Demand Driven Dispatch and Revenue Management

by

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ABSTRACT

The focus of this thesis is on the integration of and interplay between demand driven dispatch and revenue management in a competitive airline network environment. Demand driven dispatch is the reassignment of aircraft to flights close to departure to improve operating profitability. Previous studies on demand driven dispatch have not incorporated competition and have typically ignored or significantly simplified revenue management. All simulations in this thesis use the PODS simulator, where stochastic demand by market chooses between competing airlines with alternative paths and fare products whose availability is determined by industry-typical revenue management systems.

Demand driven dispatch (D^3) is tested with a variety of methods and objectives, including a bookings-based method that assigns the largest aircraft to the flights with the highest forecasted demands. More sophisticated methods include revenue- and profit-maximizing fleet optimizations that directly use the output of leg-based and network-based RM systems and a minimum-cost flow specification. D^3 is then tested with a variety of aircraft swap timings, RM systems, and competitive scenarios. Sensitivity testing is performed at a variety of demand levels, demand variability levels, and with an optimized static fleet assignment. Findings include important competitive feedbacks from D^3, relationships between D^3 and both revenue management and pricing, and important nuances to D^3's relationship with the level and variability of demand.

Depending on how it is implemented, D^3 may harm competitor airlines more than it aids the implementer. Early swaps in D^3 lead to heavy dilution. Late swaps lead to smaller increases in loads but substantial increases in revenue. The relationship between revenue-maximization and cost-minimization in profit-maximizing D^3 is highly influenced by the timing of swaps, revenue estimation, and demand levels. Finally, early swaps are susceptible to high variability of demand while late swaps are more robust. Findings indicate that the benefits of D^3 can be estimated at operating profit gains of 0.04% to 2.03%, revenue gains of 0.02% to 0.88%, and changes in operating costs of -0.08% to 0.13%.

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Chapter 1: Introduction

The planning process of an airline can be thought of as a series of decisions first at a strategic level and then at a tactical level as the departure date draws closer (Belobaba, 2009b). Generally, airlines begin with fleet planning, then route planning, and then schedule development. Fleet planning can take place many months to many years in advance, route planning on a closer time horizon, and schedule development usually six or more months from departure. Schedule development involves first frequency planning, then timetable development, and finally fleet assignment, where aircraft types are assigned to specific flights. At this point, crew and maintenance schedules can be determined and more tactical decisions take over—namely pricing and revenue management. Due to this linear chronology in the airline planning process, aircraft schedules and therefore capacity on every flight is effectively fixed for pricing and revenue management, with exceptions for unplanned capacity changes. These changes in capacity are then viewed from the perspective of pricing and revenue management as capacity disturbances.

Demand driven dispatch swaps aircraft of different sizes on flight legs to change capacity in response to demand. With schedules having been made perhaps six or more months ahead of the departure date, pricing and revenue management then operate with the assumption of fixed capacity to maximize revenue. Demand driven dispatch makes capacity flexible again, changing aircraft assignments nearer to departure, often called close-in refleeting. Thus, using more detailed and reliable demand information from the revenue management system, demand driven dispatch has the potential to better match capacity supplied with quantity demanded, simultaneously increasing revenues and decreasing operating costs (Berge & Hopperstad, 1993).

Theoretically promising, demand driven dispatch still poses a host of challenges, including not only potential disruptions to already complicated aircraft, crew, and maintenance schedules, but also a significant interaction with the revenue management process. Revenue management, as it is practiced, assumes a fixed capacity on each flight and optimizes fare class inventory accordingly; to date, the interaction of revenue management and demand driven dispatch in a competitive network environment has not been explored. Furthermore, attention has not been paid to incorporating the full wealth of information provided by revenue management into the fleet assignment process of demand driven dispatch.

Therefore, while demand driven dispatch is a step towards a successful integration of scheduling and revenue management, a good deal is left to do before the integration is truly complete. Both the type of information gathered from the revenue management system and how that information is put to use in fleet assignment can be better informed by the theory and application of subsequent inventory control. Second, demand driven dispatch must be analyzed in a competitive network environment. The aim of this thesis is to address these points and develop a better understanding of the impact demand driven dispatch has on the revenue and profit results of airline operations, with a particular focus on demand driven dispatch given both a competitive environment and the range of typical practices in revenue management.

1.1. Variability in Airline Demand

Variability in airline demand is a well-documented phenomenon. Demand for air travel varies by season, holidays and sporting events, day of week, time of day, the macro-economy, security threats, weather, and countless other factors. From the perspective of a single airline, variations in realized demand are affected by relative fares and fare class availability, revenue management practices, competing schedules and routings from not only other carriers' itineraries but their own as well.

Yet, nearly every facet of the airline planning process relies on forecasts of demand for flight legs or paths, from network planning, scheduling and fleeting to pricing and revenue management. Operations research has had some of its most notable applications in the airline industry, but operations research results in optimal outcomes only when its assumptions and inputs, largely forecasts, are correct. Therefore, the best possible forecasts in terms of accuracy are needed. As accuracy is lacking due to variability in demand, it is also important that the systems that use these forecasts are built robustly. Demand driven dispatch is one approach to addressing variability of demand and making the planning process more flexible, and therefore more robust. It is not as critical that the forecast that informs the original schedule and fleet assignment be accurate if the fleet assignment can be updated at a later date with presumably better forecasts.

One of the key forecast strengths of using forecasts from revenue management is that they are made relatively close to the departure date. Uncertainty diminishes in expected demand both as the forecasts are generated closer to a flight's departure date and of course as actual bookings are taken. With the notable exception of no-shows and cancellations, bookings that have already been taken are effectively deterministic demand. The original fleet assignment constrains future changes in capacity based on swapping options and crew constraints, etc., so that the original schedule and fleet assignment is certainly important. However, the ability to draw on improved forecasts from the RM system closer to departure allows an airline to manage variability in demand by making adjustments to the fleet assignment.

1.2. Current Planning and RM Process and Demand Driven Dispatch

The future of airline planning looks toward the integration of the different steps in the planning process. As is widely recognized, fleet planning depends on what routes an airline intends to fly, the profitability of routes not only depends on the available fleet but also the intended frequencies, and timetables rely on frequency plans but can also be tweaked to help optimize fleet assignment. Finally, the fleet assignment process relies on the selected timetables but also on pricing and revenue management practices such as willingness-to-pay forecasting and optimization.

Therefore, the different aspects of airline planning are interdependent and a true optimization of the whole "problem" of airline planning would have to be simultaneous—an impossible task in practice. What is much more attainable is the partial integration of components of the process. Each stage of optimization in the airline planning process constrains the solutions of the next processes, but increasing the connections between the disparate processes theoretically loosens the constraints put on subsequent optimizations. Demand driven dispatch is primarily an attempt to integrate some components of scheduling, namely fleet assignment, with revenue management.

However, demand driven dispatch incorporates not only scheduling, or more precisely fleet assignment, and revenue management, it also affects and depends on all stages of the planning process. Fleet planning is essential to demand driven dispatch as both labor agreements and industry regulation effectively allow only aircraft of the same "family" to swap flight assignments. Therefore it is important that the fleet contains multiple aircraft types of different sizes within the same family so that pilots can exploit cockpit commonality. Network planning is also important, as the architecture of the network determines both the ease of performing aircraft swaps (altering the fleet assignment) but also the number of feasible swaps at any given airport at any given time. Hub networks offer excellent opportunities for demand driven dispatch, while point-to-point networks do not disallow it but offer fewer swap opportunities.

Meanwhile, demand driven dispatch can better inform all of these aspects of airline planning. The ability to manage variability in demand with demand driven dispatch can allow airlines to strategically deploy larger aircraft to only high demand flights while the fleet at large is composed of mainly smaller aircraft, thus saving operating and ownership costs (Berge & Hopperstad, 1993). The goal of an airline to engage in demand driven dispatch may also inform an airline's decision to consolidate its fleet into swappable aircraft families, along with a host of other noted efficiencies gained from streamlined fleet composition. The ability to perform simplified demand driven dispatch can also be yet another factor in a long list that supports the recurring use of hub-and-spoke network design in the airline industry. On the other hand, demand driven dispatch can result in dilution that harms revenue performance. Pricing may have to adapt fare structures where possible to address this problem.

Demand driven dispatch is primarily an integration of components of scheduling and revenue management, but it effects and depends on all aspects of the planning process to some degree. The current airline planning process is often linear, with each decision process constrained by the decisions made before, and often by separate departments within an airline. Demand driven dispatch is a step towards breaking the information silos that come from such a process and, by increasing communication between fleet assignment and revenue management, can improve performance outcomes in operating profit by both increasing revenues and decreasing operating costs.

1.3. Motivation for Research

Demand driven dispatch thus far has largely been explored and tested as a process of taking demand forecasts from the revenue management system to repeat the fleet assignment process automatically or manually closer to departure. The act of using demand forecasts from the revenue management (RM) system in the place of more aggregate forecasts to reassign aircraft is a likely improvement and accurately called close-in refleeting by some airlines. It does not, however, signify the successful or complete integration of revenue management and fleet assignment.

This thesis aims to develop a more thorough understanding of demand driven dispatch by focusing on the revenue management portion of demand driven dispatch, an area that has been somewhat neglected in previous studies. Revenue management systems can provide information to the fleet assignment model (FAM) beyond more accurate demand forecasts such as demand by fare class with network revenue values. Demand driven dispatch is simulated for this thesis using the Passenger Origin Destination Simulator (PODS), so that demand driven dispatch and its effects can be analyzed in a network setting with complete RM systems and competition, a very important factor. The airline industry is highly competitive and passengers are both price-sensitive and have at their disposal unrivaled information when searching for the lowest fares. Demand driven dispatch must be considered in the context of competition, and it should also utilize the full body of information provided by RM and RM in turn should be informed in some fashion of capacity changes made by demand driven dispatch. Therefore, the primary contribution of this thesis is to analyze demand driven dispatch in the context of two competing network airlines using complete revenue management systems.

These revenue management systems, depending on their complexity, can supply a host of information to the fleet assignment process beyond a count of passenger demand and average selling fare. First and foremost, RM forecasts divides demand into inventory fare classes, each with its own associated fare value(s). Through effective inventory control, RM also applies a hierarchy of fare classes so that when making fleet assignment decisions with RM forecasts, it is possible to evaluate the marginal revenue value of each additional seat or block of seats on a particular flight. This detail is important, as the use of RM means that the additional revenue value of the "last" seat on a flight is necessarily less than the average selling fare. RM methods that consider the network revenue value of fare class inventory can also provide information on the revenue value of capacity on a flight not only to that flight but also to the network as a whole. Thus, the fleet assignment component of demand driven dispatch can incorporate some degree of the revenue management's information of network value to the fleet assignment decision. These opportunities to improve demand driven dispatch have not been fully explored.

Thus, the motivation for this thesis is to advance the science behind both revenue management and fleet assignment by developing a more thorough understanding of and several models for better integrating the two in demand driven dispatch (D^3), especially with regard to RM's role in informing D^3, how it can be adapted to D^3, and how it affects the outcome of D^3. These areas, to date, have not been thoroughly addressed. This thesis is also motivated by the opportunity to simulate and analyze D^3 with these innovations in a competitive network environment, something that has never been done. Thus, while existing research in demand driven dispatch promises increased operating efficiency and improved profitability for airlines, many avenues for continued research remain.

1.4. Outline of Thesis

The thesis begins with this introduction and then proceeds to a more thorough review of the background of demand driven dispatch with a literature review of pertinent topics (Chapter 2), most notably in demand driven dispatch itself but also revenue management, fleet assignment, and other topics. The different forms of revenue management systems used in this thesis will be reviewed in Section 2.2. Chapter 3 contains an overview of the Passenger Origin Destination Simulator (PODS) used to simulate demand driven dispatch for this thesis. This chapter contains details of its passenger demand components and its revenue management system components, which allow PODS to simulate imperfect knowledge of demand from the perspective of the airlines. The demand assumptions in PODS are also different from demand assumptions used in previous D^3 research in that demand for different fare classes is not independent. Passengers are generated with preferences and willingness to pay and then choose the itineraries that best match their preferences and budget. PODS also incorporates competition, an important contribution to the literature on D^3. The chapter also contains a description of Network D^3, a hypothetical airline network specifically designed and constructed for simulating demand driven dispatch in PODS.

The subsequent Chapters 4 through 7 detail the results of tests of demand driven dispatch in PODS. First, bookings-based swapping is evaluated in Chapter 4 with a simple ranking algorithm. This is to simulate the simplest form of demand driven dispatch and to form a basis for which to judge the value of more complicated demand driven dispatch techniques incorporating more information from RM. The ranking algorithm is replaced with an assigner built on a network optimization (minimum-cost flow model) in Chapter 5. This assigner is then used with a series of revenue-maximizing objective functions, starting with leg-based revenue estimation and RM optimization and culminating in the use of network bid prices. Finally, operating costs are also added to the objective function, which in turn maximizes operating profits. The results of tests using this assigner are shown in Chapter 6.

Chapter 7 presents the results of tests where demand driven dispatch is implemented for operating profit maximization under a wider range of conditions. A new static fleet assignment is introduced to test the benefits of D^3 given an optimized original fleet assignment. Then, variation in demand is increased and decreased to test D^3 benefits depending on variation in demand. Finally, the direct cost of aircraft swapping is tested at various levels. The thesis then concludes in Chapter 8 with a summary of results and concepts and suggestions for future research.

Chapter 2: Background & Literature Review

This chapter reviews the general trends in the science of airline planning over the last few decades, as well as describe current planning processes at airlines. The chapter begins with a discussion of network planning, scheduling and fleet assignment, and then pricing. These processes usually occur sequentially and typically precede revenue management and demand driven dispatch, should it be implemented. However, the approach used in these planning stages can limit or facilitate revenue management and demand driven dispatch.

Following the description of network planning, scheduling, and pricing, revenue management is discussed, including current practices and near-future developments. The revenue management section is divided into two sections—forecasting and optimization. Numerous approaches to forecasting and optimization are used in the industry, with the most recent developments being focused on forecasting and optimizing demand by willingness-to-pay rather than strictly by fare class.

The interaction between revenue management and spill (rejected demand) is discussed along with the modeling of spilled revenue. This section is brief but very pertinent to demand driven dispatch, as revenue management ultimately affects which types of demand are spilled and which are not.

Finally, Section 2.4 reviews the existing literature on demand driven dispatch. D^3 debuted in academic journals in 1993 and has been researched since. The existing research primarily developed algorithms for modifying the fleet assignment problem to meet the specific constraints of demand driven dispatch. Competition among is not considered, nor is revenue management considered beyond simple representations of RM systems and demand arrival processes. However, impressive work has been completed on assignment algorithms, and analyses of live tests have also been conducted.

2.1. Network Planning, Scheduling, and Pricing

Network planning, also known as route planning, is in some regards the beginning of the planning process for deciding how to deploy an airline's available fleet. Network planning not only includes the process of deciding what origin and destination markets (OD markets) an airline will provide transportation between, but how that transportation network will be constructed. The most obvious decision in the architecture of a network is whether to deploy aircraft point-to-point or in a hub-and-spoke system. Point-to-point systems offer convenient service to individual passengers, as they do not have to connect. On the other hand, with no connecting passengers on point-to-point flights, limited demand may result in few frequencies or no service at all. From the perspective of airlines, hubs have undeniable benefits from operational efficiencies in fleet assignment to crew and personnel scheduling. Most notably however, they allow airlines to use fewer aircraft and fewer flights to offer service to more destinations from any given origin in the hub-and-spoke network (Belobaba, 2009b).

Hub-and-spoke-systems also have economic costs related to their operations, such as decreased aircraft utilization in order to time arrivals and connecting departures from a hub, congestion at the hub airports, and extended turnaround times to allow passengers to connect. The growth of low cost carriers has caused some to forecast more point-to-point service, a trademark of the low-cost carrier model. However, with weaker demand post-2001 and 2008 and, until very recently, high fuel prices, hubs have been strengthened in recent years (Belobaba, 2009b). In fact, many airlines considered to be low-cost carriers utilize, if not hubs, focus cities. The term “hub” is difficult to define, but Southwest Airlines connects large numbers of passengers through several airports such as Midway in Chicago, and JetBlue does the same at airports such as JFK. In fact, many low-cost carriers, if they don’t have outright “hubs,” have significant focus cities, as found in an analysis of European low-cost carriers (Dobruszkes, 2006).

This observation is critical for demand driven dispatch, as wherever and whenever two or more aircraft of an airline have turns at an airport at overlapping times, the possibility for swapping exists. Thus, demand driven dispatch is possible for even dispersed point-to-point networks so long as aircraft occasionally “meet” in the network. However, hub-and-spoke networks provide for many more swapping opportunities, especially when aircraft are routed “to and from” hubs in short strings of flights. This fact has been recognized both in the literature and by airlines that have engaged in demand driven dispatch (Waldman, 1993). The practicality of demand driven dispatch, especially concerning not disrupting maintenance routings, largely rests with the continued use of the hub-and-spoke model.

Scheduling is equally important for the application of demand driven dispatch. Scheduling has also been the subject of a great deal of attention from operations research specialists. Scheduling can be seen as an umbrella term that includes frequency planning, timetable development, fleet assignment, maintenance routing, and finally crew scheduling. Frequency planning is often a part of network planning, where demand models and market analysis are used to determine the appropriate number of frequencies that should be provided to a route on any given day. Timetable development can be summarized as choosing the departure times of the frequencies that have been chosen, with the arrival times being more or less determined by the departure time. Fleet assignment is then the matching of each flight with a type of aircraft in the available fleet. Maintenance routing is focused on assigning each specific aircraft to a series of flights, i.e. “tail numbers” to flights, with the goal that each aircraft receives the required maintenance and typically balancing the utilization of aircraft. Crew scheduling is the assignment of crews to flights, with crews having a host of constraints, including what aircraft they can fly and how many consecutive hours they can fly. Thus, crew scheduling comes after fleet assignment, but not necessarily after maintenance routing.

Each of these scheduling problems has been subject to optimization techniques, and integrated optimization problems have also been addressed. A recent development is an emphasis on robust solutions to account for the fact that severe weather and other factors often prevent an “optimal” schedule from being carried out as planned (Barnhart, 2009). Another recent focus of research in schedule optimization has dealt with de-peaking hub schedules and therefore mitigating the adverse effects of hub congestion, such as in Pita, Barnhart, and Antunes (2012) and Jacquillat and Odoni (2014). Mitigating this cost of hubs makes them more attractive than otherwise in a world of increasing air traffic, thus bolstering opportunity for demand driven dispatch.

More so than determining frequencies and timetables, routing and especially fleet assignment are critical for demand driven dispatch. Routing determines the ease with which demand driven dispatch can be performed. For example, making swaps with other aircraft is more difficult if the aircraft’s routing is a complicated string of flights between a series of distinct airports throughout a schedule week. As noted before, “there-and-back” routings and modest expansions on that theme provide for excellent swapping opportunities (Waldman, 1993), as do numerous trips between multiple hubs or focus cities (Berge & Hopperstad, 1993).

Fleet assignment is the stage of scheduling that is most applicable to demand driven dispatch. In fact, the implementation of demand driven dispatch is in essence the partial integration of revenue management and fleet assignment. Many approaches to fleet assignment optimization have been developed (see section 2.4 for examples in the context of demand driven dispatch), but most solve the problem by representing the flight schedule with flight arcs and ground arcs connecting points that represent specific airports and specific moments in time in a time-space network. An aircraft (type) can travel over a flight arc (fly a flight) or travel over a ground arc (remain at an airport). Each aircraft type has an associated revenue and cost value for traveling over an arc and the objective function is to maximize operating profit. Constraints typically include balance, cover, and count. Balance stipulates that whatever enters a point must leave it, or, in other words, that if an aircraft lands at an airport it must eventually leave that airport. Cover stipulates that each of the flight arcs, representing flights in the schedule, must be traversed or operated by an aircraft. Count stipulates that the number of each type of aircraft must be the same at the beginning and end of a period of operations and at all times in between. In order to implement demand driven dispatch, a method for solving the fleet assignment problem must be used, and they typically take the form of a fleet assignment model (FAM) such as the one just described (Barnhart, 2009).

Fortunately, the FAM used in demand driven dispatch can be greatly simplified from the one used in a static assignment because the static assignment already exists. Taking the original assignment, swappable pairs or groups of flights can be identified and then a relatively simple linear model or minimum-cost flow model can be used to re-assign the fleet types from the original fleet assignment (Berge & Hopperstad, 1993). Alternatively, the original FAM can be used again in what can accurately be described as re-fleeting, although this would require significantly more computational power and more constraints as the flexibility for fleet assignment six or so months before departure does not persist in the few weeks before the departure date.

Pricing is typically the last stage of the airline planning process before sales and revenue management begin, although changes in pricing frequently continue after seats become available for sale for a particular departure. The fundamental framework used in airline pricing is revenue maximization given a basic demand curve—a downward sloping demand function.

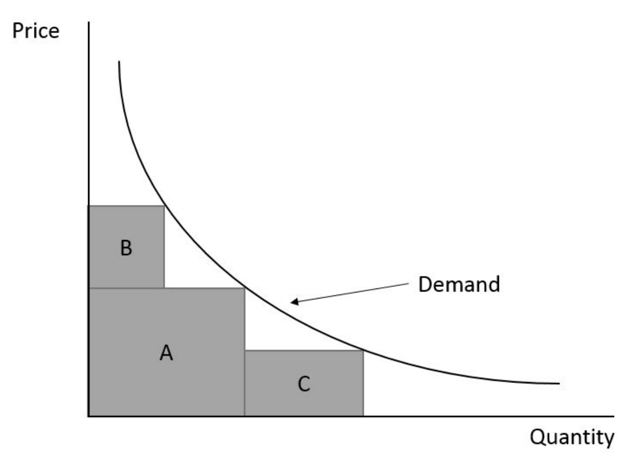

Figure 1: Demand Segmentation

As Figure 1 illustrates, with only a single price point, a firm only captures the revenue represented by the Area A. If the firm engages in classic microeconomic price discrimination and uses three price points and successfully segments demand, it can capture consumer surplus and gain the revenue represented by Area B and also sell discounted seats to take advantage of supply otherwise not utilized, thereby gaining the revenue represented by Area C. This is of course a significant simplification, but nevertheless illustrates the primary reasoning behind common pricing behavior by airlines. Typically, they provide a number of fares from a few to over twenty in a market, each fare having a set of restrictions. These restrictions are intended to differentiate fare products and to segment demand.

Typical restrictions include advanced purchase restrictions, roundtrip and Saturday night stay restrictions (a particularly powerful method of segmenting business and leisure passengers, the two primary customer groups), day of week travel restrictions, etc. (Belobaba, 2009a). The restrictions used to segment passengers by fare product are important not only for pricing but are defining assumptions for revenue management. They are therefore also important for demand driven dispatch. A recent trend in pricing has been the removal of many fare product restrictions. This allows passengers who would be willing to pay more and were previously deterred from buying the lowest fares by restrictions to now do so. This trend has in turn resulted in innovations in revenue management (Belobaba, 2011), and therefore has important and heretofore underappreciated implications for demand driven dispatch.

2.2. Revenue Management

Revenue management is a vital component of demand driven dispatch. Demand driven dispatch and revenue management are simulated with PODS, the Passenger Origin Destination Simulator, which simulates multiple revenue management systems designed to resemble those used in the airline industry, including systems with forecasters and optimizers with assumptions of independent fare class demand and without that assumption. Multiple variations of optimizers will also be simulated, leg-based and OD-based, to be described in further detail in section 2.2.2. Section 2.2 as a whole describes the general trends in revenue management and in more detail the systems used in PODS for the experiments conducted for this thesis.

After discussing general trends in revenue management (RM), the section is divided into two more specific parts: forecasting and optimization. These roughly represent the two main steps in the revenue management process, with the forecasts of demand being required as input along with the fares as determined by pricing for optimization. Optimization, and subsequently inventory or availability control, aims to determine the optimal number of seats to allocate to each of the fare classes, or price points, in order to maximize revenue.

Revenue management has the objective of maximizing revenue and not profits as is more typical in economic theory because of the underlying assumption that supply, and therefore costs, are fixed. Given this assumption, profit maximization and revenue maximization become equivalent. This assumption is in large part true, although demand driven dispatch weakens the assumption by allowing planned changes in capacity, and therefore operating costs, during the revenue management process. Therefore, it is important that the decision making process for swaps have an objective of profit maximization and also that the potential for capacity disruption to revenue management be accounted for.

