Award Passengers and Total LF. As shown in the table, this was mainly due to an increase in passengers carried as well as a better network performance than EMSR, which can be seen for all OD optimization methods in the table.

<table>
<thead>
<tr>
<th></th>
<th>EMSR</th>
<th>DAVN</th>
<th>ProBP</th>
<th>UDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Revenue</td>
<td>2.93 M$</td>
<td>+0.5%</td>
<td>+0.7%</td>
<td>+1.0%</td>
</tr>
<tr>
<td>Ticket Revenue</td>
<td>2.88 M$</td>
<td>+0.3%</td>
<td>+0.7%</td>
<td>+0.3%</td>
</tr>
<tr>
<td>Award Revenue</td>
<td>0.05 M$</td>
<td>+20%</td>
<td>+20%</td>
<td>+40%</td>
</tr>
<tr>
<td>Paid Passengers</td>
<td>8.72 k pax</td>
<td>-0.2%</td>
<td>+0.3%</td>
<td>-0.1%</td>
</tr>
<tr>
<td>Award Passengers</td>
<td>0.62 k pax</td>
<td>-2%</td>
<td>-13%</td>
<td>+7%</td>
</tr>
<tr>
<td>Total LF</td>
<td>83.9%</td>
<td>-0.19pp</td>
<td>-0.16pp</td>
<td>+0.54pp</td>
</tr>
</tbody>
</table>

Table 6-1: Changes in main metrics over an EMSR base for different RM Schemes

Another interesting finding was that UDP was able to increase by 40% award passengers, due in large part to the Poisson assumption used to calculate bid prices. The low variance of the Poisson distribution results in lower bid prices in early booking periods, giving higher availability to the award class, even at low fare values.

When analyzing the impact of reducing in days the Advance Purchase (AP) rule, Award Passengers increase as expected, but Total Revenue decreases as shown in Table 6-2. As the AP decreases, the award class is available closer to the departure date, increasing its bookings but also diminishing ticket revenue, as it competes directly with paid classes of higher value. Although award revenue increases up to 35%, it cannot compensate the loss in ticket revenue, decreasing total revenue for all three scenarios tested.
Table 6-2: Changes in main metrics over a 21-day AP base for different APs

Up to this point, there was an important assumption used to value the award revenue component, and that was that the RM value for determining availability for the award class was equal to the revenue that the airline receives when one of these passengers books an air ticket. As described in Chapter 2, this is not necessarily true, since the real benefit to the airline of miles or points redemption depends on a large series of factors, and therefore the value for assigning availability might be defined by other strategic or tactical variables. In Chapter 5 the Award Valuation was introduced to compute the real value that the airline gets when allowing an award passenger, while the Award RM Value input still determines the value that RM optimizer uses for assigning availability for the award class. The difference between these two variables was measured by the Award RM Value ratio.

Measuring the Net Award Revenue that award passengers generate was the main objective of this thesis. The methodology proposed in Chapter 5 identified and assessed the main effects seen when allowing these passengers into the current RM optimization. Three effects were defined and quantified; Award Revenue, Displaced Revenue and Sell Up. The first one computed the benefit of each award passenger at the defined award valuation. The second studied the ticket revenue loss due to the introduction of new award passengers. And finally, the sell up aggregates the change in ticket revenue as a result of the change in paid average fare. All of these effects were computed as a change compared to a baseline with no award passengers.

A set of 60 experiments were run to understand the impacts on total revenue, testing different RM Schemes, Award Valuations, Award RM Values and Demand Levels. The results were consistent to show that at Award Valuations lower than 100% of the lowest
fare class (FC10), Total Revenue percent variations were negative, whereas at valuations higher than 100% of FC10, Total Revenue percent variations were positive, for all RM Schemes, at both medium and high demand. This result had to do with the differences of growth rate between Award Revenue and Displaced Revenue, where at Award Valuations lower than 100% of FC10, Award Valuation cannot compensate for Displaced Revenue, whereas at valuations higher than 100% of FC10, Award Revenue surpassed the change in Displaced Revenue. The 100% of FC10 Award Valuation scenario turned to be a breakeven point for most cases, where Total Revenue variation was almost zero, regardless of the Award RM Value ratio implemented. In this case, since most of the passenger tradeoff between paid and award passengers happened between FC10 and the award class, when the award class had exactly the same value and availability of FC10, the final outcome was nearly the same as when no award passengers were allowed to book flights.

In general, Award Revenue resulted to be positively related with Award Valuation and Award RM Value ratio, due to its higher valuation per passenger and availability control over award passengers. A similar behavior was then observed with Displaced Revenue, where, with more award passengers the more the paid passengers displaced, and therefore the more ticket revenue lost. But, Displaced Revenue decrease (more negative) at a lower rate than the Award Revenue increment seen. This was mainly due to the tradeoff between FC10 paid passengers and award passengers, commented before, having a steadier Displaced Average Fare, regardless of the Award Valuation. Changes in higher classes were only seen when Award Valuation was 150% of FC10 and the Award RM Value ratio was 1.5, having high availability and competing directly with higher classes.