RM optimization relies on demand forecasts for each fare class. In leg-based RM, the forecasts are needed for each leg, or departure. For original and destination revenue management (OD RM), forecasts are typically for each path of connected flights taken through the airline's network (Gorin, 2000). Hence, these forecasts are called path-class forecasts as opposed to leg-class forecasts. The class refers to the fare class or fare bucket that demand is observed in. Forecasts are based on observed demand, or bookings, which are inherently constrained by both capacity and by revenue management itself via booking limits placed on each fare class. Therefore, these forecasts are unconstrained or detruncated to reflect an estimation of true demand, an approach widely used in statistics for censored data (Weatherford & Polt, 2002). Multiple approaches to this detruncation exist, but the result is demand forecasts by class that exceed or equal observed demand depending on the historical availability of the fare classes in question.

Each fare class, as well as having an estimate of its demand, is also associated with a revenue value, such as the average selling fare for itineraries in that fare class on a specific leg or departure. This allows the optimization and availability control portions of revenue management to weigh the expected revenue value of capacity allocated to one fare class against that allocated to another. When forecasted demand exceeds capacity, revenue management's underlying purpose is exposed—it is the science of when to reject the lower-valued demand.

A common leg-based RM optimization technique known as EMSR has proven remarkably popular among airlines. Its central concept is serial nesting of fare classes combined with the expected marginal revenue of each additional seat allocated to a fare class (Belobaba, 1989). When the expected marginal revenue of the next seat allocated to the highest fare class is less than the expected marginal revenue of the first seat allocated to the next lower fare class, the seat protection level has been found. Namely, that many seats should be protected for the highest fare class from all lower fare classes. If more seats than that number are available, the next lowest fare class should be allowed to take bookings.

This reflects how the fare classes are serially nested. The highest fare class, being the most valuable, should be allowed to take as many bookings as there are seats available on the aircraft. However, only a limited number of bookings for the highest fare class are expected, so that each seat protected for the highest fare class has a diminished expected revenue value. Therefore, after protecting a number of seats for the highest fare class, as stipulated by the protection level, the next lower fare class would have an availability equal to the remaining capacity minus the seats protected for the highest fare class. The third fare class would have an availability equal to the remaining capacity minus the seats jointly protected for both of the two higher fare classes (Belobaba, 2009a). This concept is illustrated in Figure 2.

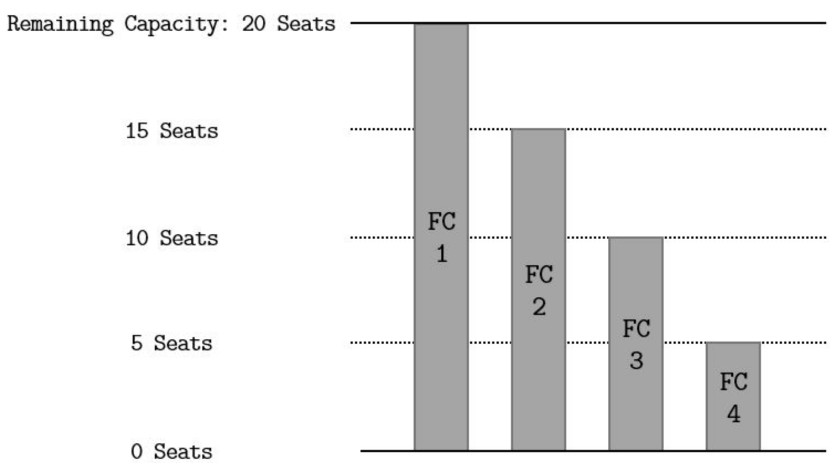

Figure 2: Serial Nesting

In Figure 2, Fare Class 1 (FC 1), being the highest value fare class, has an availability of 20 seats, its booking limit. Its protection level is 5 seats, so that FC 2's booking limit is 15 seats. FC 1 and FC 2 have a joint seat protection level of 10 seats and FC 3 therefore has a booking limit of 10 seats and so on.

This concept was extended to origin-destination (OD) RM optimization techniques where local and connecting itineraries are controlled separately with optimization techniques such as Displacement Adjusted Virtual Nesting (Hung, 1998). Here, the fare classes are replaced with virtual buckets with ranges of dollar values for each bucket. An itinerary is valued for a specific leg based on its total fare minus the estimated revenue displacement on any other connecting legs it uses. With this new valuation, it is mapped to the virtual bucket that contains its adjusted valuation and then EMSR optimization is applied to the leg's virtual buckets.

From leg-based to OD-based RM, the next major development has been the adaptation of RM to less restricted fares. This adaptation is important because less restricted fares make the assumption of independent demand for different fare classes much less valid (Belobaba, 2011). The primary response has been to forecast and optimize not by fare class but rather by willingness-to-pay; optimization input fares can be adapted to account for the fact that passengers who would be willing to pay a higher fare may buy a lower fare if it is available (Fiig, Isler, Hopperstad, & Belobaba, 2010). Willingness-to-pay forecasting and optimization represent the current frontier of revenue management. The tests of demand driven dispatch in this thesis use several revenue management systems, including leg-based EMSR, OD RM, and willingness-to-pay forecasting and optimization.

2.2.1. Forecasting

As stated, revenue management optimization models require as an input forecasts of demand for each fare class for each leg, or more granularly for each path. In the PODS simulations, three types of forecasts are used: standard leg-class forecasting, standard path-class forecasting, and hybrid path-class forecasting. Each of these are briefly described below with references for further details.

Standard leg-class forecasting in PODS is more specifically implemented as leg-based pick-up forecasting with booking curve unconstraining. All of the forecasting methods used in the experiments utilize the pick-up forecasting methodology which is widely used in industry. Pick-up forecasting refers to calculating at each day or data collection point (DCP) the mean "pick-up" of bookings to come (BTC) before departure. In other words, at each time period prior to departure, pick-up forecasting averages the historical bookings that were taken between that time period and the departure date and uses it as the forecasted BTC after unconstraining. Adding forecasted BTC to bookings in hand (BIH) yields estimated bookings at departure (BAD).

The final component for this forecasting methodology, used in conjunction with the pick-up methodology to generate the forecasted BTC, is booking curve unconstraining. This unconstraining or detruncation method replaces closed observations (those observations whose demand was constrained by a booking limit) with an increased estimate of demand constructed from the mean of open observations (those observations whose demand was not constrained) multiplied by ratios that reflect the magnitudes of bookings from one data collection point (DCP) to the next. Details and an example can be found in Weatherford and Polt (2002), there called “booking profile unconstraining.” Finally, this pick-up forecast with exponential smoothing and booking curve detruncation is applied to each fare class for each departure or leg. Therefore, it is a leg-class forecast and will be referred to as a standard leg-class forecasting.

Standard path-class forecasting in PODS is an extension of standard leg-class forecasting. It also uses pick-up forecasting with booking curve unconstraining. However, rather than forecasting for each class on each leg, it forecasts, as the name suggests, for each class on each path in the network. The result is that there are many more forecasts and they are considerably smaller in magnitude than a leg forecast. For example, for the OD-pair SEA-BOS, with a hub at MSP, there would be a forecast for demand in FC 3 for the path SEA-MSP-BOS. This is in contrast to the leg-based forecast where there would be a forecast for FC 3 for the leg SEA-MSP, with demand to all final destinations aggregated together. In path-class forecasts, there is also a forecast for FC 3 for SEA-MSP, but this forecast only includes demand whose final destination is MSP.

Hybrid forecasting in PODS is a combination of standard forecasting and what is known as Q-forecasting and will be used as the alternative to “standard” forecasting. Hybrid forecasting and Q-forecasting were developed to account for unrestricted fares and the ensuing spiral down (Belobaba & Hopperstad, 2004). Passengers who were otherwise deterred by fare restriction purchase lower fare classes and are therefore recorded as demand in lower fare classes. This shift to lower fare classes in demand forecasts causes lower protection levels for higher fare classes and higher booking limits for lower fare classes, exacerbating the problem. This circuitous process whereby demand falls to the lowest fare classes is known as spiral down. Q-forecasting and hybrid forecasting, both forecasting techniques that incorporate concepts of willingness-to-pay (WTP), are meant to combat spiral down and preserve the benefits of revenue management.

Q-forecasting operates first with an estimate of passengers’ WTP. This input, typically in the form of a negative exponential demand function, estimates what percentage of passengers would be willing to sell-up from the lowest fare class, the “Q class” and hence the name Q-forecasting, to a higher fare class. It also assumes that nearer to departure, potential passenger’s WTP increases, such that WTP estimates vary throughout the booking period. Q-forecasting also operates on the assumption that fare products are only differentiated by price, and therefore all passengers will choose either the lowest available fare product or choose to not fly. Given this assumption and estimated WTP, historical booking data is transformed into a forecast for the demand of the lowest fare class should it be left available. Then, the demand is redistributed to the higher fare classes based on their fare ratio relative to the lowest fare class if they should be the lowest fare class available. The result is a forecast that consistently distributes forecasted demand to the higher fare classes, regardless of observed distributions of fare class bookings. Full details of Q-forecasting can be found in Belobaba and Hopperstad (2004).

Hybrid forecasting is the combination of Q-forecasting and the aforementioned standard forecasting. Customers are separated into two groups: product-sensitive and price-sensitive passengers. If a booking is made in a fare class that is the lowest open fare class, the passenger is assumed to be price-sensitive and the booking is subject to Q-forecasting. If a booking is made in a fare class that is not the lowest open fare class, the passenger is assumed to be product-sensitive and the booking is subject to standard forecasting. When both a standard forecast of product-sensitive demand and a Q-forecast of price-sensitive demand are completed, they are added together to create the *hybrid* forecast (Belobaba & Hopperstad, 2004).

A final step that is paired with hybrid forecasting to combat spiral down is known as marginal revenue fare adjustment. The method also uses sell-up estimates to estimate how much total demand is available in each fare class, should that class be the lowest open. The marginal revenue of a fare class represents both the revenue gained due to a lower available price stimulating increased bookings and the revenue lost due to spiral down. This marginal revenue of the fare class is then used to calculate the revenue value of a booking in that fare class—the *adjusted* RM input fare. Details for methodologies for fare adjustment and the underlying theory can be found in Fiig, Isler, Hopperstad, and Belobaba (2010).

The result is that the highest fare class retains an identical fare-value, while lower fare classes see reduced fare-values. The higher the estimate of the sell-up rate, the more aggressively fare adjustment devalues the lower fare classes. It is possible that the lowest fare classes have a negative marginal fare-value, and would therefore never be available, regardless of remaining capacity. This is an important point; when fare adjustment is used, the availability control may not allow a low fare class to be sold even when the joint protection level for higher fare classes is less than capacity. The sell-up rate used in fare adjustment can be tempered with a parameter (intended to adjust for the fact that the fare products are not completely unrestricted), and in the experiments in this thesis, that parameter is 0.25 which is multiplied with the estimated sell-up rate. These adjusted fares are then used rather than the actual fares as input to the optimization process.

2.2.2. Optimization

The optimization process takes the input fares and forecasts and uses them to create booking limits for each of the fare classes, or alternatively a bid price that a fare must exceed in order to be booked. In this thesis' tests, three alternate RM optimization techniques are employed: EMSRb, DAVN, and ProBP. EMSRb is paired with standard leg-class forecasting while DAVN and ProBP are paired with either standard or hybrid path-class forecasting. When hybrid forecasting is used, the optimizer is also given adjusted fares. In this section, EMSRb, DAVN, and ProBP will be described and references for further study provided.

As discussed earlier, EMSR is a leg-based optimization technique developed by Belobaba (1989) and EMSRb is a follow-up improvement to the technique (Belobaba & Weatherford, 1996). EMSR stands for expected marginal seat revenue. By applying cumulative Gaussian distributions to the demand forecast (mean and standard deviation), there is a 50% chance of realizing at least the mean demand forecast, a greater chance of less bookings, and a lesser chance of more bookings. Multiplying the probability of realizing a booking by its fare yields the expected marginal seat revenue for that booking. When the EMSR of a booking in a higher fare class is less than the EMSR of the first booking in the next fare class, no more seats should be protected for the higher class from the lower class. Thus, serial nesting is employed. For the availability decision, each fare class has a booking limit. When that booking limit is reached, the fare class is "closed" and no more bookings can be taken. Thus, the availability decision for EMSRb optimization is whether or not a fare's class is open or closed. EMSRb is perhaps the most widely used RM method in the airline industry, and is therefore the base case optimization technique in most experiments in this thesis.

Displacement Adjusted Virtual Nesting (DAVN), described in greater detail in Williamson (1992) and Hung (1998), takes the same logic and extends it to full OD inventory control. The actual fare classes on each leg are replaced by virtual buckets, or value buckets. Each bucket is associated with a range of fare values. For example, the lowest virtual bucket may contain all itineraries that traverse the leg valued at $0 - $100, while the highest virtual bucket may contain all itineraries that traverse the leg valued greater than $1,200. These virtual buckets are then controlled with the EMSRb technique. If an itinerary is deemed available on all of the legs that it traverses after it has been mapped to each legs' virtual bucket and EMSRb is applied, it is available to book.

How are itineraries mapped to the virtual buckets? Each fare, when valued on a leg, is valued as the itinerary's fare minus the sum of the network displacement costs of the *other* legs the itinerary uses. These network displacement costs are derived from the shadow prices for each leg's capacity constraint in a network linear program and represents the economic opportunity cost of other bookings that could have utilized the space this itinerary will use. Therefore, DAVN allows, through several layers of heuristics, for inventory control to be performed on the OD level rather than on the leg level.

Probabilistic Bid Price Control (ProBP), approaches the same OD revenue management problem from a slightly different approach (Bratu, 1998). Rather than employing the EMSR concept at the end for availability control, it applies it at the beginning for the calculation of the network bid prices, whose function is the same as the network displacement cost (Bratu, 1998). These network bid prices are generated with the following iterative algorithm:

1) For every leg, calculate the EMSR values for all path-classes that traverse a particular leg with no regard to network displacement costs.
2) For each leg, find the EMSRc, or the EMSR value of the last seat on the leg, and designate it as the displacement cost for the leg.
3) Prorate the original fares by the relative displacement costs across multiple legs and find the new EMSRc for each specific leg.
4) Repeat Step 3 until the network displacement costs converge for all legs.

The result is a probabilistic network bid price (displacement cost) for each leg in the system. Control of inventory is done by bid price: each itinerary's fare is compared to the sum of the bid prices of the legs it traverses. If the fare is greater than the sum of the bid prices, the itinerary is available. If the fare is less than the sum of the bid prices, the itinerary is not available. Thus, ProBP, like DAVN, allows for full OD control of inventory.

2.3. Airline Demand: RM, Spill, and Incremental Capacity

With the application of revenue management (forecasting, optimization, and inventory control) described in the previous sections, it is apparent that the "first and last seats" available on a flight are not of the same revenue value. The last seats on a flight will be allocated to the lowest available fare classes, and the first seats on a flight will be protected for the highest fare classes. This hierarchy of demand has important implications for spill (demand that cannot be accommodated due to capacity constraints) and therefore for demand driven dispatch which makes capacity flexible. The quantity and value of demand to arrive in the future is critical to inventory control but also to the determination of the optimal capacity on future departures. Demand is often modelled with a Gaussian distribution and some authors have argued other distributions may be more appropriate (Li & Oum, 2000) & (Swan, 2002). However, the actual *revenue value* of spilled demand is a critical consideration, regardless of the exact shape of its distribution. Belobaba & Farkas (1999) and Abramovich (2013) investigated the effects of RM on spill estimation and valuation.

Abramovich (2013) discusses the results of passenger choice and revenue management on the value of spill and therefore on the value of incremental capacity. The findings included the importance of considering passengers ability to choose between flights, recognizing that increasing capacity on one flight could increase revenue on that flight but decrease revenue on another flight operated by the same carrier. Likewise, when fare products are unrestricted and the RM system does not account for WTP, increased capacity can result in spiral down such that incremental capacity can have a negative revenue impact for the network and for that specific flight. Therefore, when considering the value of spilled demand, it is important to consider the revenue value of the demand being spilled and, given lower restrictions, the potential for incremental capacity increases to result in spiral down.

2.4. Previous Research in D^3

Demand driven dispatch traces its origins to discussions found in a presentation at an AGIFORS conference (Etschmaier & Mathaisel, 1984) and an internal memo at the Boeing Company (Peterson, 1986). The concept of the "rubber" airplane, capable of matching any level of demand, as imagined at The Boeing Company in the late 1980s and early 1990s, was to be the "penultimate hub aircraft." Berge and Hopperstad (1993) formulated and tested the process. They developed an LP formulation and a sequential minimum-cost flow method for assigning aircraft; they then tested demand driven dispatch in a simulation with a single carrier performing EMSR-based revenue management and the assignment process solved with heuristics. With a number of side studies, the results of their simulations showed a significant increase in operating profits, from 1% to 5%. These were in part due to increased revenue but largely due to decreased operating costs, where smaller aircraft were assigned to routes when more accurate demand forecasts predict low demand. This paper broke ground on demand driven dispatch and is heavily cited in all subsequent works.

Waldman (1993) analyzes the practicality and profit potential of demand driven dispatch. He cites Berge and Hopperstad's conclusion that feasible maintenance schedules are possible with demand driven dispatch, as well as provides solutions to other operational challenges: aircraft families with cockpit commonality and reserve cabin crew to solve crew scheduling and reserving certain cabin sections until after final fleet assignment to solve seat assignment. He also cites KLM's successful implementation of demand driven dispatch. In a simulation of demand driven dispatch in a single hub network with one airline performing EMSR-based RM, he finds profit enhancements consistent with Berge and Hopperstad. Cots (1999) simulates a single airline performing demand driven dispatch on a repeated flight, managing inventory with EMSRb-based RM. It then tests delaying swaps until later in the booking process and changing the RM input capacities to the minimum and maximum possible. As with the prior experiments, demand is assumed to be independent between fare classes. It also assumes a Poisson arrival process with demand variance fixed to equal the mean demand.

Next, a series of papers were published describing and focusing on models and algorithms for re-assigning aircraft. The first is a model for efficient airline re-fleeting (Jarrah, Goodstein, & Narasimhan, 2000) which does not explicitly cover the topic of demand driven dispatch but offers numerous modules to assist schedule users in manually re-fleeting, one scenario being changes in forecasted demand and fare levels. This reflects how demand driven dispatch has been implemented more on an ad hoc basis using decision support tools rather than in a systematic way.

Bish, Suwandechochai, and Bish (2004) wrote on strategies for managing flexible capacity, including what they term demand driven swapping (DDS). They claim that swaps more than four weeks out will not disturb revenue management but utilize poorer forecasts, while swaps nearer in disrupt airline operations. They predict positive revenue results using analytical models based on data from United Airlines. Sherali, Bish, and Zhu (2005) developed a polyhedral analysis and algorithms for re-fleeting; they restrict swaps between aircraft that share "loops," or strings of flights that begin and end at the same airport at the same times. They relaxed the leg fare class-based passenger demand and allowed path fare class-based passenger demand. They also cite United Airlines and Continental Airlines testing the swapping of aircraft for altered demand forecasts and that both airlines experienced significant gains as a result.

Jiang (2006) explored techniques for optimizing re-fleeting and de-peaking hub-and-spoke systems, primarily using demand driven dispatch models generalized by Berge and Hopperstad (1993) and Bish et al (2004) for its schedule re-optimization model. It also seeks to de-peak the hubs busiest times to increase flexibility for dynamic re-fleeting. Passengers are generated by itinerary or path, with each itinerary having a single fare/fare class. Thus revenue management is not simulated. Profit increases of between 2.0% and 4.9% are predicted.

A study of the potential for dynamic airline scheduling, both re-fleeting and retiming, was conducted by Warburg, Hansen, Larsen, Norman, & Andersson (2008) primarily based on Jiang (2006) with additional components. By adapting both the choice model and the operating cost model to match observed data and simulating with demand data from SAS, they predicted profit increases of -0.8% to 1.6%. Jiang & Barnhart (2009) addresses the same topic. It utilizes both flight refleeting and retiming to optimize the schedule. Tests using data from a major US carrier indicate profit increases of 2.5% to 5%. Demand was generated for OD markets with a single average fare, such that revenue management was not simulated.

Hoffman (2011), on dynamic airline fleet assignment, essentially reuses the fleet assignment model (FAM) from the original, static fleet assignment to adjust for deviations from expected demand. A single airline implements re-fleeting with simulated profit gains of approximately -0.1% to 0.6% using data from Lufthansa. Notably, the study found that a version of the FAM emphasizing robustness outperformed other versions at all demand variation levels. Finally, Pilla, Rosenberger, Chen, Engsuwan & Siddappa (2012) developed a multivariate adaptive regression splines cutting plane approach to solving a two-staged stochastic programming. They then applied the approach in demand driven dispatch as outlined in Berge and Hopperstad (1993) and estimated, by comparing objective function values, that the value of demand driven dispatch was approximately a 6.74% improvement in profitability. Neither revenue management nor stochastic demand arrivals were simulated.

Two works attempt to fully integrate the fleet assignment optimization with yield management optimization, first by using dynamic yield management with swapping allowed (Wang & Regan, 2006). This work, where a pair of flights are designated as swappable with each other, the dynamic RM technique is given a regularly updated probability of swap given current demand. Three fare classes are used and controlled by bid price determined by expected revenue recursion while simultaneously determining fleet assignment. Demands for the fare classes are independent in the tests with Poisson arrival rates. Revenue increases are estimated to be between 0.12% and 1.61% depending on the heuristics used to solve the dynamic optimization. Wang & Meng (2008) extends the same logic to more systemic fleet reassignment based on current bookings. While impressive in its theoretical framework, the practicality of an airline replacing its revenue management system and fleet assignment system to install such an integrated system is questionable.

On a practical level, two papers have analyzed the results of live tests of demand driven dispatch. The first (Feldman, 2002), briefly discusses the positive results of a manual implementation at Continental Airlines of swapping aircraft in leisure markets based on estimated revenue increases and also of a large test at American Eagle, where more than 10% of flights were swapped. Shebalov (2009) discusses the same instances of demand driven dispatch in the US and emphasizes that in live tests successfully estimating the revenue of potential swaps is critical.

Based on this review of the existing literature on demand driven dispatch, several points are evident. First, a great deal of effort has been put into the improvement of fleet assignment models and algorithms, usually as extensions of the original FAMs used to create the static assignments prior to the implementation of demand driven dispatch. Second, in the vast majority of tests of such methods, revenue management is either not considered or given a secondary role. Fare classes are simplified, with no fare rules or restrictions, and demand is independent between fare classes and typically arrives via a Poisson process, the same demand model used in the development of the optimization methods. Where industry data is used to estimate results, a single airline's booking data is used. Competition does not exist in any tests of demand driven dispatch, as far as the author of this thesis is aware. Finally, through many live tests and implementations at US carriers and European carriers, demand driven dispatch has been shown to be possible and has been found to have positive results. The opportunity exists for this thesis to further develop demand driven dispatch by incorporating a more comprehensive analysis of D³ with a focus on current revenue management tactics and in a *competitive network environment.*

Chapter 3: About PODS

The Passenger Origin Destination Simulator (PODS) is the simulation tool used for the experiments described in this thesis. PODS, originally developed at Boeing to test passengers' preferred travel windows, now simulates the generation of demand (each passenger with a set of attributes and preferences), several airlines, and complete RM systems. Critically, the demand is not generated with the same assumptions as those made in the RM models and the airlines must forecast and optimize using demand generated from historical bookings only—they do not have access to the actual demand.

PODS therefore allows for the simulation of realistic revenue management systems in a full network setting *with competition*. Competition in PODS is critical, as ultimately revenue management and demand driven dispatch are competitive actions. Engaging in either has significant impacts on competitor airlines, and competitor airline actions have significant impacts on the subject airline. This chapter will describe the PODS simulator in greater detail. All information and figures in sections 3.1 through 3.4 are from a recent presentation of processes in PODS by Belobaba (September, 2010).

3.1. Overview and Structure

The structure of PODS consists of two components—the passenger demand component and the airline component. The passenger demand component is characterized by demand generation and a passenger choice model. The airline component is characterized by each airline's revenue management system and the revenue results of its use. The only interaction between the two components is when passengers choose an itinerary and book and when the revenue management systems of the airlines provides fare class availability to the passengers via a choice set. Thus, the true demand, both the quantity and the arrival process, are not known by the airlines. Instead, they must rely on historical bookings to generate forecasted demand. Furthermore, passengers may choose any itinerary to their destination provided the itinerary is available via inventory control. This structure is displayed in Figure 3.

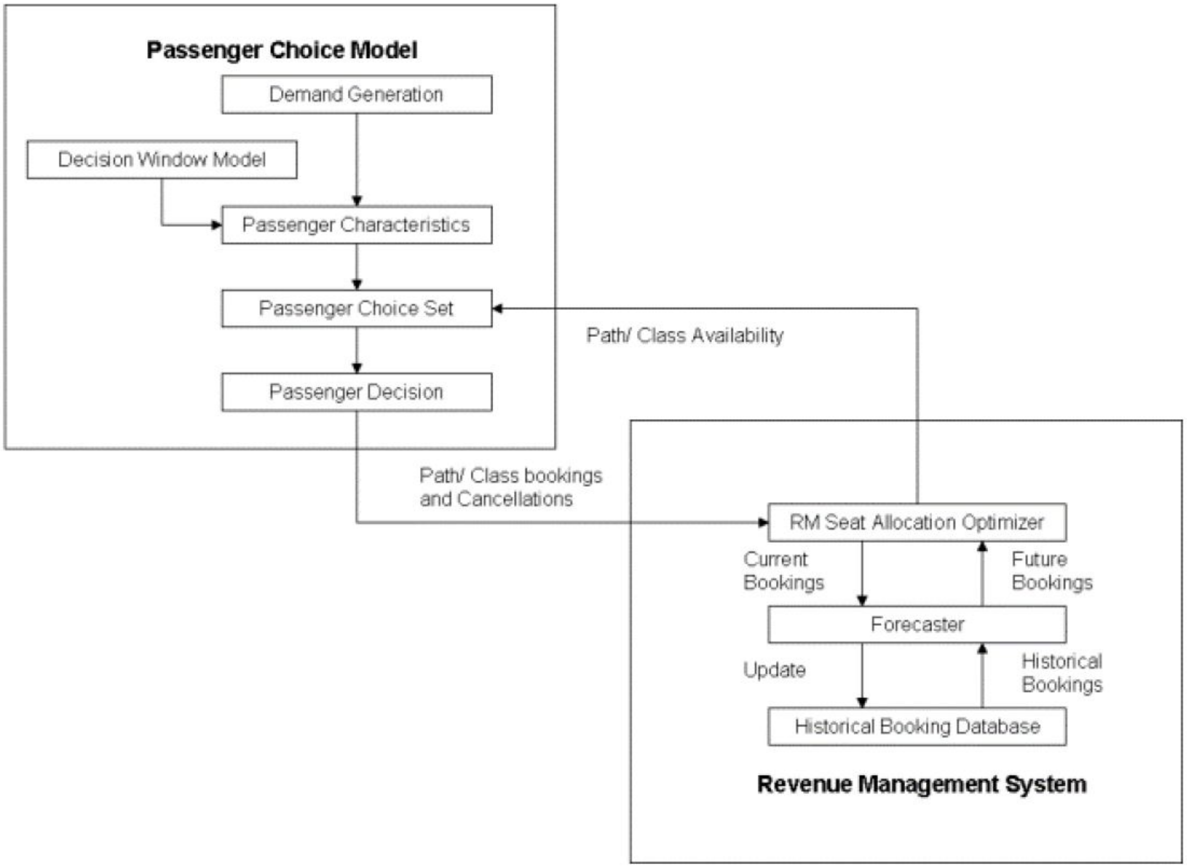

Figure 3: Structure of PODS

The passenger demand in PODS is generated stochastically for each market. This each passenger is then assigned, along with other characteristics, a preferred departure time or window, via the decision window model. These passenger characteristics then apply to the passenger's choice set, also determined by the airline's availability. The passenger makes a decision which has a revenue result to the beneficiary airline and that booking is recorded in the historical bookings for that airline. These historical bookings are then used in generating demand forecasts; the demand forecasts along with fare class revenue valuations are used to by each airlines' optimizations and inform the airlines' availability decisions. The resulting fare class availabilities define the choice set for future departures.

The process detailed in Figure 3 also has a time dimension. The bookings period in PODS is 63 days, meaning passengers can book their itineraries up to 63 days prior to departure. Figure 4 displays the timeframes in PODS, which are dispersed through these 63 days.

Time Frame	Days until Departure	Time Frame Duration (days)
1	63	7
2	56	7
3	49	7
4	42	7
5	35	4
6	31	3
7	28	4
8	24	3
9	21	4
10	17	3
11	14	4
12	10	3
13	7	2
14	5	2
15	3	2
16	1	1

Figure 4: TF Definitions

The time frames (TFs) are essentially PODS's version of RM system data collection points (DCPs). At each of them, forecasted BTC and BIH are reassessed and reoptimization takes place or updated booking limits are calculated. The nearer the departure date, the closer together the TFs. At the beginning of the booking period, TFs are a week apart while at the end of the booking period TFs 15 and 16 are one day apart.

3.2. Competitive Networks

Beyond the processes of PODS, the setting in which passengers are generated and airlines practice revenue management is important to the insights provided by the simulation: PODS has competitive networks. In the network used in this thesis, Network D, two airlines compete in the continental United States for passengers in every market. Therefore, passengers not only have a choice of path and fare class but also which airline to fly.

Network D[3] has passenger flow in two directions, East to West and West to East. Hub airports are also points of origin for passengers and points of destination. Each airline has its own hub and serves the spokes of the network with direct flights to and from the hub. Therefore, most markets are only served via connecting itineraries and airlines compete with their offered connecting itineraries. Direct flights to and from the hub have a service quality advantage over connecting service. Therefore, the networks employed in the PODS simulator provide a setting, both as full networks and with competition, that other revenue management simulations do not provide. It is also a unique opportunity for testing demand driven dispatch.

3.3. Demand Generation and Passenger Choice

Every passenger is generated for a specific OD market with a set of characteristics. Each market has a mix (which fluctuates stochastically) of business and leisure passengers, and each passenger's unique characteristics are dependent on what type of passenger they are. These unique characteristics, with means dependent on the passenger type, are also randomized. Thus, a fair degree of variability is achieved in passenger demand. The characteristics of each passenger include a decision window, a maximum willingness to pay, and a set of disutility costs. Also randomized is the number of passengers who demand air travel in any given market and at a system level.

A passenger's decision window is simply when they prefer to fly. If a passenger is not able to fly at that time, these less preferable times incur a re-planning cost. Business travelers are more inclined to have narrow decision windows than leisure passengers, and are therefore more time-sensitive.

A set of disutility costs give dollar values to disutilities associated with the various restrictions applied to the fare products in each market. Disutilities also apply to re-planning and path quality costs, as well as having to fly on each passengers "unfavorite" airline, or simply not flying on their favorite airline (randomly assigned). Re-planning costs are associated with not being able to fly at the preferred time, as described above. The path quality cost is more or less a penalty for having to connect versus having a non-stop flight. The disutilities associated with restrictions include such restrictions as Saturday night stays and change fees, which business passengers dislike more than leisure passengers on average.

The maximum willingness to pay is a dollar amount that the passenger is willing/able to pay for travel. It is defined as a ratio of the lowest fare in each market, so that if a hypothetical business passenger is willing to pay 4 times the base fare of $150, their maximum willingness to pay would be $600. Business travelers on average have larger budgets than leisure passengers.

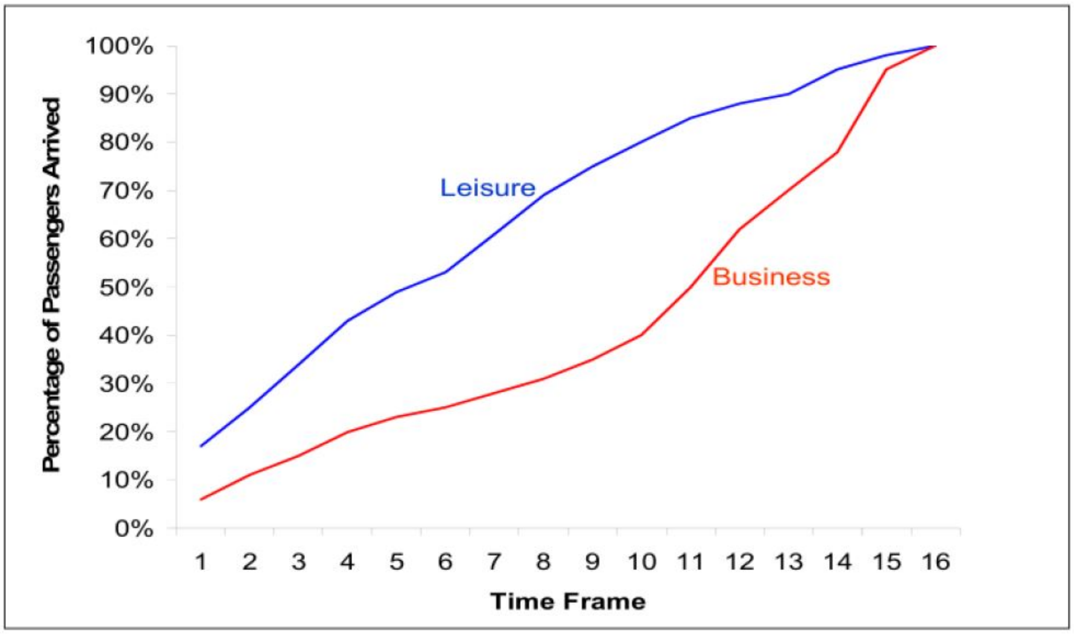

Figure 5: Demand Arrival

As Figure 5 shows, business and leisure passengers also differ in their arrival times, or when, on average, they shop for their travel. Leisure passengers appear earlier in the booking period and business passengers appear later in the booking period. Because of the differences in traits of business and leisure passengers, this means that passengers that appear early in the booking process are likely to have lower maximum willingness to pay and to be more price-sensitive. Passengers that appear late in the booking period are more likely to have higher maximum willingness to pay and be more product-sensitive. This is keeping with industry experience. Furthermore, airlines in the simulation do not know when passengers shop or book what type of passenger they are, but PODS does report these statistics.

Once these passengers are generated, they must choose an itinerary. All path-classes that match the passenger's desired OD market are added to the choice set. Then, any path-classes with fares greater than the passenger's willingness to pay are removed, as are any path-classes that are not available due to the airlines' inventory control or advanced purchase restrictions. This narrows the options to the true choice set for the passenger. Not traveling is also a choice.

These path-class options are then ranked by generalized cost, with the least costly being the preferred choice. The generalized cost is the sum of the actual fare (which is the only cost paid to the airline as revenue) and the dollar values of the disutilities associated with the fare product. In the event of a tie, the passenger's airline preference (randomly assigned) breaks the tie. Note that because path-classes, or itineraries, are ranked by generalized costs, that passengers do not always choose the least expensive, available itinerary. Instead, if a passenger is product-sensitive and the costs associated with disutilities exceed the difference between a higher and lower fare product, the passenger will choose the higher fare product. However, most leisure passengers will, as their first choice, desire the lowest fare product (i.e. fare class 6). If this is closed by availability or advanced purchase restrictions, they may or may not be persuaded to purchase a higher fare class. PODS therefore allows users to observe the choice behavior of passengers to a degree not possible in the real world. It also models a variety of passenger types whose unique characteristics create the variety of demand observed in practice, enhancing the quality of the revenue management simulation.

3.4. Modeling Demand Driven Dispatch in PODS

Modeling demand driven dispatch in PODS involves primarily changing the capacity of the flight legs. For each PODS simulation, the revenue management system, for input to RM and for determining bookings limits for preventing denied boarding, takes a network file that includes capacities for every departure in the network, for all airlines. In swapping aircraft, these capacities change. Therefore, in base cases without demand driven dispatch the capacities from the calibrated network file are used throughout the simulation but in cases with demand driven dispatch the network file capacities are only used as the starting point—the original static fleet assignment.

In changing capacities, legs are designated as swappable or not, and can only be swapped as leg-pairs to and from the hub. This will be described in greater detail in Section 3.5., but its purpose is to constrain the number of swaps that are possible to rudimentarily model the constraints from practical operations and also to maintain balance, count, and coverage. The decision of how to swap capacities is determined by a series of assignment models, first with a greedy bookings-based method and then with network optimization methods utilizing a minimum-cost flow model that maximizes either expected revenue or operating profit. These assignment methods are described in detail in the respective chapters in which their results are reported.

3.5. PODS Network D^3

Network D^3 was designed within PODS specifically for the testing of demand driven dispatch. Its architecture allows for the simulating of demand driven dispatch in a full network setting with competing airlines, something that has not been done previously. It is also designed so that coverage, count, and balance can be maintained when swapping aircraft assignments. PODS with Network D^3 allows demand driven dispatch to be simulated not only in a competitive environment but also with different RM systems, including full O&D RM systems. This is also a first for simulating demand driven dispatch.

The network has twenty airports on the West Coast of the PODS' simulated U.S. and another twenty airports on the East Coast. There are two hub airports in the Midwest. Airline 1 has its connecting hub at MSP, Airline 2 at DFW. From each of the forty spoke cities, there are two non-stop flights a day to each airline's Midwest hubs, and then two non-stop flights a day to the opposite coast. The hubs serve connecting passengers. There are also local passengers whose origin or final destination is MSP or DFW. With passengers traveling from West to East and East to West, as well as to and from the hubs, there are 964 OD markets available to PODS' simulated travelers. These 964 markets are served by the two airlines with 336 legs or flight departures daily, each airline operating 168 in competition with the other.

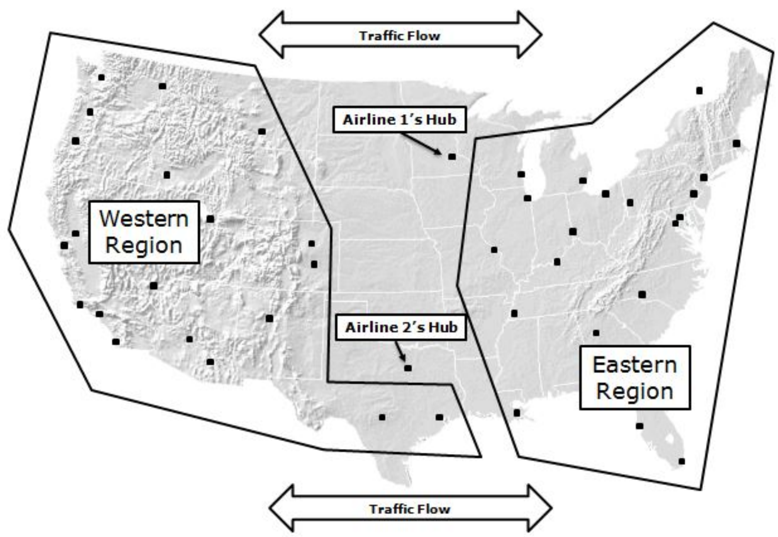

Figure 6: Network D^3 Markets

Figure 6 illustrates the destinations in Network D^3 with two regions and two central hubs that are also destinations and points of origin. Figures 7 and 8 show the route maps for Airline 1 and Airline 2.

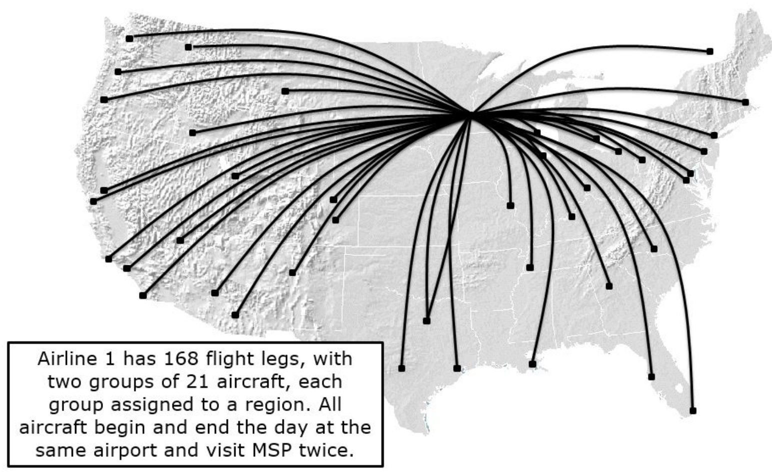

Figure 7: Airline 1 Route Map

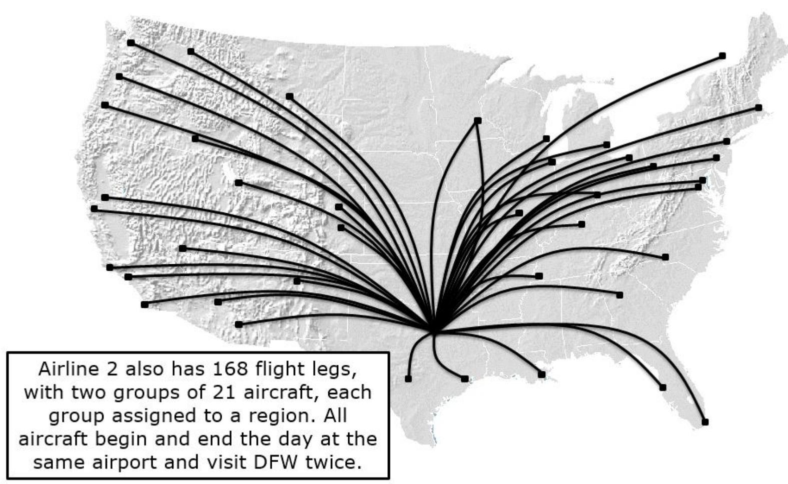

Figure 8: Airline 2 Route Map

Each of the airlines operates 168 legs divided into strings of four legs each. Every day, each simulated aircraft operates one string of four legs. Each string originates on one coast, flies to the Midwest hub, the opposite coast, back to the Midwest hub, and finally returns to the original airport on the originating coast.

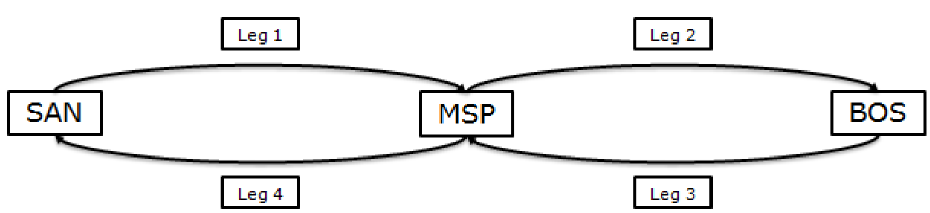

Figure 9: Flight String Design

Figure 9, illustrates the design of a flight string. In this case, the hypothetical string would belong to Airline 1 with its hub at MSP. The aircraft originates at SAN and flies to BOS and back, with two stops at MSP. At each of those stops at MSP, the aircraft participates in a connecting bank, allowing passengers to connect to many OD markets and also allowing swaps. Passengers can connect at both of the two daily connecting banks. However, aircraft swaps are only allowed at the first connecting bank of each day. Therefore, aircraft always return to their originating airport at the end of the day and are in position for the next day. However, they are allowed to be swapped to routings that include any airport in the opposite coastal region. Therefore, in Figure 9, BOS may not be the East Coast turn location and Legs 2 and 3 are subject to capacity changes due to demand driven dispatch.

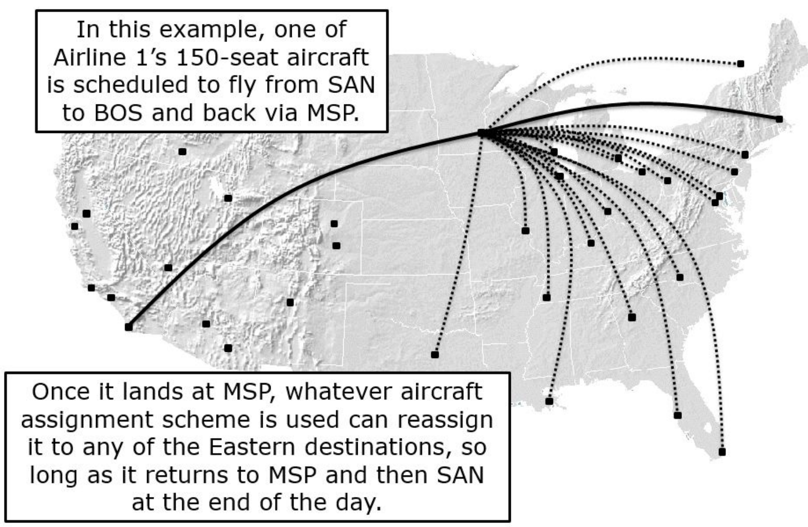

Figure 10: Routing Options

Figure 10 illustrates the options available daily to the aircraft originally assigned on the hypothetical SAN-MSP-BOS string. Any of the East Coast destinations are potential turn-around locations for the aircrafts second turn of the day. It must return to SAN, however, so that every day its two legs between SAN and MSP are not swappable. Hence, only half of the flights or legs are swappable—the second and third flights of the day to the opposite coast. Swappable pairs of legs form a there-and-back routing from the hub with no overnight stay.

The constraints determining the swappable set of flights or legs not only stipulate that half of the total set of flights are swappable but also stipulate that all flights or legs must be swapped in pairs—the leg from the hub and the leg back to the hub. From here on, such swappable sets are referred to as swappable "leg-pairs."

For simplicity, each aircraft fleet has one aircraft family, the assumption being that the same crew can fly every aircraft. This hypothetical aircraft family is a mainline narrow-body aircraft with three sizes: 130 seats, 150 seats, and 170 seats. Thus, the simulated aircraft family is comparable to the A320 and B737 aircraft families, which comprise a large proportion of most airline fleets today and in some cases the entire fleet.

Both Airline 1 and Airline 2 have fourteen of each aircraft size, seven of each stationed on each coast for each airline. With these aircraft sizes and swappable leg-pairs, each aircraft has a set of 21 possible daily itineraries. From another perspective, for each day, an airline has the ability to choose from approximately 0.51×10^{19} options for scheduling its West Coast aircraft and the same for its East Coast, even in this relatively small network. If you narrow the choices by ignoring specific aircraft or tail numbers and only consider that each leg-pair in an airline's network has three capacity options, the set of feasible leg-pair/capacity assignments is still approximately 399 million per day for each coast's fleet. This is therefore a large number of swapping possibilities even in a small and schedule-constrained network.

Finally, Network D^3 has a fare structure for each OD market. Both airlines offer the same fares (and restrictions) on each OD market. This is a simplifying assumption, but not altogether unrealistic given the current industry's competitive pricing practices. Both airlines have six fare class products with a range of fares and fare restrictions. Figure 11 illustrates the restrictions associated with each fare class in Network D^3:

Fare Class	AP	R1	R2	R3
1	0	0	0	0
2	3	0	1	0
3	7	0	1	1
4	14	0	1	1
5	14	0	1	1
6	21	0	1	1

Figure 11: Network D^3 Fare Restrictions

Each of the fare classes has an associated advanced purchase restriction (AP), ranging from zero days to twenty one days. Restrictions 1 through 3, signified by R1, R2, etc., represent such restrictions as minimum stay, refundability, and so on. A "1" in the restriction's column signifies that the restriction is in place for that fare class. Each passenger is generated with unique and randomly distributed disutilities for restrictions R1, R2, and R3, so that some passengers are product-sensitive rather than merely price-sensitive.

Each fare class in each OD market also has an associated fare. Table 1 shows a range of information of representative fares in each of the fare classes, with FC 1 being the “Full” Y fare and FC 6 being a restricted discount fare:

Table 1: Network D³ Fare Structures

	FC **1**	FC **2**	FC **3**	FC **4**	FC **5**	FC **6**
Maximum Fare	$ 742.52	$ 514.82	$ 297.02	$ 247.52	$ 198.02	$ 153.00
Average Fare	$ 412.86	$ 293.34	$ 179.01	$ 153.03	$ 127.05	$ 101.06
Minimum Fare	$ 188.33	$ 136.83	$ 87.58	$ 76.39	$ 65.19	$ 54.00
Max. Fare Ratio	5.00	3.47	2.00	1.67	1.33	1.00
Avg. Fare Ratio	4.09	2.91	1.77	1.52	1.26	1.00
Min. Fare Ratio	3.20	2.36	1.55	1.37	1.18	1.00

The fares range from $742.52 to $54.00 depending on the OD market and the fare class. The average fare ratio between the highest and lowest fare classes is 4.09, with the maximum and minimum ratios being 5.00 and 3.20. In conjunction with increasing fares, the difference between the fares of the highest fare classes is also larger than the difference between the lowest fare classes. Figure 7 illustrates this.