The proposed methodology and its result lead to interesting conclusions. First, understanding the real value of each award passenger is critical to defining the availability level that the award class should have. The relationship between award value and award availability can lead easily to negative results if not managed in a proper and objective manner. Furthermore, the methodology proposed captures and quantifies the effects of these passengers, allowing airline managers to take action where one of these metrics is out of bounds or harming the overall result.

Secondly, the results showed a consistent trend, where at 100% of FC10 valuations there is a breakeven point for changes in total revenue. This means that if the real value of each award passenger is less than the lowest fare, allowing them to redeem flights, will result in negative changes in total revenue. On the contrary, having valuations higher than the lowest fare, will result in positive changes in total revenue.
Third, at any given valuation higher than 100% of FC10, total revenue performed better at higher availabilities, even at 50pp more than the actual valuation. This means that if the award valuation is 125% of FC10, there is no incentive to give less availability than its real value, which would lead to a lower change in total revenue. This might sound trivial, but since most of the loyalty programs want to show positive profit out of each redemption, sometimes the availability value might be lower than the real value, to have a margin on each transaction. It is important to note that the analysis only considered availabilities 50pp higher than the actual valuation. But, up to that point, total revenue always showed a higher growth. On the contrary, for valuations lower than FC10, giving more availability than the actual value, led to lower total revenues. This result was driven by a higher displacement of ticket revenue, not compensated by award revenue, due to its lower value.

Table 6-3: Total Revenue percent variation for different RM Schemes, Demand Levels, Award Valuations and Award RM Values ratios
All results for change in Total Revenue are summarized in Figure 6-1, where all 60 experiments are grouped by Award Valuation, Award RM Value ratio and RM Scheme-Demand Level. It can clearly be seen how the 100% of FC10 valuation is a breakeven point as mentioned before, and how both Award Valuation and Award RM Value ratio (award availability), drive the change in Total Revenue. A more detailed analysis, showing how the three effects mentioned before drive these changes, can be seen in Chapter 5.

In conclusion, the methodology proposed was able model, quantify and analyze the impacts of award passengers in the revenue management optimization. It also allowed us to understand the drivers behind the changes that these passengers, and loyalty programs in general, generate in the current optimization process, by testing several environment settings. These results might play a guidance role for taking current tactical or strategic decisions, as well as enlighten future research for this particular branch of revenue management or others.

### 6.1. Suggestions for Future Research

As the first approach to model an award demand using existing simulation techniques, there is a rich space to conduct future research related to this topic. Some studies can continue on the same path but with deeper understanding and analysis, while others can build new avenues over the methodology already developed.

Improvements to the current model might consider changes in how the demand and availability definition are controlled. Some of the assumptions were that the award class was only available for leisure passengers, which is not true. In reality, airlines deal with a portion of business passengers as well that use their points to redeem a ticket. Since this portion can be high for some routes, it might be necessary to let business passengers to book the award class. As a different type of demand, their behavior and willingness to pay is different, and therefore other parameters should be introduced to take into account the particular characteristics of this demand. One example is the disutility introduced to model the value that leisure passengers assign to their points. Since the rate of accrual, advance booking patterns and sensitivity to fare restrictions, among others, are different for business travelers, the disutility for these passengers should be modeled considering their specific value assignation.

On the same topic, the disutility modeled is static as it only depends on the lowest fare. Members from the PODS Consortium suggested to vary the disutility depending on advance purchase, distance or even based on the current lowest paid fare available at
the time of the booking decision. These last two might be the most used by frequent flyer travelers, as they usually compare the value of the fare with the value in points, but having different values for domestic, short haul and long haul routes. Generally, the perceived value of points tends to increase with distance and cabin, making it a point to consider to enhance the current model.

Regarding fare structures, the current model only considers just one award class. In reality, airlines offer different prices with different availabilities for award bookings. This can be also introduced by having a parallel structure just for award passengers, needing to define all parameters accordingly.

Another interesting problem to tackle is that airlines might want to decrease as much as possible the displaced revenue, while maintaining a healthy level of award bookings. This opens two fields of study. On the one hand, identifying and understanding the drivers of displacement is crucial to define strategies to diminish the ticket revenue loss due to award passengers. But, on the other hand, determining a healthy level of award bookings has to do with long term variables not contemplated in this model. These variables need to consider burn to earn ratios, breakage rate and revenue, liabilities, program satisfaction level and long term loyalty value. The latter, currently introduced by some airlines to enhance their business decision-making process, measures the changes in ticket revenue due to changes in the policies of the frequent flyer program. For example, if an airline decides to increase the price in points to redeem a certain route or affect negatively the expiry policy of points, this might result in the loss of passengers buying air tickets on that airline, losing market share over time, and therefore decreasing ticket revenue over time. This input can be helpful to determine the level of award bookings should offer for air rewards, subject to the displaced ticket revenue and award benefit generated.

How loyalty programs as business units interact with revenue management optimization is a topic that has huge impacts on the bottom line of an airline. Understanding the effects of short and long term decisions is important for both sides of the business, going through the path together to accomplish the best possible scenario for the airline as a whole.
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