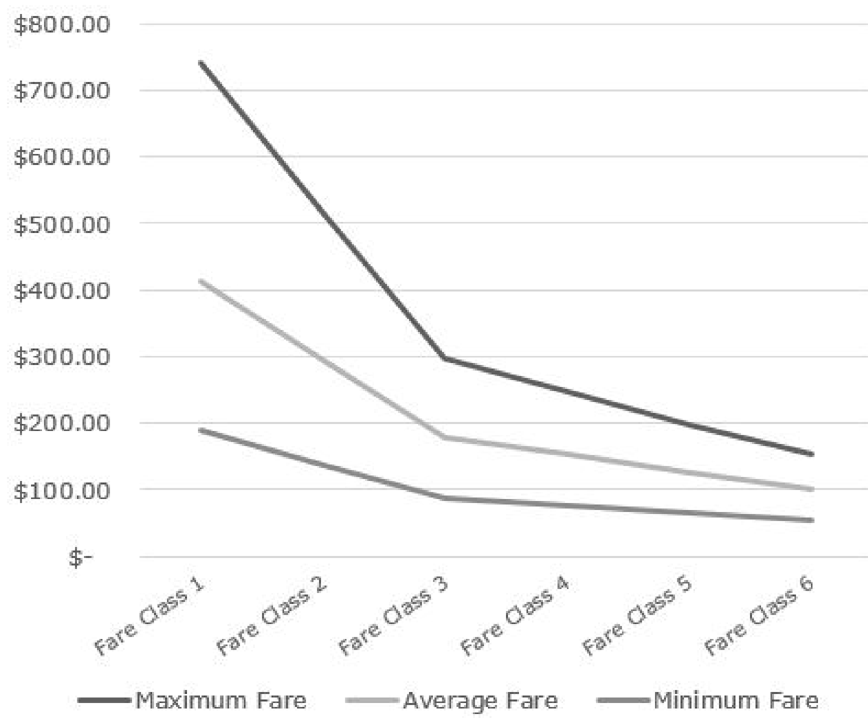

Figure 12: Network D^3 Fare Structures

These fare structures approximate actual fare structures to allow for realistic revenue analysis of the impacts of both revenue management systems and also demand driven dispatch. For example, the spread of fares and highest and lowest fares will be important when distinguishing the differences of swapping based on bookings or revenue. It will also be shown that advanced purchase restrictions in the fare products becomes critical in timing swaps for D^3. Thus, taking all of these factors into consideration, from the fare products to the aircraft routing, Network D^3 provides a comprehensive setting in which to simulate D^3.

Chapter 4: Bookings-Based Swapping

The simplest method of assigning capacities to legs in a network is by ranking estimated bookings at departure (BAD). It is intuitive in that the flights with the highest estimated demand will be assigned the largest aircraft. It makes it possible to explore different dimensions of implementing demand driven dispatch and its competitive and revenue management context. Demand driven dispatch with bookings-based swaps also provides a useful benchmark for estimating the benefits of attempts at making revenue- and operating profit-based swaps in subsequent chapters.

Chapter 2 begins with the testing of demand driven dispatch in PODS with a bookings-based algorithm for determining the final fleet assignments for each leg. The effects of demand driven dispatch will be explored, with special attention paid to the differences in the effects based on the timing of the swapping as well as the underlying demand levels and the RM systems employed by the airlines.

4.1. Swapping Methodology

The first swapping methodology will be called bookings-based swapping. The methodology is simple and intuitive, albeit not optimal. Each leg-pair has a set capacity from the original fleet assignment. Each leg-pair also has an associated estimated bookings at departure (BAD) and bookings-in-hand (BIH). These attributes are the only criteria used in the bookings-based swapping methodology. Estimates of BAD are used to rank leg-pairs, where the leg-pairs with the larger BAD estimates receive larger aircraft. Meanwhile, it is important to consider BIH to prevent denied boarding.

Estimated BAD for each leg is the combination of BIH and forecasted bookings to come (BTC). As the simulation does not have cancellations or no-shows, the BIH are deterministic. BTC are not deterministic, but rely on separately generated forecasts. Standard pick-up forecasting with booking curve unconstraining generates forecasted BTC in the airlines' RM systems. This is a typical forecasting methodology with current airlines. In the simulation as in reality, the airlines' forecasts are based on the airlines' historical booking data, as described in the forecasting section of Chapter 2. Thus, actual demand can vary greatly from forecasts. As a direct result, there is a great deal of uncertainty in demand, but that uncertainty in the total BAD diminishes as the departure date draws closer. This is because BIH comprise a greater proportion of the forecasted BAD and BTC comprise a smaller proportion. The estimated BAD for each leg-pair is the sum of the estimated BAD for the two legs comprising it. The BIH for each leg is the number of bookings that have taken place thus far in the booking process. The BIH attributed to a leg-pair is the maximum of the two BIH of the two legs.

The assignment of aircraft to leg-pairs is based on a ranking algorithm. The available aircraft/capacities are ranked largest to smallest. Then the leg-pairs are ranked by sum of BAD largest to smallest. The leg-pair with the lowest estimated sum of BAD is assigned to the smallest available capacity such that the capacity is greater than or equal to the leg-pairs' BIH. The leg-pair with the second least estimated sum of BAD is assigned to the smallest available capacity such that the capacity is greater than or equal to the leg-pair's BIH, and so on until all leg-pairs have been assigned a capacity.

Aircraft	Capacity		Leg-Pair	Sum of BAD's	Max BIH
1	170		1	366	140
2	170		2	354	135
3	150		3	352	122
4	150		4	328	119
5	130		5	302	131
6	130		6	256	97

Figure 13: Bookings-Based Assignment Example

Figure 13 illustrates the assignment algorithm. Leg-pair 6, with the lowest estimated sum of BAD, is assigned Aircraft 6, with the lowest capacity. Leg-pair 5 would be assigned Aircraft 5, except that its max BIH exceed 130, so it is instead assigned Aircraft 4. Leg-pair 4 then gets Aircraft 5, as it is the smallest available aircraft, and so on until all leg-pairs and aircraft are matched.

This bookings-based methodology has several merits that make it a good place to begin the testing of demand driven dispatch, as well as several drawbacks. First, the methodology is simple and intuitive. It assigns the largest aircraft to leg-pairs with the largest estimated BAD. In the simplest terms, it gives the biggest planes to the flights with the most forecasted bookings. Meanwhile, it prevents denied boarding due to aircraft swaps. This methodology provides intuitive swapping decisions for aircraft assignment and opens the door to a wide variety of tests with demand driven dispatch. It does not require cost inputs and allows it to be applied at any time in the booking process and with *any revenue management system*.

The first drawback is the result of the process of summing estimated BAD to rank leg-pairs. Figure 14 displays a scenario in which this weakness results in a suboptimal aircraft assignment.

Leg-Pair	Leg A BAD	Leg B BAD	Sum	BAD Assignment	Optimal Assignment
1	50	150	200	130-Seat	150-Seat
2	125	125	250	150-Seat	130-Seat

Figure 14: Example of Suboptimal Assignment

Suppose, in a very simple example, an airline has two swappable leg-pairs and two aircraft, a 130-seat aircraft and a 150-seat aircraft. No bookings have been taken so far. Leg-pair 1 has the smaller sum of estimated BAD and would therefore be assigned a 130-seat aircraft. Leg-pair 2 would be assigned the 150-seat aircraft. Yet, if the estimated BAD are correct for each leg, Leg-pair 2 would never use the additional seats provided by the 150-seat aircraft, while Leg-pair 1 would spill twenty units of demand on Leg B. This suboptimal solution is the direct result of a 1-stage ranking algorithm. To overcome this problem, either a two-stage ranking method or a linear program-like specification is needed.

The most notable drawbacks of the methodology, however, are the ignoring of both operating revenue and cost. In revenue terms, the last fifty seats of a flight whose average selling fare is $500 are not worth the same to the network as those on a flight whose average selling fare is $125. For costs, the longer the flight, the more operating costs incurred, and the larger the aircraft generally the greater the operating costs per mile. The bookings-based methodology does not consider these factors.

Still, the methodology acts as both a proof of concept for testing demand driven dispatch in the PODS simulator and as a benchmark for more advanced swapping methodologies, providing a baseline against which to measure the gains of performing demand driven dispatch with more sophisticated revenue and cost inputs and optimization techniques.

4.2. Dimensions of D^3 Experiments

The bookings-based algorithm, effectively maximizing expected average leg load factor, is used for implementing demand driven dispatch in a variety of experiments. Demand driven dispatch is implemented at a variety of times in the booking period, ranging from 42 to 5 days prior to departure (PODS has a 63 day booking period). Next demand driven dispatch is performed with a variety of RM systems and with different competitive scenarios. Finally, demand driven dispatch is performed at a variety of overall system demand levels. These tests provide important insights as to how demand driven dispatch interacts with its context—especially the context of a competitive network environment with revenue management.

4.2.1 Timing Swaps

The first set of tests involve the timing of demand driven dispatch. In these tests, swaps occur only once in the 63-day booking period of PODS. These swaps are tested at varying times throughout the booking period, however. Both airlines use identical RM techniques—leg-based forecasting with standard pick-up forecasting and booking curve unconstraining. These leg-based forecasts are then fed to an EMSRb optimization along with full OD fares, a simplifying heuristic that gives higher value to connecting itineraries.

In the base case, the results of five trials of 400 sample departure days display a relatively equal outcome for the airlines. Both airlines provide approximately 25 million ASMs and sell approximately 20 million RPMs. This in turn results in system load factors for both airlines of around 80-81%. Yield for both airlines is about 9.0 to 9.3 cents per mile. Revenue for both airlines is about $1.8 million and they split market share roughly equally based on enplaned passengers. Airline 1 has slightly more market share with slightly fewer RPMs because MSP is more centrally located in the network as compared to DFW, as evidenced by Airline 1's fewer ASMs. Table 2 provides the key metrics for the output in the base case.

Table 2: Base Case Output with EMSRb

Airline	ASMs	RPMs	System LF	Yield	Total Revenue	Market Share
Airline 1	24,589,596	19,971,592	81.22%	0.0934	$1,864,432	50.19%
Airline 2	25,365,524	20,396,679	80.41%	0.0902	$1,839,813	49.81%

In the base case, neither airline engages in demand driven dispatch. In the alternate cases, only Airline 1 engages in demand driven dispatch. All results will be in the form of changes in key metrics as well as bookings by fare class, etc. from the base case.

In each of the alternate cases, Airline 1 swaps aircraft at one of six times during the booking period. These swap times are distributed throughout the range of the 63 days available as one of PODS' data collection points or timeframes (TF), ranging from 42 to 5 days prior to departure. Figure 15 highlights the TFs in which D^3 is applied and displays the base case number of bookings taken in the system as well as the percentage of total final bookings.

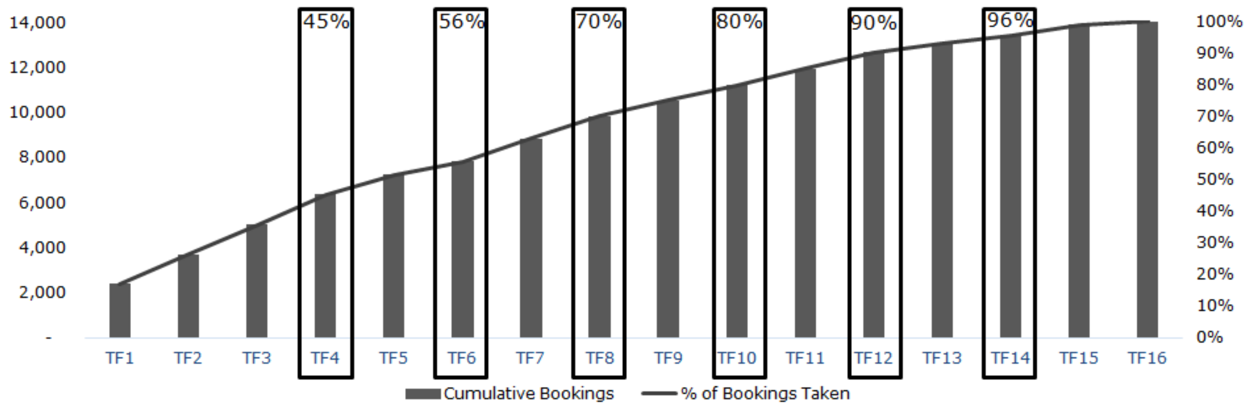

Figure 15: Swap Times

For example, at TF4, 42 days prior to departure, 45% of system bookings, approximately 6,000, have arrived. The timeframes TF4, TF6, TF8, TF10, TF12, and TF14 correspond to 42, 31, 24, 17, 10, and 5 days prior to departure, respectively. The booking period begins 63 days prior to departure. By TF14, 5 days prior to departure, 96% of bookings have arrived. Thus, swaps at this timeframe will be constrained by BIH and any changes in capacity will only effect the latest arriving demand. On the other hand, swaps in TF4 will take place soon enough that BIH will constrain few or even none of the potential swaps and, depending on the availability control of the RM system, the lowest fare classes may still be available.

Tests of swaps at TF8 and TF10 will be insightful because of their interaction with advanced purchase restrictions. A majority of bookings are in the lowest fare class, FC 6, which is closed by an advanced purchase restriction 21 days prior to departure. TF8 is 24 days prior to departure and TF10 is 17 days prior to departure. Therefore TF8 and TF10 fall on either side of the cutoff for bookings FC 6 and the test results will illustrate the importance of timing swaps relative to the fare structures in the market.

This importance is apparent in the Figure 16, which shows the total system revenue results of bookings-based demand driven dispatch at the various timeframes, with the earlier timeframes on the left and the later timeframes on the right.

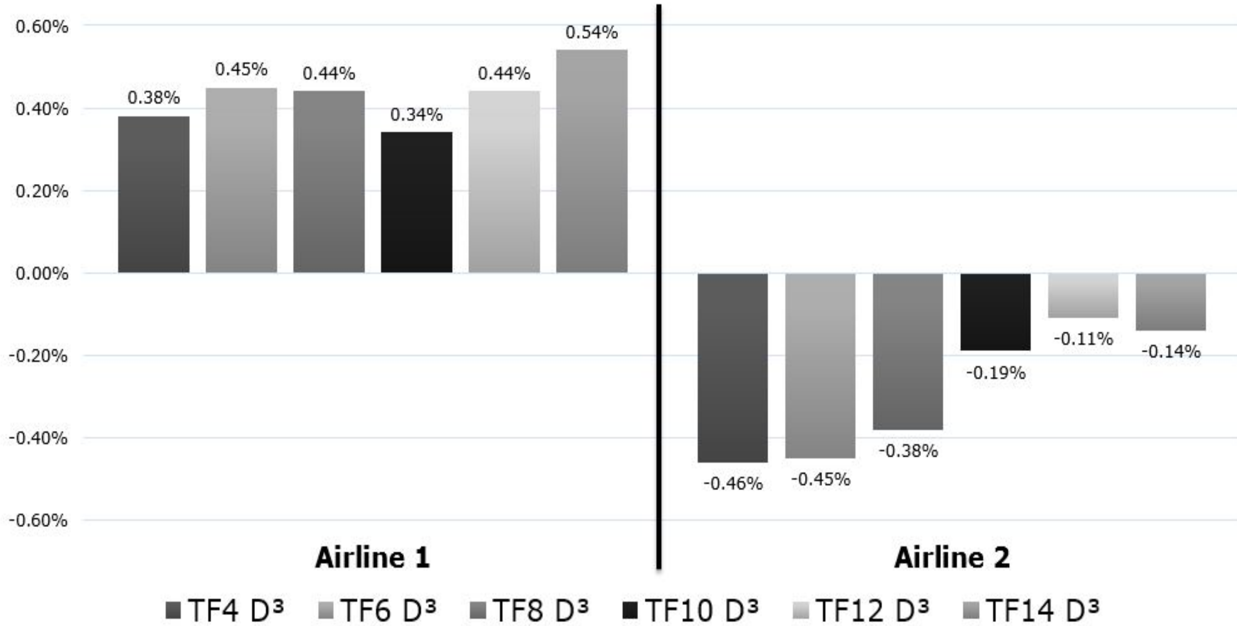

Figure 16: Changes in System Revenue from Bookings-Based D³ at Different TFs

For Airline 1, which has engaged in demand driven dispatch, the revenue results are increases of between 0.34% and 0.54% in total system revenue. Note that generally the later the swaps occur in the booking process the more positive the change in revenue, the exception being implementation in TF10. As discussed previously, this is due to the closure of FC 6 due to advanced purchase restrictions. Additional capacity due to a swap is filled with FC 6 passengers when possible, as will be shown, and this is no longer possible in TF10.

Airline 2 experiences inverse results from Airline 1's implementation of demand driven dispatch. In TF4, Airline 2 actually loses a greater percentage of system revenue than Airline 1 gains, as Airline 1 captures more demand. As the implementation of demand driven dispatch moves closer to departure, additional capacity proved by D³ does not capture as much additional demand, as the majority of demand has already arrived and either been booked or rejected. Thus, the effect on Airline 2 decreases when Airline 1 implements D³ closer to departure. These findings show that at least some and in some cases most of the gains of demand driven dispatch, especially in earlier implementation, come at the expense of the competitor. This narrative is supported by looking at percentage changes in RPMs by airline and by time of implementation. Figure 17 shows these percentage changes in RPMs, which illustrates this pattern.

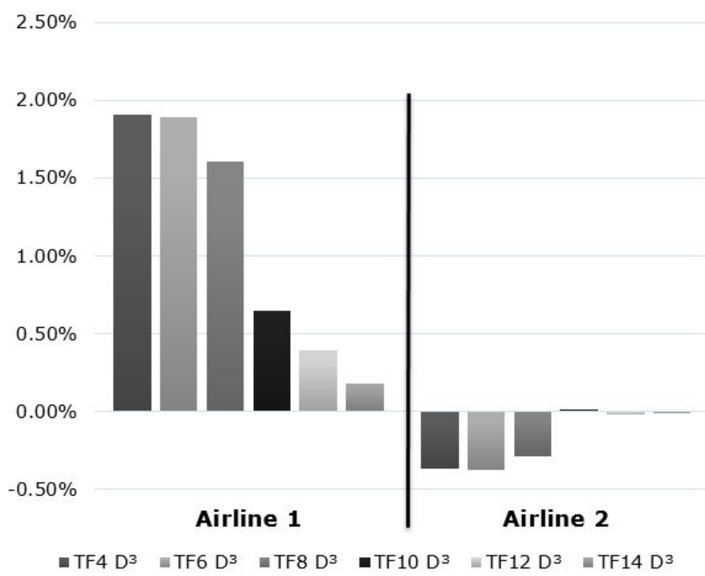

Figure 17: Changes in RPMs from Bookings-Based D^3 at Different TFs

Note how RPMs decrease for Airline 2 in the earliest timeframes but level off in the later time frames. Also note the sharp decline in the RPM increase for Airline 1 between TF8 and TF10 as FC 6 is closed and the number of additional bookings is limited when capacity is increased. The changes in ASMs are shown in Figure 18.

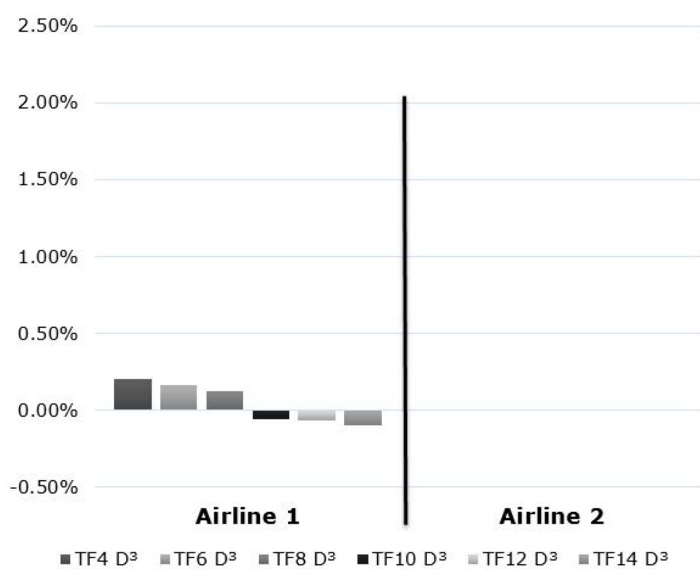

Figure 18: Changes in ASMs from Bookings-Based D^3 at Different TFs

With later implementation, shorter routes in Airline 1's network receive larger aircraft, slightly lowering ASMs and suggesting that in Network D^3 shorter OD markets have a higher concentration of late-arriving demand. Airline 2's ASMs do not change because none of its aircraft are swapped. Figure 19 displays absolute changes in system load factor percentage points.

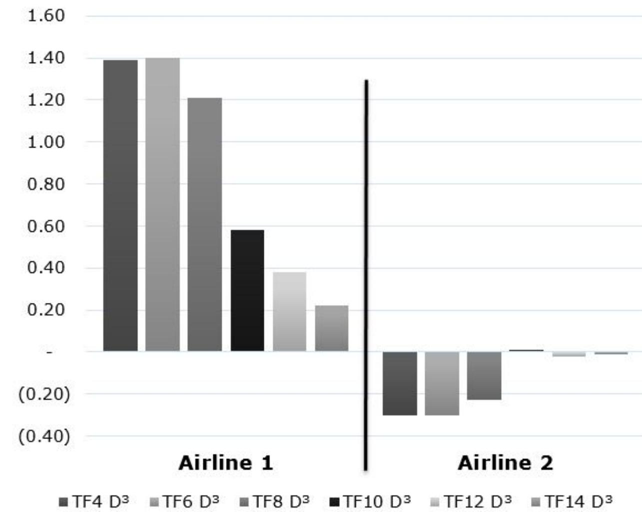

Figure 19: Changes in System LF Points from Bookings-Based D^3 at Different TFs

As ASMs for Airlines 1 and 2 changed either a small amount or none at all (Figure 18), the change in system load factor percentage points mirrors very closely the changes in RPMs. The increases in load factor are significant given current industry interest in maintaining high load factors. It is however, also an indication of dilution, or a decrease in yield.

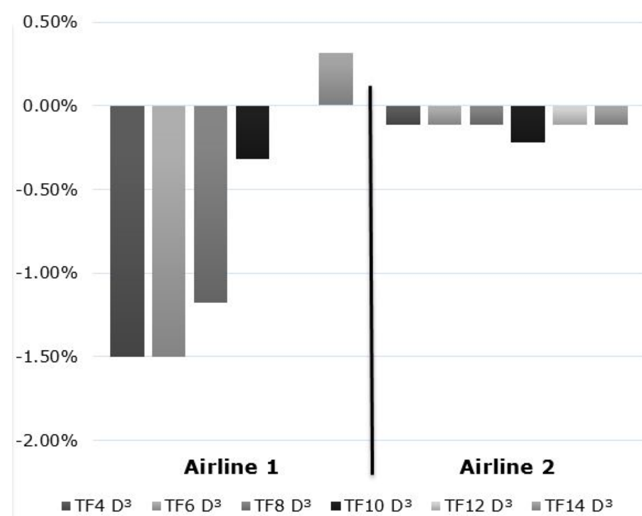

Figure 20: Changes in Yield from Bookings-Based D^3 at Different TFs

Figure 20 displays the percentage changes in yield, which does decrease for Airline 1 in the earliest time frames by as much as 1.5%. The later the implementation, the less dilution occurs. Again, the AP cutoff between TF8 and TF10 is clearly visible in the results of D^3

being applied. In the latest timeframe, yield and RPMs both increase. The yield is increased due to additional capacity being allocated to the highest fare classes, the only ones still open five days prior to departure. Meanwhile, the targeted shifting of capacity to higher demand flights allows for an increase in RPMs. Although only about 4% of demand is yet to arrive at this point, this increase in both RPMs and yield leads to D^3's most positive revenue impact of 0.54% when implemented in TF4. This impact is due to booking more of the highest fare classes, to be shown in the discussion of changes in bookings by FC.

To provide a better understanding of the number of swaps taking place and their effects on bookings by fare class, Figure 21 displays the number of swaps occurring out of the set of all swappable leg-pairs.

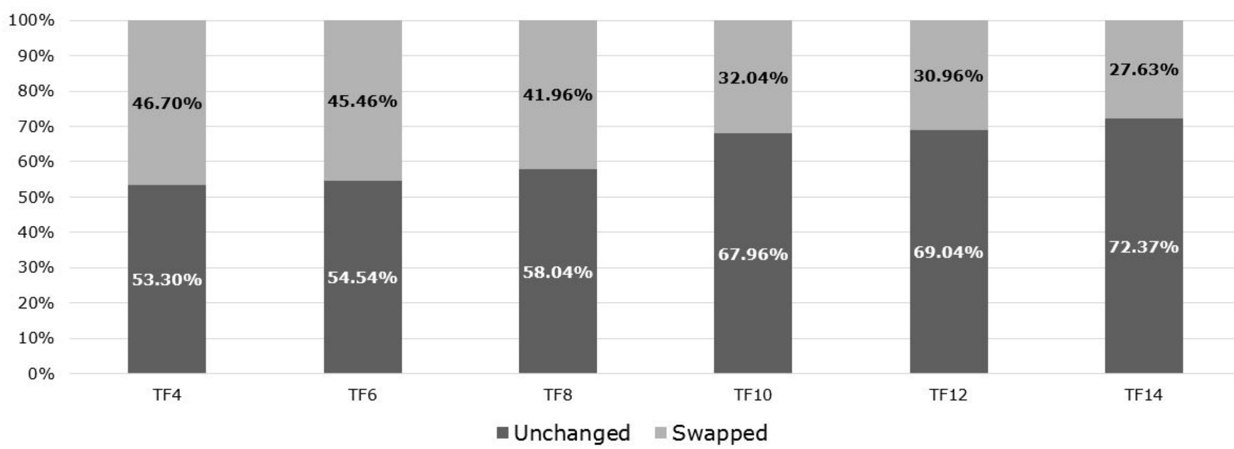

Figure 21: Percentage of Swappable Leg-Pairs Swapped, Bookings-Based D^3 at Diff. TFs

In TF4 implementation, 46.70% of swappable leg-pairs experience a change in their capacity. This proportion monotonically decreases the later the implementation, leading to only 27.63% of swappable leg-pairs experiencing a change in capacity in TF14 implementation. This means that in this simulation of demand driven dispatch, given bookings-based swapping and the current set of advanced purchase restrictions, the most positive change in revenue is the result of the latest time frame implementation when only on average 13.82% of the flights in Airline 1's system are engaged in swapping.

The number of swaps is expected to decrease the later the implementation of D^3. First, as revenue management rejects demand, especially early arriving demand, the actual variability in realizable BAD decreases. Second, as bookings in hand increase, with many flights being full by TF12 or TF14, the number of leg-pairs still eligible for down-gauging decreases, and therefore the number of leg-pairs that can be up-gauged decreases.

Both the number of swaps and the remaining realizable demand by implementation time is clearly visible when analyzing the changes in bookings by fare class. Figure 22 displays the average changes in bookings for all swappable leg-pairs by fare class, by the type of change in gauge, and by the timing of the swaps.

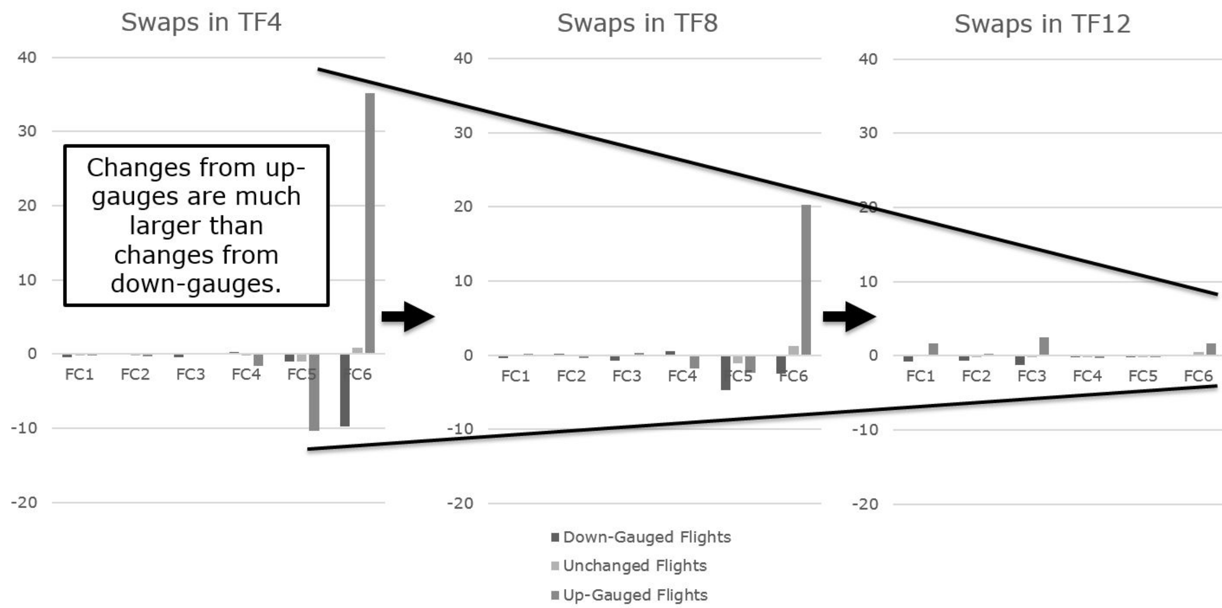

Figure 22: Magnitudes of Booking Changes from Bookings-Based D^3 at Different TFs

First, note the significant decrease in the magnitude of changes between the earliest time frame implementation (TF4) and the later TF12. While FC 6 takes about 35 additional bookings on average on up-gauged flights, in TF12, FC 6 only takes about 2 additional bookings on up-gauged flights. Second, note that until TF14, almost all increases in bookings on up-gauged flights take place in FC 6. This is a very important result due primarily to the nature of revenue management—it is, fundamentally, protecting seats for higher fare classes. The forecasts for these higher fare classes are not changing due to a swap, and therefore the booking limits for lower fare classes are dependent primarily on changes in capacity, not changes in protection levels for higher fare classes. When capacity increases during an up-gauge and the joint protections levels for the higher fare classes do not change (due to relatively static forecasts) the result is higher booking limits for FC 6, and therefore more bookings in FC 6.

Finally, note that increases in bookings on up-gauged flights are greater than decreases in bookings on down-gauged flights. This is of course necessary for the observed increases in RPMs but also is the consequence of spill probability. Flights that are up-gauged are typically up-gauged due to being forecasted to spill demand. Thus, up-gauged flights are likely to result in more bookings, assuming accurate forecasts. Meanwhile, down-gauged flights are down-gauged due to lacking forecasted demand. Assuming accurate (or unbiased) forecasts, this means a lower probability of spilling demand.

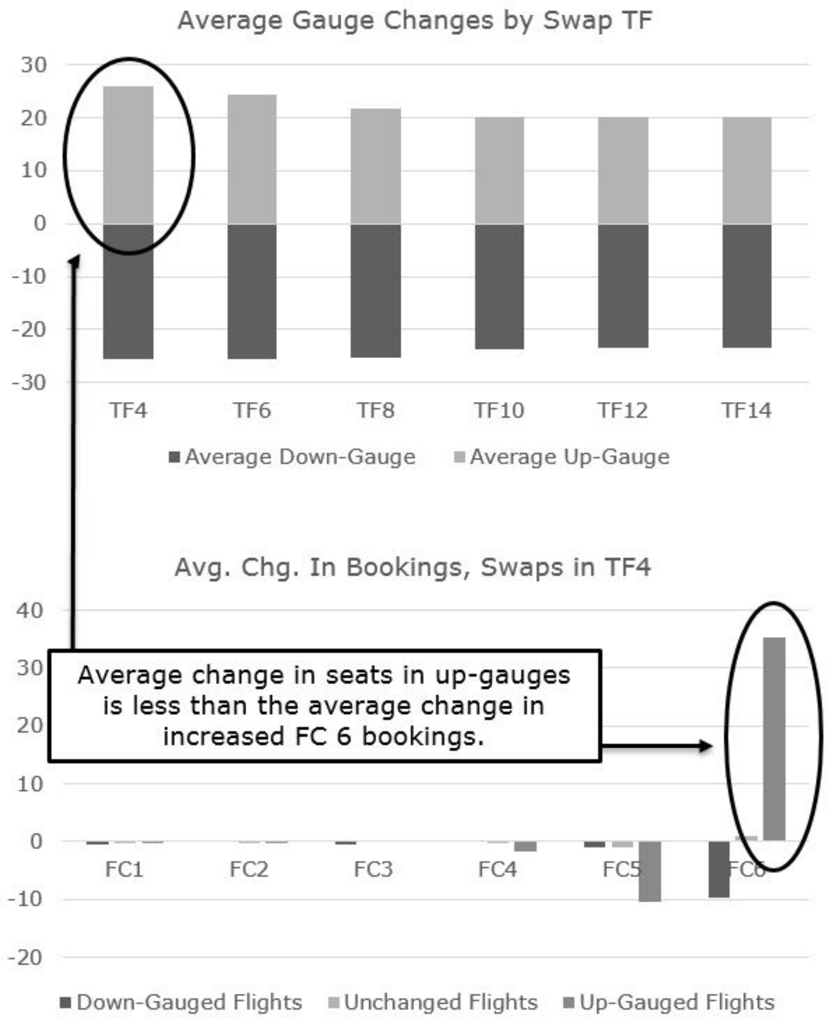

Figure 23: Changes in Gauge vs. Changes in Bookings

Aircraft can either be up-gauged 20 or 40 seats, as aircraft have capacities of 130, 150, and 170 seats. When D^3 is implemented in TF4, the average up-gauge is an increase of 26 seats, as shown in Figure 23. However, the average increase in FC 6 bookings due to an up-gauge is 35. These appear to be contradictory results. However, it important to observe the decreases in all other fare classes after an up-gauge, averaging a decrease of about 12 bookings. Thus, the average total increase in bookings across fare classes after an up-gauge is 23, 3 less than the average number of seats added.

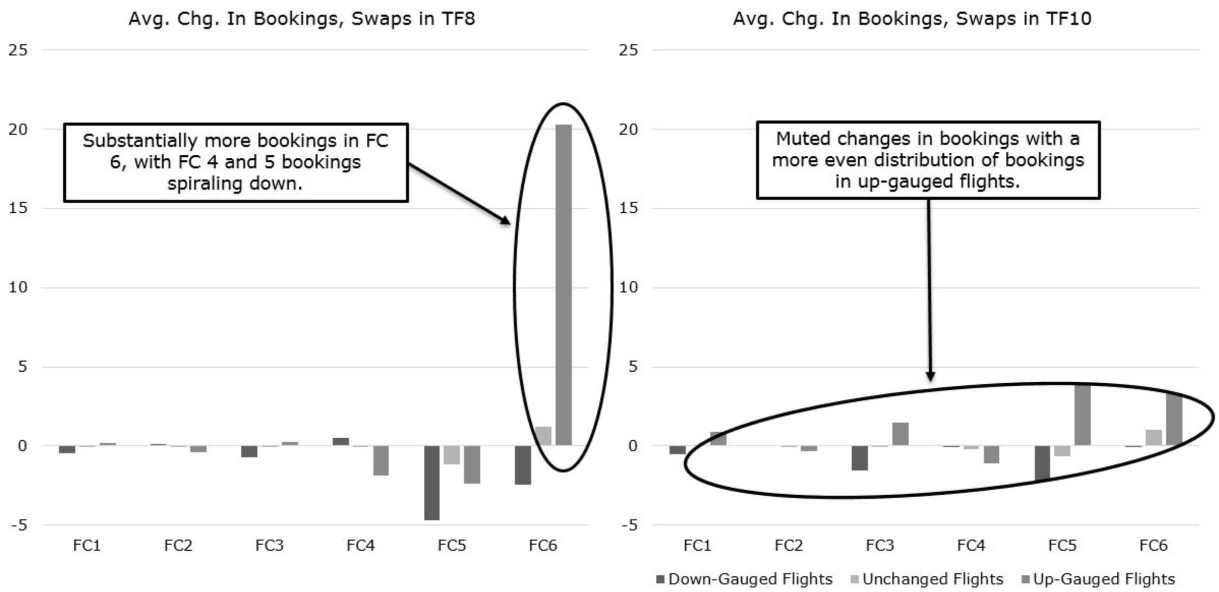

Figure 24: Timing Effects in Bookings from Bookings-Based D^3 at Different TFs

Figure 24 shows the same information as Figure 22, focusing on only TF8 and TF10. These two time frames are 24 and 17 days prior to departure, respectively, and therefore fall on either side of the 21-day advance purchase restriction. Note that before the 21-day AP restriction almost all increases in bookings due to an up-gauge take place in FC 6, the lowest. After the 21-day AP restriction, FC 5 has a larger increase in bookings than FC 6 (which still sees increases in bookings due to feedback effects) and FC 1 and FC 3 also see increases in bookings. Also note that the average total increase in bookings across fare classes is much smaller than prior to the 21-day AP restriction. Figure 24 illustrates the importance of timing implementation of D^3 relative to the characteristics of the fare restrictions in a market.

Figure 25 also shows average changes in bookings, focusing on swaps occurring after the 21-day AP restriction, TFs 10, 12, and 14. These correspond to 17, 10, and 5 days prior to departure. The same conclusion can be drawn as from Figure 24—advanced purchase restrictions are important to determining the fare class composition of additional bookings due to up-gauges. Large increases in bookings are no longer possible because the lowest fare classes are no longer available. Simultaneously, spiral down is no longer possible and therefore increased bookings are seen in higher fare classes.

As more AP restrictions set in, increases in FC 5 bookings become increases in FC 3 in TF 12 and, in TF14, all increases in bookings occur in FCs 1 and 2. Thus, in TF 14 D^3

not only results in increased RPMs, it also results in increased bookings in the higher fare classes and therefore increased yield.

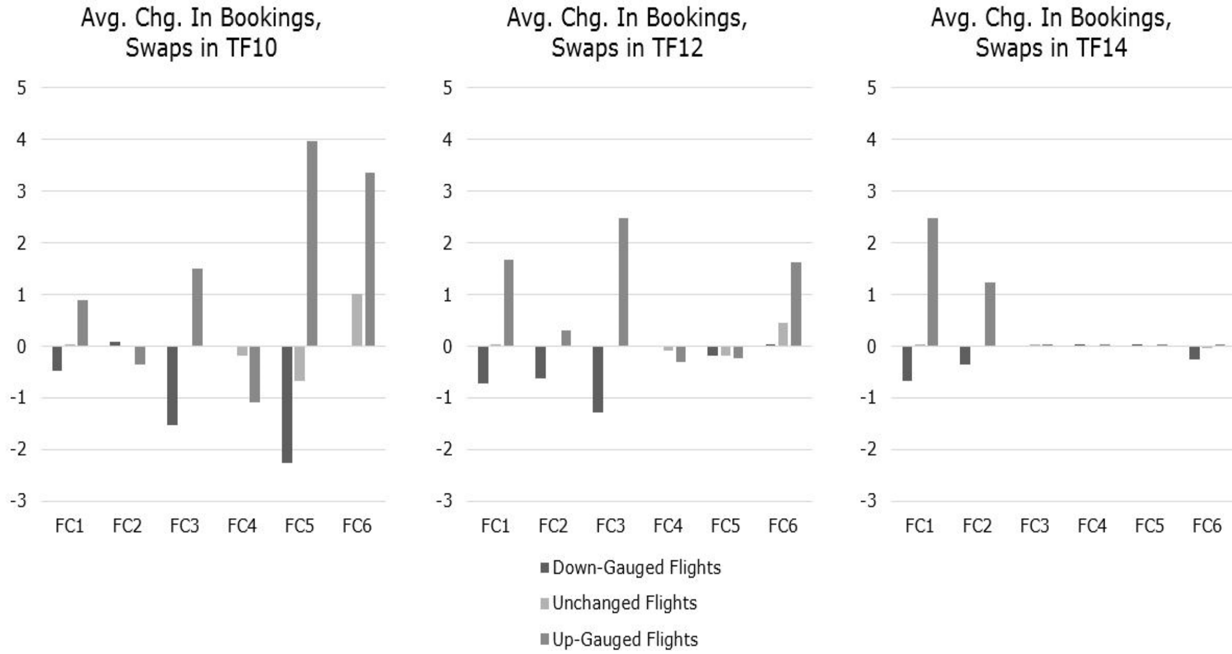

Figure 25: Changes in Bookings after 21-Day AP, Bookings-Based D³

By testing the implementation of D³ at various timeframes, the effects of AP restrictions on the outcome of D³ become key results. Throughout the booking period, demand driven dispatch has a tendency to result in significant dilution. By preventing the sale of lower fare classes via AP restrictions, this dilution is successfully countered.

4.2.2. Swaps with Different RM Systems & Competition

The next section of tests for bookings-based swapping explores the implementation of D³ with different RM systems and with different competitive environments. As shown in the section on timing swaps, demand driven dispatch, like revenue management, is a competitive action, and thus it is important to not only test what happens when Airline 1, the focus airline, engages in demand driven dispatch, but also what happens when Airline 2 engages in demand driven dispatch and when both airlines implement it.

Therefore, for each revenue management system employed, three tests will be run: Airline 1 engages in D³, Airline 2 engages in D³, and both airlines engage in D³. In each of these cases, demand driven dispatch is implemented at TF8 with the bookings-based swapping algorithm. The only variable component is whether or not demand driven dispatch is used. When used, the airlines use it identically. The base case for all tests is that neither airline uses demand driven dispatch.

To further simplify the tests, both airlines will use identical forecasting and revenue management systems. In the first set of three tests, Airlines 1 and 2 use EMSRb optimization with standard leg forecasting just as in the previous tests of timing swaps. Hence, the first test, with Airline 1 engaging in demand driven dispatch, the simulation parameters and results are identical to the TF8 test in the previous section, as shown in Figure 26.

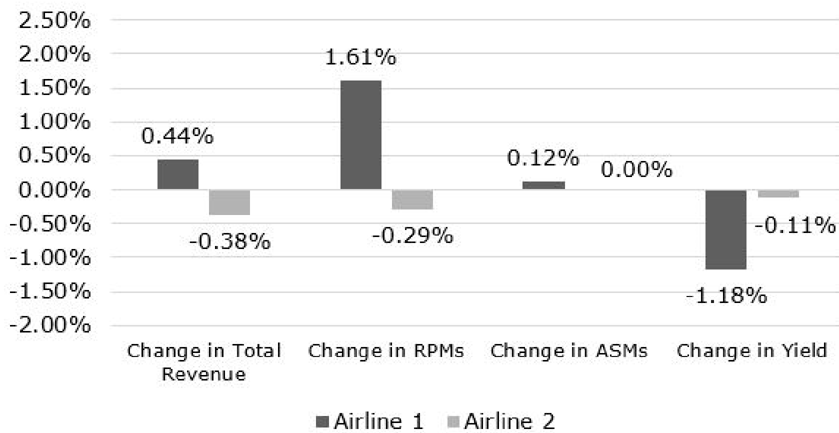

Figure 26: EMSRb, Airline 1 Uses Bookings-Based D³

Revenues increase for Airline 1 by 0.44% and decrease for Airline 2 by 0.38%. RPMs increase for Airline 1 by a substantial 1.61% and decrease for Airline 2 by a more modest 0.29%. ASMs increase only slightly for Airline 1, at 0.12%. Therefore a significant increase in system load factor percentage points can be inferred (in this case 1.21 %pts). Yield declines by 1.18% with the large increase in FC 6 bookings observed before. This is the benchmark result of bookings-based swapping for implementation in TF8, or 24 days prior to departure with 70% of demand having already arrived. Figure 27 displays the same information with Airline 2 implementing demand driven dispatch, and Airline 1 not. The results are very similar.

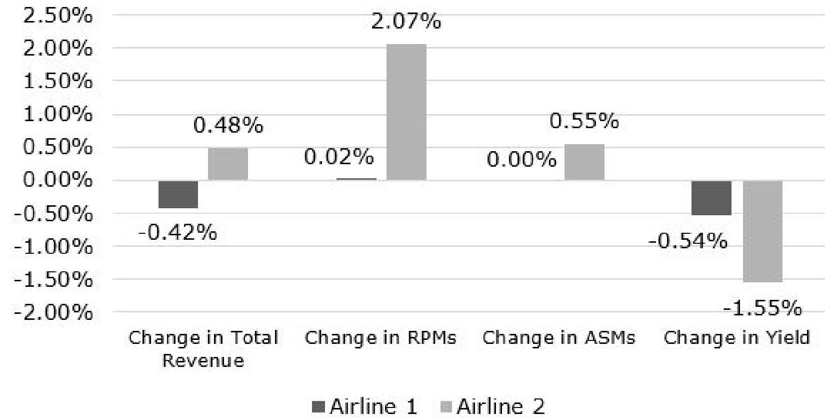

Figure 27: EMSRb, Airline 2 Uses Bookings-Based D³

Airline 2 sees a revenue increase of 0.48%, as compared to Airline 1's 0.44%. RPMs, meanwhile, increase by 2.07% and ASMs also increase by 0.55%. This is markedly more than Airline 1's ASMs increased, suggesting that Airline 2's initial fleet assignment is not as good as Airline 1's, and that therefore Airline 2 has more to gain from demand driven dispatch. Changes in yield also follow consistently, with a decrease of 1.55%.

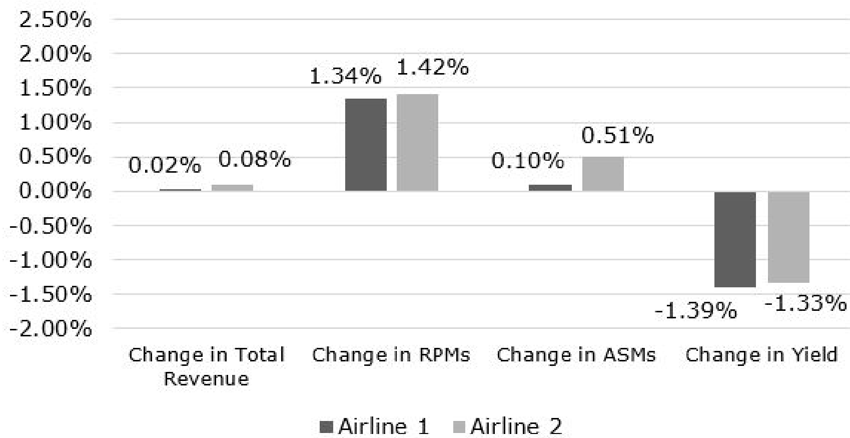

Figure 28: EMSRb, Both Airlines Use Bookings-Based D³

Figure 28 displays the results of the test of both airlines engaging in bookings-based demand driven dispatch at TF8. As can be seen, their changes in revenue have become nearly neutral. Rather than one airline seeing increases and the other decreases of about half a percent, both airlines see slight increases in revenue of 0.02% and 0.08%, respectively. However, the bookings-based swaps still causes substantial increases in RPMs, from 1.34% to 1.42%, and decreases in yield, from 1.39% to 1.33%. Again, Airline 2 has a greater change in ASMs, suggesting an inferior initial fleet assignment. For implementation at either Airline

1 or Airline 2, the patterns are very consistent for changes in all primary metrics, and the results of both airlines engaging in demand driven dispatch are symmetrical. Interestingly, when both airlines implement demand driven dispatch, they realize almost identical changes in ASMs, similar but smaller changes in RPMs, similar changes in yield, but much less increase in revenue. They do much better, however, than they would if only their competitor engaged in demand driven dispatch.

The results shown in Figure 28 are very important to understanding the competitive effects of demand driven dispatch. As when only one airline engages in D^3 in TF8, both airlines see significant dilution. FC 6 takes increased bookings while FC 5 and higher either lose bookings or experience little change. This in turn results in fewer historical bookings in higher fare classes, lower protection levels for higher fare classes, and so on—spiral down. When only one airline engages in demand driven dispatch, increases in RPMs (capturing of more demand) are greater than decreases in yield. Therefore the revenue results are positive. When both airlines engage in demand driven dispatch, they are both in effect strategically assigning larger aircraft in hopes of capturing the same peaks in demand. There is not enough demand, however, for both airlines to succeed in overcoming losses in yield with increases in RPMs. Hence, the results show characteristic decreases in yield and increases in revenue, but decreases in yield are now as great as the increases in revenue. This balance in yield and RPM change leads to the relatively neutral revenue outcome.

Next, the bookings-based swapping algorithm is tested with a full O&D RM system, displacement adjusted virtual nesting (DAVN) with standard path class forecasting. This RM system is similar to those employed at several large legacy carriers and assigns OD itineraries to virtual fare classes after adjusting their fares for network displacement costs, as calculated by a deterministic network linear program. Then bookings limits for these virtual fare classes are determined using the EMSRb method. The results of the first test, Airline 1 implementing demand driven dispatch when both airlines use DAVN, are displayed in the Figure 29.

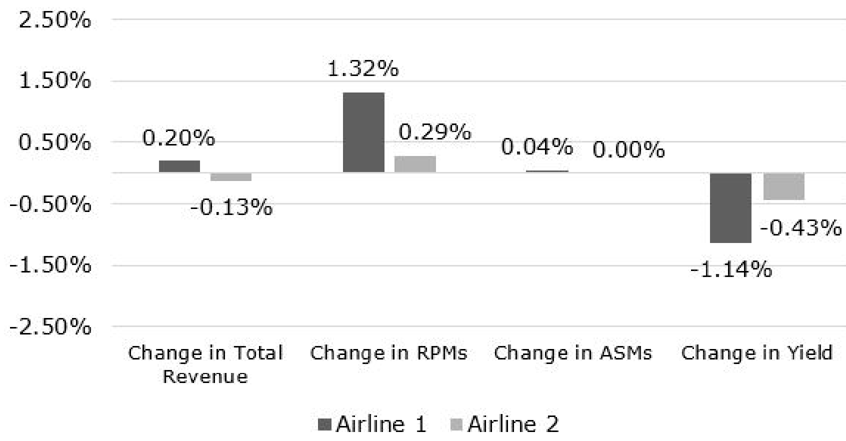

Figure 29: DAVN, Airline 1 Uses Bookings-Based D³

The revenue changes are smaller than those with EMSRb. Airline 1's revenue increases by 0.20% and Airline 2's decreases by 0.13%. Changes in RPMs are similar, with Airline 1 seeing an increase of 1.32%, as compared to 1.61%. However, rather than Airline 2's RPMs decreasing by 0.29% as they did with EMSRb, they now increase by that much. This suggests Airline 1 is being more aggressive with DAVN (providing less availability to low revenue-value itineraries) than it was with EMSRb, and is therefore spilling some demand to Airline 2. ASMs change very little with Airline 1, and again yield decreases, this time by 1.14% rather than 1.18%. The pattern of changes in primary metrics is very consistent whether the RM system employed by Airlines 1 and 2 is EMSRb or DAVN. The revenue changes are slightly less, however, and this might suggest that with "better" RM, there is less revenue to be gained through demand driven dispatch, or at least with the bookings-based swapping algorithm. This conclusion is premature, however, as shown by Figure 30.

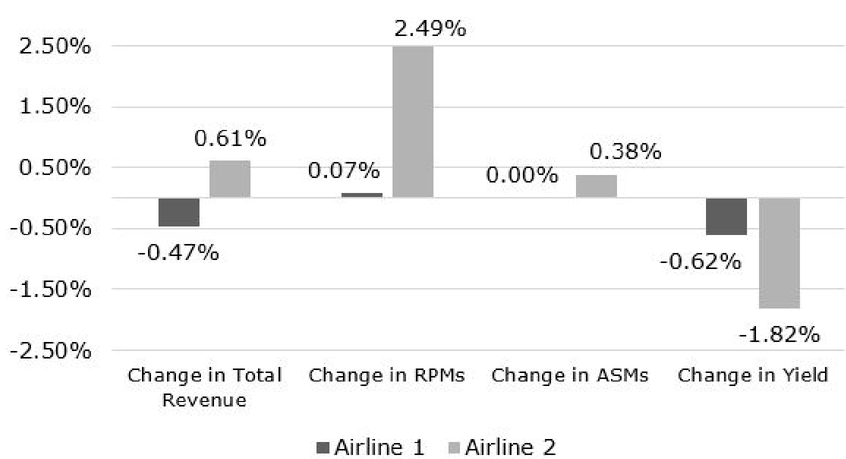

Figure 30: DAVN, Airline 2 Uses Bookings-Based D³

The results of Airline 2 implementing demand driven dispatch is a revenue gain of 0.61%, more than it realized with EMSRb. This is a reminder of how the details of an airline's network, schedule, fare products, competition and RM system interplay. Airline 2 also realizes a gain in RPMs of 2.49%, an increase in ASMs of 0.38%, and a decrease in yield of 1.82%, consistent with the changes from the other tests.

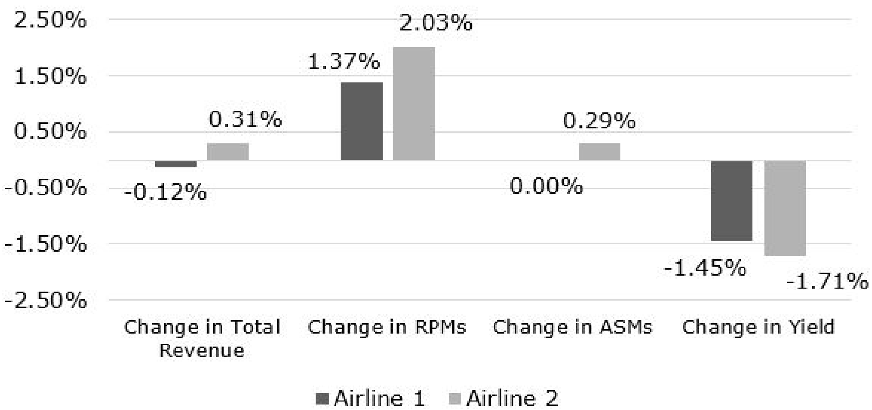

Figure 31: DAVN, Both Airlines Use Bookings-Based D^3

Figure 24 displays the changes from both airlines, using DAVN, implementing demand driven dispatch in TF8. The results are again very similar, with the revenue results being a balance of the two cases where only one airline implemented D^3. RPMs increase, yield decreases, and ASMs change slightly, again more for Airline 2. As with both airlines implementing D^3 while using EMSRb, yield decreases and RPM increases are of similar magnitudes, leading to more neutral revenue outcomes. When both airlines implement D^3, they are competing with capacity adjustments for the same low fare class demand; this competition leads to decreases in yield becoming more pronounced and increases in yield less so.

The same tests are conducted with a different O&D RM system, ProBP, or probabilistic bid price control (Bratu, 1998). This methodology uses EMSR curves and an iterative algorithm to calculate stochastic bid prices for each leg, and then uses these bid prices to control availability where each itinerary must have a fare-value greater than the sum of the bid prices of the legs it traverses. Figures 32 and 33 show the results of only Airline 1 and then only Airline 2 implementing demand driven dispatch with ProBP.

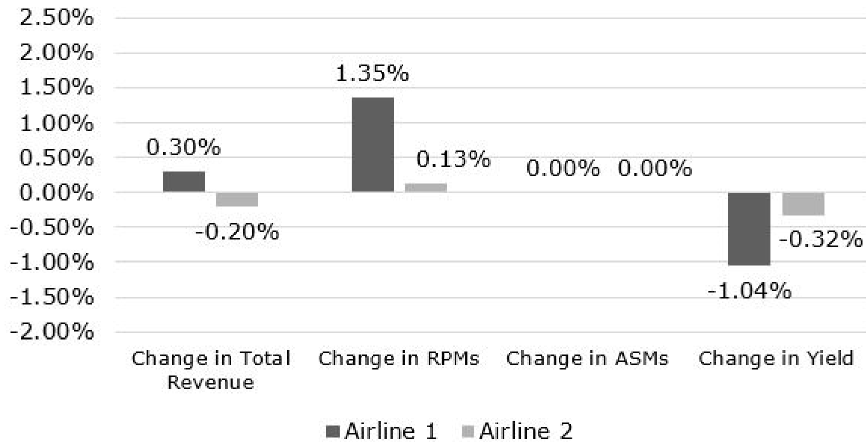

Figure 32: ProBP, Airline 1 Uses Bookings-Based D³

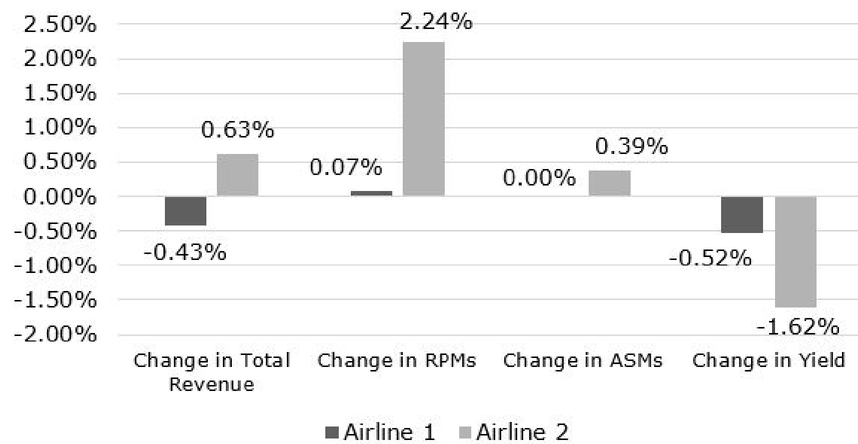

Figure 33: ProBP, Airline 2 Uses Bookings-Based D³

These results are very similar to those with DAVN, with changes in the primary metrics within 0.1%. Again, Airline 2 gains more than Airline 1, with a greater change in ASMs, suggesting an inferior initial fleet assignment. RPMs increase and yields decrease. Figure 34 shows the results of both airlines implementing demand driven dispatch.

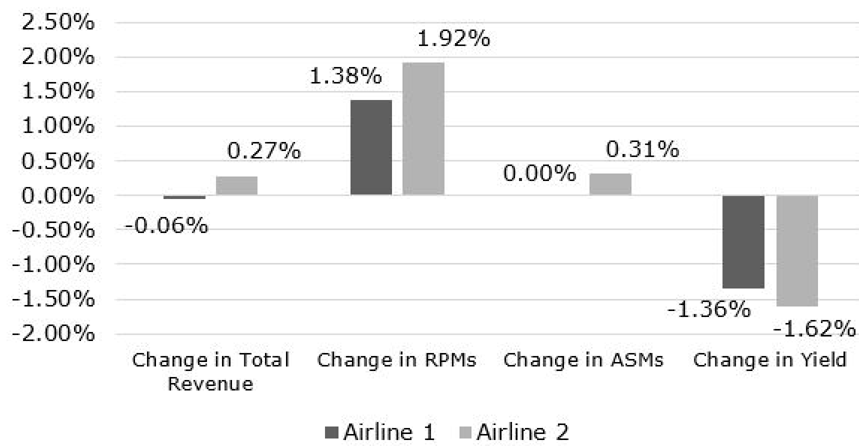

Figure 34: ProBP, Both Airlines Use Bookings-Based D^3

Again, the results with ProBP are almost identical to those with DAVN. The revenue effects fall from the results of one of the airlines implementing, RPMs increase, yields decrease, and Airline 2 experiences a greater change in ASMs.

Finally, the fourth set of tests involves both Airline 1 and Airline 2 using DAVN and standard path class forecasting and hybrid forecasting and fare adjustment (HF/FA) to relax the assumption of independent fare class demand. Because hybrid forecasting and fare adjustment work to prevent spiral down by closing lower fare classes earlier than capacity would require (Fiig, Isler, Hopperstad, & Belobaba, 2010), the expectation would be that demand driven dispatch with hybrid forecasting and fare adjust would result in less dilution and a smaller increase in RPMs.

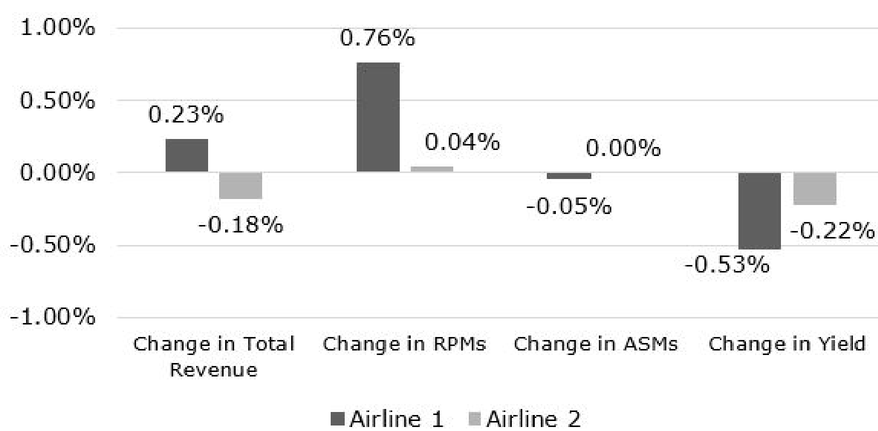

Figure 35: DAVN w/ HF/FA, Airline 1 Uses Bookings-Based D^3

This is in fact the case, as shown in Figure 35 which illustrates the results of Airline 1 implementing demand driven dispatch with both airlines using DAVN and HF/FA. Airline 1 experiences an increase in revenue due to D^3 of slightly more than with DAVN without HF/FA, while RPMs increase less and yield decreases less. The same occurs for Airline 2's implementation, as well as when both airlines implement demand driven dispatch, show in Figures 36 and 37.

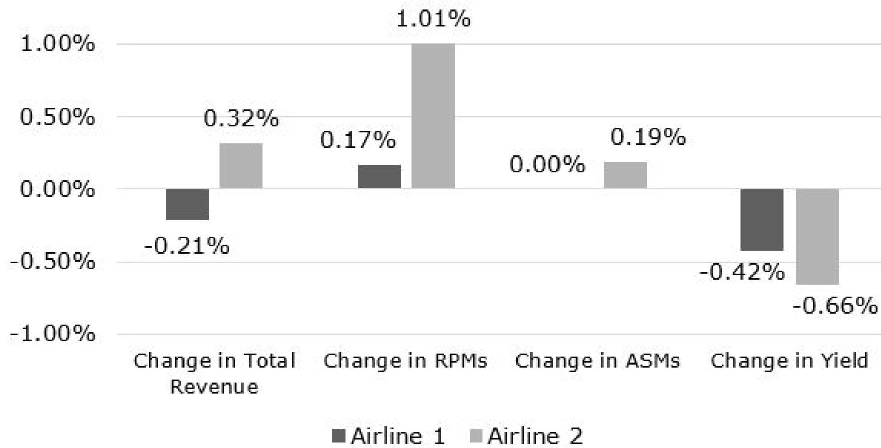

Figure 36: DAVN w/ HF/FA, Airline 2 Uses Bookings-Based D^3

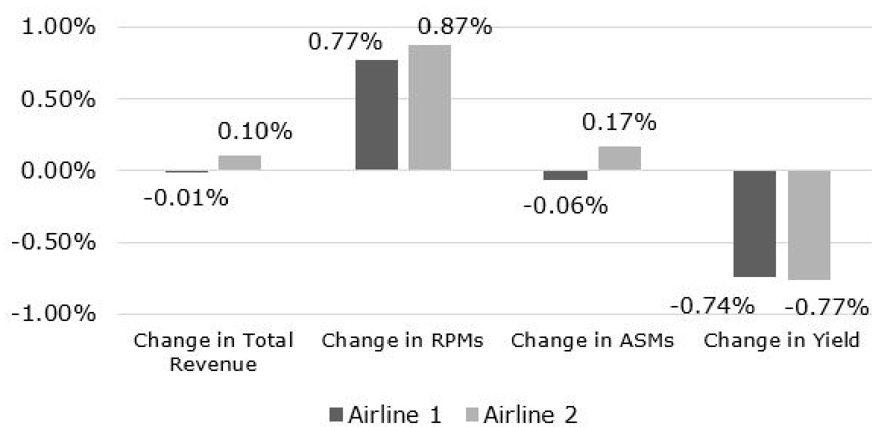

Figure 37: DAVN w/ HF/FA, Both Airlines Use Bookings-Based D^3

As can be seen in Figures 36 and 37, revenue increases for the airlines that implement demand driven dispatch compared to cases where they do not, RPMs increase and yield decreases, but not as much as without HF/FA. As usual, Airline 2 experiences a greater change, always an increase, in ASMs due to D^3. Similar tests were conducted with ProBP and HF/FA, but for brevity the results are shown in the appendix. They are consistent with DAVN with HF/FA.

It is important to note that HF/FA prevents some of the dilution inherent to implementation of D^3 at TF8. Increases in RPMs and decreases in yield are considerably reduced as compared to tests where HF/FA are not used. However, HF/FA still does not prevent dilution and spiral down from resulting in neutral revenue results when both airlines implement demand driven dispatch. When both airlines are adding capacity to the same high demand flights, competing for the same low fare class demand, decreases in yield become similar in magnitude to the increases in RPMs, regardless of the presence of HF/FA.

These trends can also be seen when examining changes in load factor percentage points alongside changes in yield. Figures 38 and 39 show these changes when either Airline 1 or Airline 2 implement demand driven dispatch.

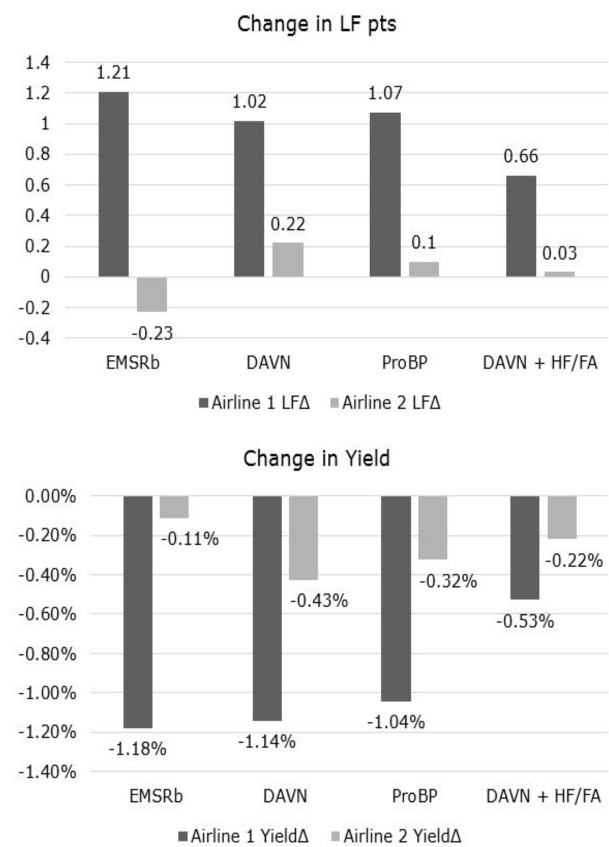

Figure 38: AL 1 Implements D^3, LF & Yield

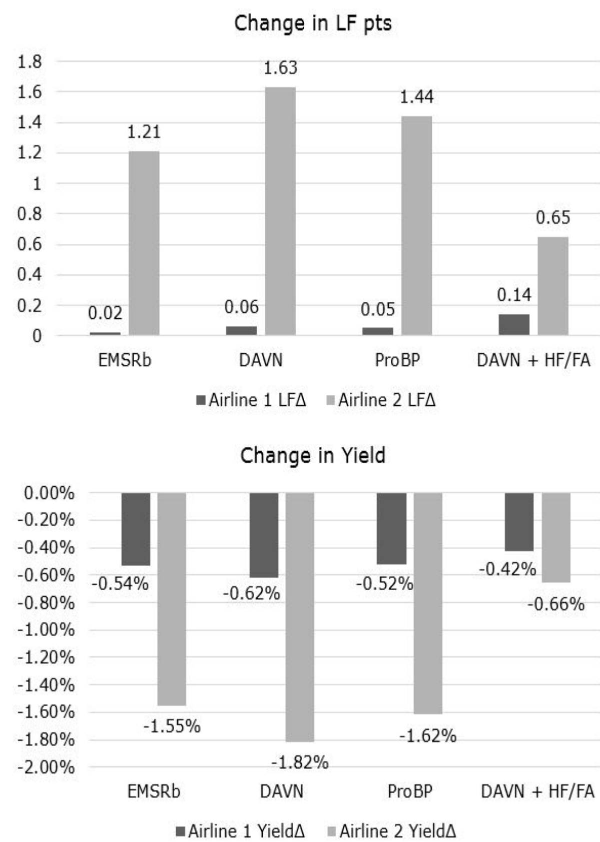

Figure 39: AL 2 Implements D^3, LF & Yield

When Airline 1 or Airline 2 implement demand driven dispatch, the effects of D^3 are very consistent across RM systems, with the notable exception of DAVN with HF/FA. Either airline sees large increases in its own LF with much smaller changes in the other airline's LF. Meanwhile, without HF/FA yield decreases by about -1.1% for Airline 1 when it implements D^3 and by roughly 1.65% for Airline 2 when it implements D^3. The airline that does not implement demand driven dispatch has decreased yield, but only moderately relative to the airline that does. With HF/FA, the gap in yield decrease between the two airlines narrows, as does the decrease in yield itself.

When both airline implement demand driven dispatch, they both see significant increases in their LFs and drops in yield. Figure 40 shows these results.

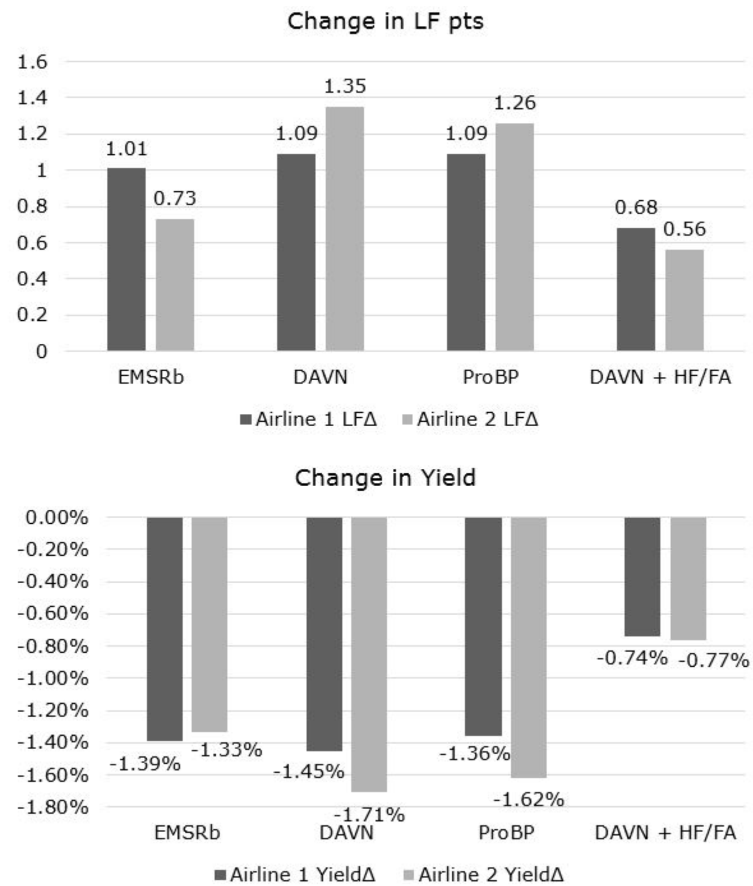

Figure 40: Both Airlines Implement D³, LF & Yield

Again, HF/FA tempers the changes in LF and yield when both airlines implement, but the general trends remain the same. Increases in LF for Airline 1 are slightly less or about the same as when it alone implements D^3. Airline 2 experiences less of an increase in LF with all RM systems. Meanwhile, Airline 1's yield drops more when both airlines implement D^3 as compared to when it alone implement D^3. When Airline 2 implements D^3, its yield drops about the same amount whether or not Airline 1 implements D^3. This corresponds to revenue results being worse when both airlines implement D^3 as compared to when only one does, and it also corresponds to Airline 2 having a better revenue result when both airlines implement D^3 as compared to Airline 1.

A brief summary of the findings from demand driven dispatch with different RM systems and competitive action include several important points. First, the magnitude of revenue benefits from demand driven dispatch is related to the quality of the original fleet assignment. Second, although the magnitudes of percentage changes differ somewhat between Airline 1 and Airline 2 when they engage in demand driven dispatch, the trends in all of the primary metrics are the same. The RM systems affect the magnitudes of changes, but not the trends. Specifically, hybrid forecasting and fare adjustment helps to decrease dilution while limiting the increases in RPMs. Differences in the effects of D³ when the airlines use leg-based or network-based RM are small.

In all cases, demand driven dispatch has a positive effect on revenue, but when both airlines implement D³, increases in RPMs are not of a greater magnitude than decreases in yield leading to neutral revenue results. Still, either airline has a better revenue outcome as compared to if it did not implement D³, and therefore both airlines implementing demand driven dispatch is, in these tests, the Nash Equilibrium (no player in a non-cooperative game can improve their outcome by changing their own strategy). It is important to note, however, that, especially when both airlines engage in D³ competitively, D³ results in significant dilution because of increased capacity on high demand flights.

4.2.3. Demand Level Effects

The final set of tests using the bookings-based algorithm have Airline 1 implement demand driven dispatch at different base case demand levels. Previous studies, including *Revenue Management under Demand Driven Dispatch* (Cots, 1999), have suggested that as the base case demand increases and flights reach capacity more often the revenue gains of demand driven dispatch decrease. To test this hypothesis in the PODS simulator, seven demand levels were used, as shown in Figure 41.

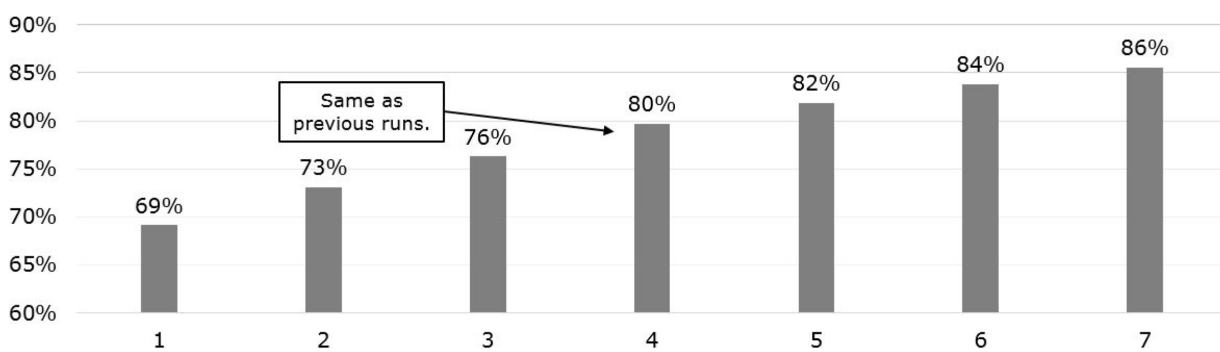

Figure 41: Base Case System Load Factors for Seven Demand Levels

All previous simulation runs occurred at demand level 4, or a base case system load factor for Airline 1 of about 80%. The full range of demand levels used for this test include a system load factor for Airline 1 as low as 69% and as high as 86%. At each demand level, the base case is without demand driven dispatch and the alternative case is the implementation of demand driven dispatch by Airline 1.

In all cases, Airline 1 implements demand driven dispatch at TF8 using the bookings-based swapping algorithm. Both airlines are using DAVN with standard path class forecasting for their RM systems. Thus, the results of the test of demand level 4 are identical to those of testing Airline 1 with DAVN in the previous section. For simplicity, only the results for Airline 1 are shown.

The first set of results, shown in Figure 42, are percentage changes in total revenue due to the implementation of demand driven dispatch at each demand level, shown in the figure below. Fitting the results to a trend line, the expected decline in revenue benefits at the higher load factors does occur. However, there also is a marked decline in revenue benefit in the middle demand levels with base case system load factors of about 76% and 80%.

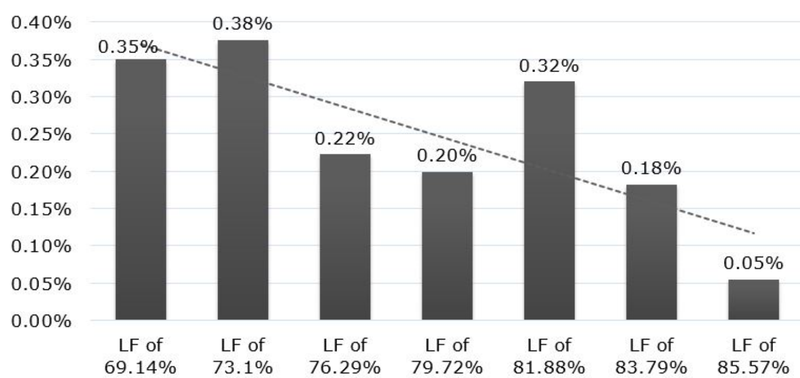

Figure 42: Revenue Changes from Bookings-Based D^3 at Different Demands

Looking at changes in LF percentage points, ASMs, and RPMs, shown in Figures 43 and 44, reveal that the same pattern is occurring at all demand levels: ASMs change very little while RPMs increase substantially. Changes in LF therefore resemble changes in RPMs. Here, however, the general trend is that RPMs increase more with higher levels of demand. And again, there is a depression in the magnitude of changes in the middle demand levels.

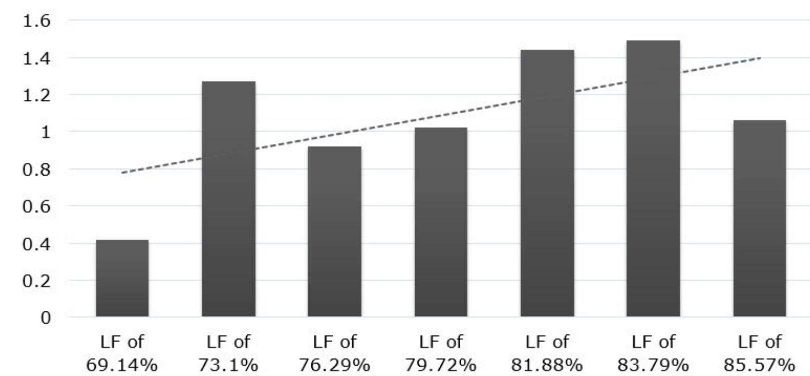

Figure 43: LF % pt. Changes from Bookings-Based D³ at Different Demands

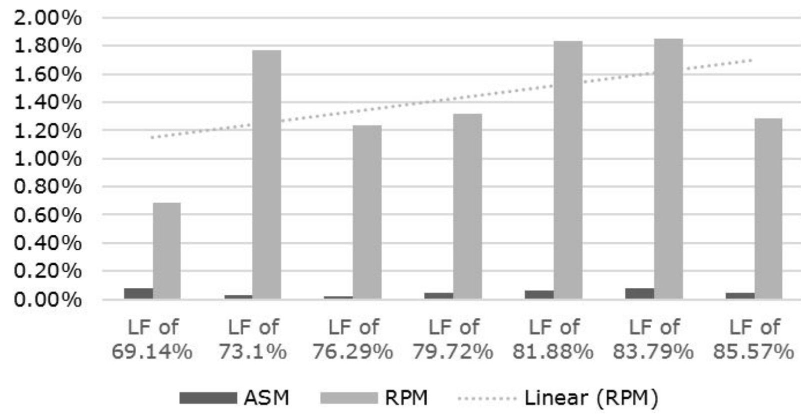

Figure 44: Changes in ASMs and RPMs from Bookings-Based D³ at Different Demands

The increase in RPMs becoming more pronounced at higher demand levels is likely due to the additional capacity, given to the highest forecasted flights, being more likely to realize additional bookings when more total demand exists in the system.

Changes in yield, shown in Figure 45, are also consistent with previous patterns. The increases in RPMs from implementation of demand driven dispatch at TF8 are accompanied by dilution. In these cases, as RPMs increases more at higher demands, yield decreases more at higher demands. Hence, it appears that while higher demands may limit the number swaps that are feasible due to capacity constraints, the primary cause of declines in revenue gains at higher demand levels is in fact greater dilution from up-gauged flights seeing large increases in bookings in the lowest fare classes.

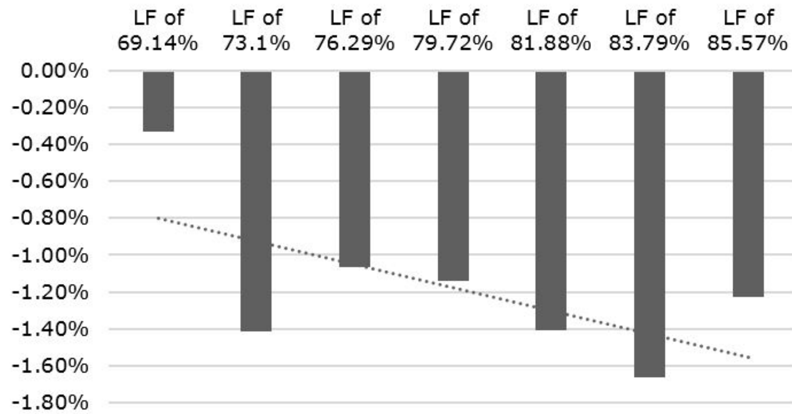

Figure 45: Changes in Yield from Bookings-Based D^3 at Different Demands

The decrease in magnitudes of changes observed around the middle demand levels can be explained by the number of swaps taking place, as shown in Figure 46.

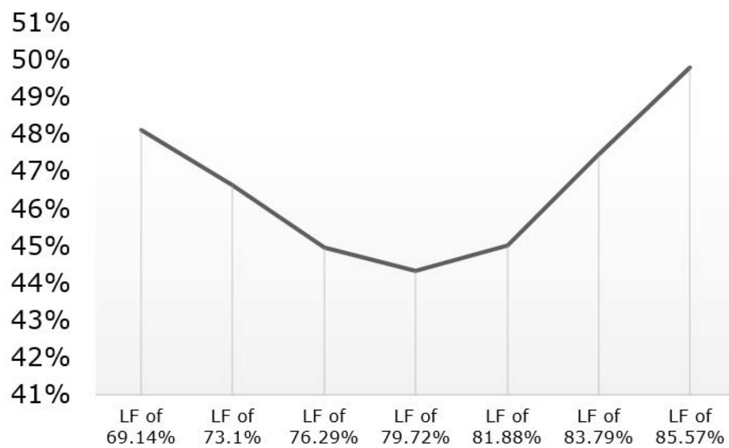

Figure 46: % of Swappable Leg-Pairs Swapped, Bookings-Based D^3 at Diff. Demands

Figure 46 displays the percentage of leg-pairs *in the swappable set* that were in fact swapped. Note the decline in swaps that reaches its minimum at a base case system load actor of about 80%. It follows that if fewer swaps are taking place, or put another way, demand driven dispatch is being used less, demand driven dispatch would have a lesser effect on the revenue, RPMs, yield, etc. However, the question remains as to why fewer swaps are taking place at the middle demand levels. As the swaps are driven by forecasted BAD with the bookings-based swapping algorithm, the forecasted BAD likely hold the answer. In the figure 47, observe the average absolute difference of the forecasted BAD minus the initial assigned capacity for each leg.

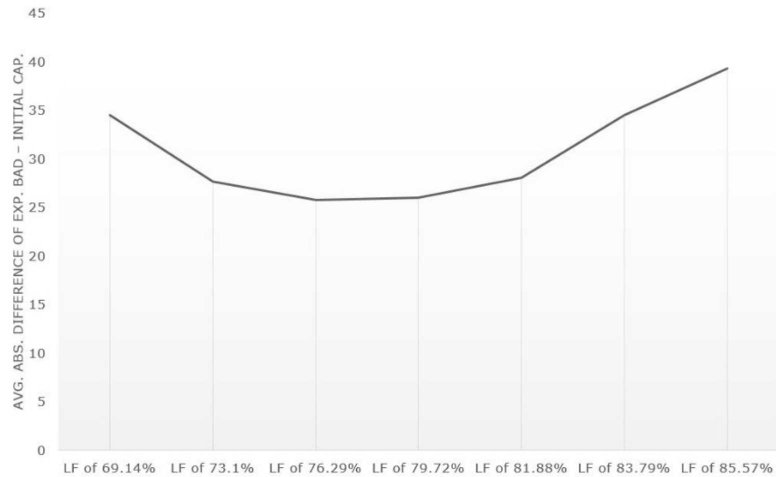

Figure 47: Average Differences of Initial Capacity and Forecasted BAD

At the lowest demand level, the average difference is about 35, meaning the average flight has a difference of about 35 between its expected bookings at departure and its initial capacity. At the high demand level, the average flight is forecasted to have a capacity/expected BAD discrepancy of about 40. At the medium demand level, discrepancies between the expected BAD and initial capacity are at their minimum. Thus, one would expect less motivation to engage in swaps, as well as fewer opportunities.

4.3. Conclusions from Bookings-Based D^3

The first set of tests in Chapter 4, dealing with the timing of swaps, illustrate that early swapping leads to greater increases in RPMs and greater decreases in yield, while late swapping leads to small increases in RPMs and small decreases to small increases in yield, depending on advance purchase restrictions and fares in the associated fare products. The timing of swaps in relation to not only the proportion of demand that has arrived but also the fare restrictions in the market is critical to the outcome. For implementation of D^3 at any time, the revenue impact is positive.

The second set of tests, dealing with the RM systems and competitive environment, illustrate that the trends in key metrics from the implementation of demand driven dispatch remain consistent throughout the various combinations, while the details of the RM system effect the magnitudes of the changes. When one airline engages in demand driven dispatch, the competitor airline loses revenue. When both airlines engage in demand driven dispatch, revenue changes are very small while both airlines gain RPMs and see decreases in yield. Hybrid forecasting and fare adjustment successfully prevent some of the dilution from demand driven dispatch and lessen the increase in RPMs.

In all cases where one airline implemented D^3, demand driven dispatch improved revenue, ranging from increases of 0.10% to 0.63% depending on the RM system and the quality of the initial fleet assignment, as signaled by greater changes in ASMs. However, when both airlines implement D^3, up-gauging the same high demand flights in competition for the same low fare class demand, yield decreases as much as or more than RPMs increase, leading to neutral revenue results. Still, an airline has better revenue performance when it engages in D^3 given that its competitor is also doing so. Thus, both airlines implementing D^3 is the Nash Equilibrium in this competitive, non-cooperative game. This outcome is an important contribution to the understanding of D^3 in a competitive environment.

The third set of tests with ranges of base case demand levels illustrated the expected decline in revenue gains from demand driven dispatch at higher demand levels and suggest that the primary cause of this decline is greater dilution. Furthermore, the magnitudes of changes in revenue, RPMs, yield, etc. are effected by the number of swaps that occur, which are in turn determined by the relationship between initial capacity assignments and their associated forecasted bookings at departure.

In summary, although bookings-based swapping represents only the simplest (and suboptimal) method for re-assigning aircraft in demand driven dispatch, testing it has shown robust revenue improvements. The tests have also shown important relationships between the benefits of D^3 and the initial fleet assignment, the RM system, timing of swaps relative to fare restrictions, and the competitive environment.

Chapter 5: Network Optimization Fleet Assignment

Bookings-based swapping assigns the largest aircraft to the flights with the most forecasted demand, effectively maximizing average leg load factor. Its simple inputs (BIH and forecasted BAD) allow it to be implemented with any RM system at any time in the bookings process. As shown in Chapter 4, this flexibility allowed for simulating D^3 in a wide variety of scenarios that resulted in important insights. However, bookings-based swapping only represents a starting point in researching the interaction of revenue management and demand driven dispatch with a fleet assignment optimization being the next step.

Chapter 5 describes the network optimization methods used for fleet assignment in all subsequent experiments. Rather than a ranking algorithm, further tests of demand driven dispatch utilize a network optimizer that estimates either the incremental revenue or incremental operating profit potential of swapping aircraft and changes aircraft assignments to maximize either the total revenue or operating profit of the network. Section 5.1 discusses the network optimization fleet assignment model (FAM), specified as a minimum-cost flow problem, in detail, first its specification and then its underlying assumptions.

In order to use this FAM, it is necessary to estimate both incremental revenues and costs for each flight leg. This task is more complicated than it may seem, in large part due to the effects of revenue management and the need to allocate revenue and costs that are a function of the broader network to specific legs. Section 5.2 discusses revenue estimation techniques used in conjunction with different RM systems. Section 5.3 discusses the estimation of costs, confined to aircraft block hour costs in this thesis.

5.1. The Network Optimizer

To avoid the greedy nature of the ranking algorithm, all subsequent tests are conducted with a network optimizer. This eliminates the risk of suboptimal swaps such as that described in Figure 13. Another key component of the network optimizer is that it works in units of currency rather than bookings, allowing swaps to be made so as to maximize revenue and/or minimize costs rather than maximize bookings or LF. This point is critical in that there is wide variation in the revenue value of bookings by market and by fare class and that a swap that improves bookings or revenue may not offset the additional operating costs associated with the swap. As will be shown, attempting to maximize revenue by swapping, as some airlines have done (Feldman, 2002), is not necessarily beneficial in terms of operating profit. It is important to consider both revenues and costs when capacity constraints are flexible, something that is not necessary in revenue management with static fleet assignments. Thus, a network optimizer that assigns aircraft to maximize the operating profit of the network is critical to understanding the full interaction between demand driven dispatch and revenue management in a competitive network environment.

5.1.1. Optimization Model

The network optimizer is specified as a minimum-cost flow problem. Each aircraft or equipment type is modeled as a left node and each leg-pair (a pair of flight legs to and from a hub that must be operated by the same aircraft) as a right node in a bipartite network structure. The left nodes are source nodes that supply aircraft and the right nodes are sink nodes that demand aircraft. Each left node is connected to each right node by an arc that can take a binary value signifying whether or not that aircraft type operates the connected leg-pair. Therefore, the effective capacity of each arc is 1. Figure 48 shows a simple representation of the form of the model.

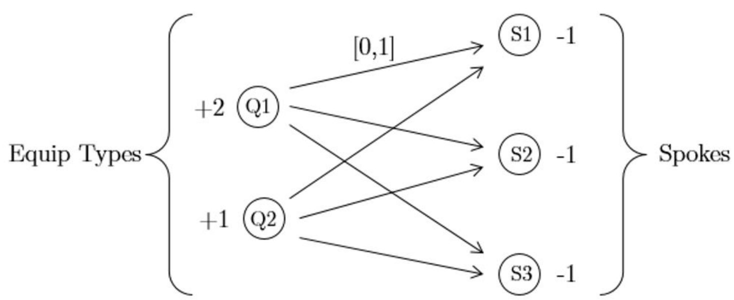

Figure 48: Example of Min-Cost Flow Specification (by Matthew Berge)

Q1 and Q2, the two left nodes, represent two aircraft/equipment types. In this small hypothetical scenario, the fleet is composed of only three aircraft, two aircraft of type Q1 and one aircraft of type Q2. The number of aircraft is equal to the number of leg-pairs in the set of leg-pairs eligible for having their fleet assignment changed. Hence, there are three right nodes, representing the eligible leg-pairs (or spoke cities that these leg-pairs fly to and back from). Each leg-pair must be operated by exactly one aircraft. If aircraft type Q1 is assigned to leg-pair S1, the arc between Q1 and S1 is set to a value of 1 and all other arcs ending at S1 are set to 0. One unit of supply (one of the Q1 aircraft) is used and the demand for S1 is satisfied.

Each arc has an associated revenue and cost value. The associated revenue value is the expected incremental revenue to come of operating each aircraft type given the originally assigned aircraft type. Revenue to come is the revenue value of forecasted bookings to come.

The incremental revenue to come for an aircraft size would be the difference between that aircraft's expected revenue to come minus that of the originally assigned aircraft. For example, suppose that leg-pair S1 was originally assigned aircraft type Q1. The incremental revenue to come (RTC) of aircraft type Q1 would be zero. The incremental RTC of aircraft type Q2 is the RTC of aircraft type Q2 minus the RTC of aircraft type Q1.

$$IncRTC_{Q2} = RTC_{Q2} - RTC_{Q1};\ given\ original\ assignment\ is\ Q1.$$

The associated cost value is constructed in the same way—it is the incremental aircraft operating cost of operating each aircraft type given the originally assigned aircraft type.

$$IncBHC_{Q2} = BHC_{Q2} - BHC_{Q1};\ given\ original\ assignment\ is\ Q1.$$

Thus, the incremental profit contribution of any assignment over the original assignment is the incremental expected revenue to come minus the incremental operating costs. To fit the specification of a minimum-cost flow problem, each arc's incremental profit contribution is multiplied by -1 and then by the binary value assigned to the arc. The sum of all assigned arcs' incremental profit contributions is then minimized.

$$Objective\ Function{:}\quad Minimize\ z(x) = \sum_{(i,j)\in A} -1\left(x_{ij}\left(IncRTC_{ij} - IncBHC_{ij}\right)\right)$$

$$Decision\ variable{:}\quad x_{ij}, (i,j) \in A$$

In the objective function, each arc $(i,j) \in A$ connects source node i with sink node j, where each source node $i \in N$ is an aircraft type and each sink node $j \in N$ is a swappable leg-pair. The following constraints apply, where b_i is the number of aircraft type i in the fleet:

$$Constraints{:}\quad \sum_{j\in N} x_{ij} = b_i\ for\ each\ i \in N$$

$$\sum_{i\in N} x_{ij} = 1\ for\ each\ j \in N$$

$$x_{ij} = 0\ or\ 1\ (also\ arc\ capacity\ constraint)$$

First, for every source node i, the sum of the values of the arcs leaving it must equal the number of aircraft of type i. In other words, the fleet assignment solution must assign exactly as many of each type of aircraft as exist in the fleet. Second, the sum of the values of the arcs arriving at each sink node j must equal exactly 1. In other words, only one aircraft can be assigned to each swappable leg-pair. Third, each arc can take the value 1 or 0. This requirement insures that each assignment possibility is either chosen for the fleet assignment solution or not. It is not possible for half of an aircraft to be assigned to one leg-pair and the other half to another. Nor is it possible for one aircraft assigned to a leg-pair to be offset by a "negative" aircraft assigned to the same leg-pair. This constraint also operates as the capacity of each arc, the capacity being 1.

Using this minimum cost flow specification, designed by M. Berge and closely resembling that used in Berge and Hopperstad (1993), it is possible to quickly and efficiently solve for an optimal fleet assignment using a general minimum-cost flow solver (the model's form allows it to be relaxed from an integer problem (IP)).

Not only is the model simple to formulate and solve, especially relative to an IP, it is also adaptable to specific requirements for the fleet assignment process. For example, no aircraft swap should result in denied boardings. Therefore, the cost associated with an arc that would result in denied boardings is made to be prohibitively large. Effectively, the solution will never contain an assignment where capacity is less than the current bookings in hand for the legs in a leg-pair. The specification of the minimum-cost flow model allows these costs to be added directly to the incremental aircraft operating costs, requiring no structural changes to the model.

Thus, the minimum-cost flow specification of the fleet assignment problem in demand driven dispatch is a flexible and efficient method to find optimal fleet assignments given estimates of incremental operating costs and revenues for potential swaps.

5.1.2. Modeling Assumptions

The model also relies on many simplifying assumptions, some true in the context of PODS Network D^3 and some not. First, the specification of the model assumes that all daily aircraft routings go from one coast to the opposite and back via two stops at directional connecting banks. This is true, as per the design of Network D^3 (see Section 3.5). Network D^3 is intentionally designed to facilitate the simulation of demand driven dispatch, and therefore the aircraft in the two complexes (one starting on the West Coast and one on the East Coast) all operate four flight legs a day and all arrive and depart from directional connecting banks at the same time. Then, it is assumed that only the leg-pairs that travel from the hub to the spoke and back in the middle of the day are "swappable." Hence, the fleet assignment problem in demand driven dispatch becomes to assign each aircraft to a leg-pair, half of the leg-pairs in the network being "swappable."

This assumption could be relaxed to most types of routing. So long as the aircraft types in question can interchangeably meet the operational constraints of each of the leg-sets (they do not need to be pairs) and the leg-sets begin and end at the same time and location, the minimum-cost flow specification can be applied. Therefore the binding assumptions are that a predefined group of leg-sets can be operated by the aircraft eligible for reassignment and that these leg-sets are chronologically and spatially linked.

An additional assumption that is more problematic is the assumption of leg-independent demand. Because both airlines in Network D^3, as well as most airlines in reality, rely on connecting traffic through hubs, the capacity of aircraft on connecting flights does affect the realizable demand of those flight peers at a connecting bank or de-banked hub. For example, should the capacity of the SAN-MSP flight be down-gauged from 150 seats to 120 seats and the path class for SAN-MSP-BOS sees reduced availability, the allocated revenue potential for both SAN-MSP and MSP-BOS is affected while the assignment process only considers the revenue potential for SAN-MSP. Furthermore, as shown in Abramovich (2013), the demand realized by one flight leg between a city pair is not independent of the capacity of other flight legs between the same city pair—passengers are free to choose the airline, departure time, and fare class of their liking.

In order to account for the presence of connecting traffic, the minimum-cost flow problem would need to be replaced with a linear program such as the one generating displacement costs for DAVN that allocates seats to each path-class in the network with the addition of decision variables for the capacities of all flight legs. This would be considerably less practical to implement, although from an operations research perspective it is straightforward. However, it would still not account for passengers' ability to choose between flight legs, for which some type of spill and recapture model would be necessary.

For this thesis, the assumptions described above are taken to allow for the implementation of the efficient minimum-cost flow problem. It is the author's belief that while the model clearly has shortcomings, it is suitable for approaching the achievements possible through demand driven dispatch and more than suitable for exploring the interaction of demand driven dispatch with revenue management in a competitive network.

5.2. Revenue Estimation

A critical component of swapping aircraft dynamically in the booking process is to estimate the incremental revenue of a swap. This component is also the primary point of contact between revenue management and demand driven dispatch. In most previous research and implementations, the revenue management system is the source of the forecasted demand to be multiplied by an average selling fare or some variation on that approach. For the implementation of demand driven dispatch in this thesis, the estimates of incremental revenue from swaps will directly use the demand and revenue output of the revenue management process rather than simply demand forecasts. The assigner effectively values capacity identically to the RM system.

Three revenue management systems will be used in tests—a system using the EMSRb heuristic to determine booking limits, DAVN, and DAVN with hybrid forecasting and fare adjustment (HF/FA). Descriptions of these systems can be found in Sections 2.2.1 and 2.2.2. For each RM system, demand driven dispatch will use estimates of revenue to come (RTC) derived directly from the output of the RM system.

The benefits of this approach are twofold. First, by directly using the output of the RM system employed by the airline, the information provided by the RM system is used in generating the estimation or forecast of revenue to come for each leg. This includes the diminishing marginal revenue returns of additional capacity on a flight implicit in the use of revenue management. No estimates of fares at different capacities is necessary—the technique draws precisely from the booking limits or protection levels to be employed by the RM system and the fares that that RM system is using to value each fare class or virtual bucket. With DAVN, the use of displacement costs in generating a revenue to come estimate for demand driven dispatch is identical to its use in determining fare class mapping and valuation in DAVN. The second benefit of this approach to revenue to come estimation is a practical consideration: it uses output already generated from the RM that is therefore easy to obtain.

5.2.1. Estimating Revenue with EMSRb

Estimating revenue to come when the RM system is calculating booking limits via the EMSRb heuristic uses a method called the EMSRb Hull (coined and programmed by C. Hopperstad). The method borrows from the calculation of EMSRc's, or the "critical" EMSR (expected marginal seat revenue), on each leg when using EMSRb. The EMSRc represents the expected marginal seat revenue value at the capacity limit of a particular leg. Thus, if you consider only the upper hull of the EMSR curves for a leg, you have a piecewise function of EMSRc's as a function of remaining capacity.

Figure 49 illustrates the EMSR curves in a hypothetical flight in network D^3, all markets having six fare classes. The EMSR curves represent the expected marginal seat revenues of each fare class, the vertical axis, associated with that number of bookings/seats (in remaining capacity), the horizontal axis. In this diagram, the vertical bars of 130, 150, and 170 indicate where the capacity limit of this hypothetical flight leg would be given the number of bookings that are in hand and that the flight leg has been assigned aircraft of those sizes—130-seats, 150-seats, or 170-seats.

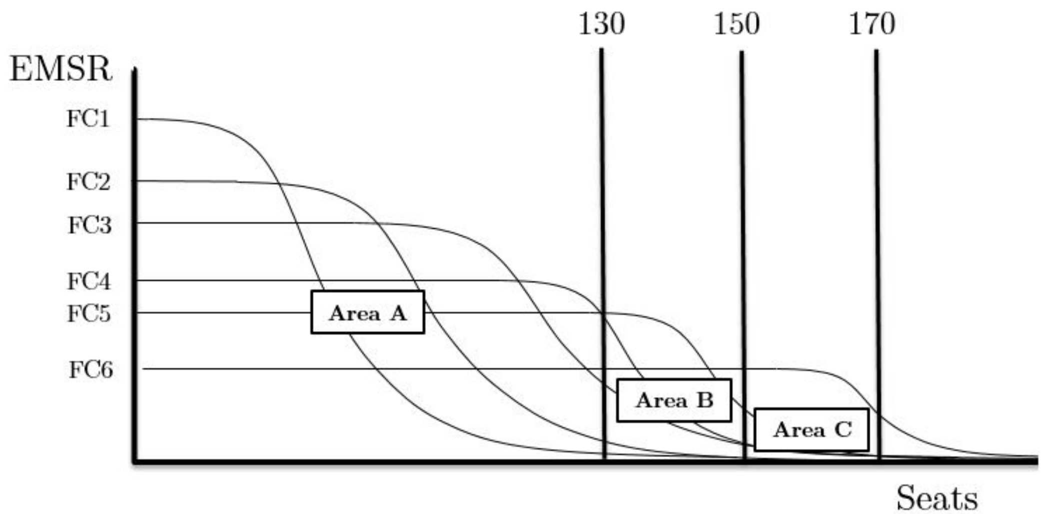

Figure 49: EMSR Hull for EMSRb

The EMSR Hull method sums the values of the EMSRc's from 0 to the remaining capacity limit for the forecasted bookings to come. As each EMSRc represents the expected marginal revenue of each seat from 0 to the remaining capacity limit, the sum of the EMSRc's, being an approximation of the area under the EMSR Hull (the top curves), is an estimate of the total expected revenue to come.

This estimate of revenue to come has multiple advantages. It directly uses the output of the RM system being used and thus is highly practical. It also takes into account fare class values and protection limits exactly as the RM system does. This estimate of revenue to come brings revenue management and demand driven dispatch closer together.

In Figure 49, Area A represents the expected revenue to come should the leg be assigned a 130-seat aircraft. Area B represents the incremental revenue to come should it instead be assigned a 150-seat aircraft. Area C, considerably smaller than its predecessors, represents the incremental revenue to come achieved by assigning a 170-seat aircraft instead of a 150-seat aircraft. The total estimate for revenue to come for the assignment of a 150-seat aircraft would be the sum of Area A and Area B. The total estimate for revenue to come for the assignment of a 170-seat aircraft would be the sum of Area A, B and C.

In order to estimate the revenue to come for a leg-pair at each capacity, first one calculates the estimated revenues to come for each separate leg at each capacity. Then, the estimate for the revenue to come for a leg-pair at a capacity is the sum of the estimates for the RTC of each separate leg at that capacity. If more than two flights legs would compose a swappable leg-set, the same principle would hold.

One additional heuristic employed with EMSRb in PODS is the use of full fare values for connecting itineraries on each flight leg. Therefore, the fare value of a fare class used in the EMSRb calculation is not the local or prorated fare value but rather the weighted average path fare in that class. The result is that the fare values are higher than the local fares, reflecting the higher connecting fares in Network D^3. Another result is that connecting revenue is then systematically double counted in revenue estimates. One solution to this double counting would be to use a distance proration scheme for allocating connecting revenue to the legs used by connecting itineraries. Another approach would be to use displacement adjusted fares, such as those used in DAVN.

5.2.2. Estimating Revenue with DAVN and Other OD Techniques

Estimating the revenue to come of leg-pairs when DAVN is the RM system employed by the airline uses many of the same principles as the revenue to come estimation with EMSRb. The EMSR Hull technique is applied to each leg's EMSR curves, as DAVN employs EMSRb on each leg's virtual buckets. Therefore, the primary difference between the revenue estimation techniques for EMSRb and DAVN is that the EMSR Hull technique is applied to the EMSR curves of DAVN's displacement adjusted virtual buckets rather than to the fare classes as defined by pricing (see section 2.2.2 for details on DAVN).

Because the displacement cost of the "other" leg is subtracted from the connecting itinerary's fare before it is mapped to a virtual bucket on a leg, the systematic double counting of revenue from connecting itineraries is diminished considerably as compared to EMSRb. This use of displacement costs also brings a dimension of network revenue management to demand driven dispatch. For example, if two legs in the network share connecting demand and one is capacity constrained, that constrained leg will have a higher displacement cost. The connecting itineraries will be valued less on the unconstrained leg because the displacement costs will be deducted from the fares. Thus, the unconstrained leg will be less likely to be up-gauged on account of connecting traffic that is dependent on the constrained leg. The more constrained leg's fares would be higher as less was deducted from them, causing the leg's estimated RTC to be higher than otherwise due to connecting traffic. Therefore the leg would be more likely to be up-gauged. Hence, the use of subtractive displacement costs to adjust connecting fares reinforces the likelihood that capacity constrained flights be up-gauged, now with network considerations.

The EMSR Hull technique as used by DAVN is also extendable to other OD RM systems. For example, the same technique is easily applicable to UDAVN, or "unbucketed" DAVN. This RM methodology is identical to DAVN except that rather than using virtual buckets, each path class gets "its own" virtual bucket. ProBP is also compatible with the EMSR Hull method; applying a "ProBP" Hull technique would be very similar to applying the EMSR Hull technique for UDAVN except that connecting fares are prorated rather than deducted by deterministic displacement costs.

Therefore, the EMSR Hull technique for estimating revenue to come for a leg is not only practical for use with the leg-based RM system, it is also versatile and applicable to a range of OD RM systems. The application of OD RM systems helps to prevent systematic double counting of connecting itineraries and, using network displacement costs to map connecting itineraries to leg virtual buckets, it provides a degree of network insight from the RM system to demand driven dispatch.

5.3. Cost Estimation

As compared to estimating revenues, estimating costs is much simpler. While some aspects of the operating costs must still be allocated to legs that are otherwise dependent on the larger network design, uncertainty in future costs is not as variable as revenue, despite recent changes in oil prices, and some costs—such as crew flight hours and fuel burn, are clearly attributable by leg. As such, for this thesis, the costs of operating a flight leg are estimated by taking the block time of that leg and multiplying it by estimates of block hour costs, a function of the aircraft type deployed.

Therefore, the key components for estimating aircraft operating costs in Network D^3 are block times for each flight leg and block hour costs for each aircraft type scheduled. Block times in Network D^3 are deterministic, and are constructed with a linear function. The intercept reflects the time required to operate a flight leg independent of distance, such as taxiing, take-off, and landing. Then, a coefficient (1 over the average cruise speed) is multiplied by the great circle distance between the origin and destination to find the flight time as dependent on the flight distance.

Block hour costs for each aircraft type have been estimated using aircraft and operating cost data (AviationWeek Intelligence Network, 2014). All block hour cost estimates for narrowbody mainline jets were first adjusted for average aircraft utilization to make ownership costs more standardized across airline fleets. The standard utilization rate used is 14 block hours per day. Second, all fuel costs per block hour were then adjusted to be 65% of those of 2013 to account for recent decreases in the cost of jet fuel. Then a linear regression was specified so that block hour costs are the dependent variable and number of seats is the independent variable along with an intercept.

These block hour cost estimates are not immediately useful in PODS, however. It is important for analyzing the resulting net operating profits that the aircraft operating costs be scaled to the same level as fares in Network D^3. The fares used to calibrate Network D^3 are meant to coincide with passenger disutilities in PODS, not match real market fare levels. Thus, the aircraft operating costs for each capacity in Network D^3 were scaled down to convert the costs to "PODS" dollars. The goal is to maintain the relative cost differences between capacity sizes as found in industry block hour cost data while scaling the set of costs so that profits of the airlines in Network D^3 are reasonable given the fares and demand in Network D^3. The resulting block hour costs by aircraft capacity, scaled by 0.65, are shown in Table 3.

Table 3: Block Hour Costs by Capacity

Aircraft Capacity	Block Hour Costs	
130-Seat	$	2,240
150-Seat	$	2,390
170-Seat	$	2,540

The block hour cost scaling results in the same relative differences by seat capacity as observed in industry data. Meanwhile, the resulting profit levels are also reasonable, given the fares and demands in Network D^3. To calibrate the total costs for each airline, the base case of both airlines using EMSRb with standard leg forecasting was used. This is the same base case used in Section 4.2.1. The results of applying a scaling factor of 0.65 (that used to generate the block hour costs in Table 3) result in the base case outcome shown in Table 4.

Table 4: Base Case Profit Results

Airline	System LF	Total Revenue	AC Op. Costs	T. System Costs	Profit	Profit Margin
Airline 1	81.22%	$1,864,432	$1,038,409	$1,730,682	$133,750	7.17%
Airline 2	80.41%	$1,839,813	$1,065,245	$1,775,408	$64,405	3.50%

Another assumption used in Table 4 is that block hour costs, or aircraft operating costs, are approximately 60% of total system costs. This is consistent with industry data. Airline 1 has a profit margin of about 7% and Airline 2 has a profit margin of about 3.5%. Although they have the same fare products and the same RM systems, Airline 1 has a geographical advantage in that its hub is more centrally located. It therefore has fewer ASMs and lower total block hour costs.

Using the aircraft operating cost estimates in Table 3, the fleet assigner in the D^3 module calculates the total aircraft operating costs of a leg-pair by combining the block hour costs of its separate legs. This mimics the combination of RTC estimates of the constituent legs. The total block hour cost or aircraft operating cost of a leg is its block time (as calculated in the construction of Network D^3) multiplied by the block hour cost of the aircraft assigned to it. Hence, the assigner described in Section 5.1.1 now has estimates of both incremental costs and revenues associated with each swappable leg-pair and the aircraft that can be assigned to them.

5.4. The Experiments

The fleet assigner is used in a variety of experiments in all subsequent tests. As with bookings-based swapping, demand driven dispatch with optimized swapping is tested at multiple times during the booking process. D^3 is also be tested at a variety of demand levels and in a variety of competitive scenarios. It is tested with EMSRb, DAVN, and DAVN with hybrid forecasting and fare adjustment. Notably, in each of these cases the assignment process for demand driven dispatch will estimate revenue in close coordination with the RM system being used—using the direct output of the RM system.

Demand driven dispatch is also be tested with the objective of revenue maximization and operating profit maximization. The new assigner allows for the estimation of block hour costs by aircraft type such that the additional revenue benefits of an up-gauge can be weighed against the additional costs of flying larger aircraft. In tests of revenue maximizing swaps, operating costs will still be calculated and operating profit reported, but the assigner will ignore the cost implications of swaps. It will be illustrative of how ignoring costs in when implementing demand driven dispatch, as is customary in revenue management, is no longer prudent when changes in capacity are possible and causal to changes in operating costs. The results of test demand driven dispatch with various RM systems and competitive network environments, as well as varying the timing of demand driven dispatch, will be shown in Chapter 6.

In Chapter 7, sensitivity testing of the results of demand driven dispatch is performed. The primary points of sensitivity testing will be the varying system demand levels, optimization of the original static fleet assignment, and the level of demand variability.

In conclusion, the network optimization fleet assignment process discussed in this chapter meets several goals for the subsequent tests in demand driven dispatch. It estimates the incremental revenue gains of swaps using detailed information directly from the RM systems. It also estimates and utilizes incremental operating costs with the ability to perform swaps to maximize revenue and operating profit. The assigner is flexible enough to incorporate direct costs of swapping as will be used in sensitivity testing. Last but not least, it represents a practical and non-greedy approach to optimizing the network fleet assignment in the context of demand driven dispatch.

Chapter 6: D^3 with Optimized Swapping

In Chapter 6, the results of a range of D^3 experiments are shown and discussed. As opposed to the D^3 implementations in Chapter 4, the aircraft scheduling component of D^3 in these experiments use a revenue or operating profit maximizing minimum-cost flow optimization, as described in Chapter 5. This specification of the aircraft scheduling problem within D^3 not only overcomes the suboptimal assignments due to the aggregation of legs, it allows the comparison of expected revenue to expected costs and therefore the maximization of operating profits—an important capability when capacity is not constant.

The layout of Chapter 6 mimics the layout of Chapter 4, except for different areas of focus in the outcomes. With bookings-based swapping, the broad trends of demand driven dispatch have been explored. Now, with revenue and operating profit maximization, greater attention is paid to the subtle effects of differences in demand driven dispatch based on the revenue management system and its valuation of future demand, as well as a closer look at the effects of demand and competitive dynamics. The first set of experiments involves implementing demand driven dispatch at different times during the booking period but this time with different RM systems. The second set of tests takes a closer look at the competitive dynamics of D^3. These tests give a thorough understanding of the effects of demand driven dispatch in a competitive network environment with revenue management, optimizing revenue or operating profit using the direct and full outputs of the RM systems themselves.

6.1. Timing the Swaps

As shown previously, the timing of the implementation of D^3 is very important to the outcome, in light of the feedback effects in revenue management and the direct effects of pricing restrictions. Therefore, the first set of tests with the new fleet assignment optimization implements D^3 at a full range of times throughout the booking process. Fundamentally, adding capacity to a flight leg opens availability to the lower fare classes. When capacity is added to high demand flights, the number of bookings increases but yield decreases. If the additional capacity is added early in the booking process, the lowest fare classes are likely to be made available by the RM system and will be available given advance purchase restrictions. Late in the booking period, additional capacity cannot be allocated by the RM system to the lowest fare classes, as their advance purchase restrictions prevent them from being sold. Thus, prior to the setting in of advance purchase restrictions, demand driven dispatch results in greater bookings and simultaneously significant dilution. After advance purchase (AP) restrictions begin to set in, the increases in bookings becomes smaller, dilution is diminished, and, in extremely late implementations, yield increases.

Figure 50 displays when demand driven dispatch is implemented in these experiments. D^3 is implemented at every other time frame (TF) in the booking process ranging from TF2 to TF14. As the days to departure decrease (approaching TF16), time frames become shorter in terms of days. Near the beginning of the booking period, TF1, TFs are more dispersed.

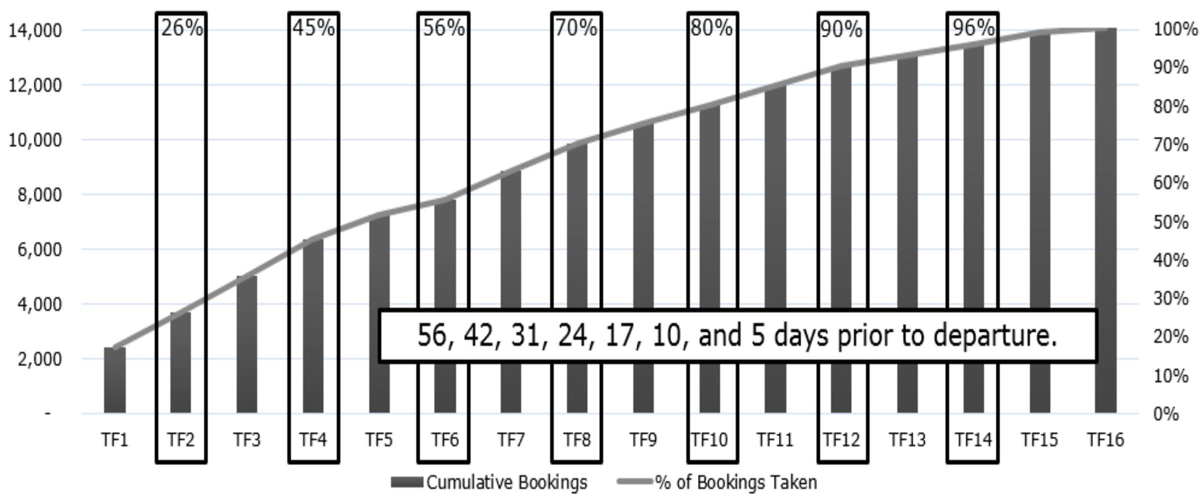

Figure 50: Times of the Optimized Swaps

TF2 is 56 days prior to departure, 63 days prior being the beginning of the booking period. TF4 through TF14 are 42, 31, 24, 17, 10, and 5 days prior to departure, respectively. On average, 26% of the total bookings at departure arrive by the end of the TF2. This percentage increases to 96% of bookings having arrived by the end of TF14, or 5 days prior to departure.

Importantly, the implementations also fall on both sides of the AP restrictions that come into effect 21 days prior to departure, squarely between TF8 and TF10, 24 and 17 days prior to departure. TF14, 5 days prior to departure, is after the 7-day AP on Fare Class 3 (FC3) and just before the 3-day AP on FC2—thus any additional capacity assigned to a flight leg in TF14 is allocated to FC1 and FC2 only.

6.1.1. Timing Swaps with Leg-Based RM

First, demand driven dispatch is implemented with EMSRb-based RM being used at both airlines with standard forecasting. Only Airline 1 implements demand driven dispatch, and D^3 is performed only once during the booking period at a set time frame as stipulated previously in Section 6.1. In addition to testing D^3 at each of the set time frames, the experiments test D^3 with either the revenue optimizing objective function or the operating profit maximizing objective function. In both cases, it is either expected revenue to come or expected operating profit to come that is optimized, with the estimates for revenue to come being identical to what the RM system estimates.

In the fleet optimizer, operating profit is defined as follows: revenue contribution minus aircraft operating costs. Note that the operating profit that is reported from here on is not the same as total system revenue (which included an additional 40% of non-aircraft operating expenses when scaling costs).There are of course many ways to define flight leg profitability, as discussed in Baldanza (1999) and others. None of them are perfect as both costs and revenues must be (arbitrarily) allocated to legs. Considerations as to whether or not a decision is short-term or long-term are also important as to what costs should be included. For the sake of simplicity, block hour costs are the only costs used. They include fuel costs, crew costs, allocated maintenance costs, and allocated ownership costs. Aircraft operating costs are the most relevant costs as they depend the most on what flight leg an aircraft is ultimately assigned to fly. Costs associated with airport servicing, etc. will likely be less dependent on D^3, as all aircraft and all airports will experience the same number of operations with aircraft of the same type. Therefore, these costs are less relevant when the optimization technique is considering only incremental costs. Variable passenger service costs are relevant because D^3 increases RPMs significantly. However, for simplicity, these costs are ignored, as is customary with revenue management itself.

With leg-based RM, the fleet assignment component of D^3 uses revenue-to-come estimates including full network contribution. Meanwhile, DAVN uses revenue-to-come estimates with full network contribution minus the deterministic displacement costs generated by the RM system. Therefore, in both cases, the revenue estimates have double-counting, albeit DAVN less so. This is not unusual for short-term profitability assessments of individual flight legs, but it has consequences for the resulting fleet assignments. Incremental revenue gains will be of larger magnitudes than incremental cost reductions when revenue is double-counted. Therefore, when DAVN revenue estimates account for displacement costs, the cost reduction component of the optimization has more sway over the ultimate fleet assignment. In conclusion, all fleet optimizations use a comprehensive definition of flight leg revenue and cost, an important factor that alters the outcome of D^3.

Table 5 displays the first results of the D^3 timing tests. Out of the swappable set of flight legs, between 46.36% and 23.67% were ultimately subject to swap depending on time frame and the objective function. The earlier demand driven dispatch is implemented, the more flight legs are swapped. The later D^3 is implemented, the fewer flight legs are swapped. This matches the results from bookings-based swapping. It is also an intuitive result: the later in the booking period, more of the higher-than-expected demand has already been rejected by the RM system and more flights are already capacity, disallowing swaps.

Table 5: Percentage of Swappable Flights that Experienced Swaps, EMSRb

	TF2	TF4	TF6	TF8	TF10	TF12	TF14
Revenue-Max.	46.36%	47.17%	46.91%	43.96%	31.59%	25.78%	23.67%
Profit-Max.	46.18%	47.00%	46.64%	43.56%	31.51%	25.58%	24.12%

Beyond the observed trends that fewer swaps take place later in the booking period, it is also worth noting that the revenue-maximizing objective and operating profit-maximizing objective used for D^3 result in a remarkably similar number of aircraft being swapped. The greatest difference is when swaps take place at TF8, but here the difference is still only 0.40% of swappable aircraft.

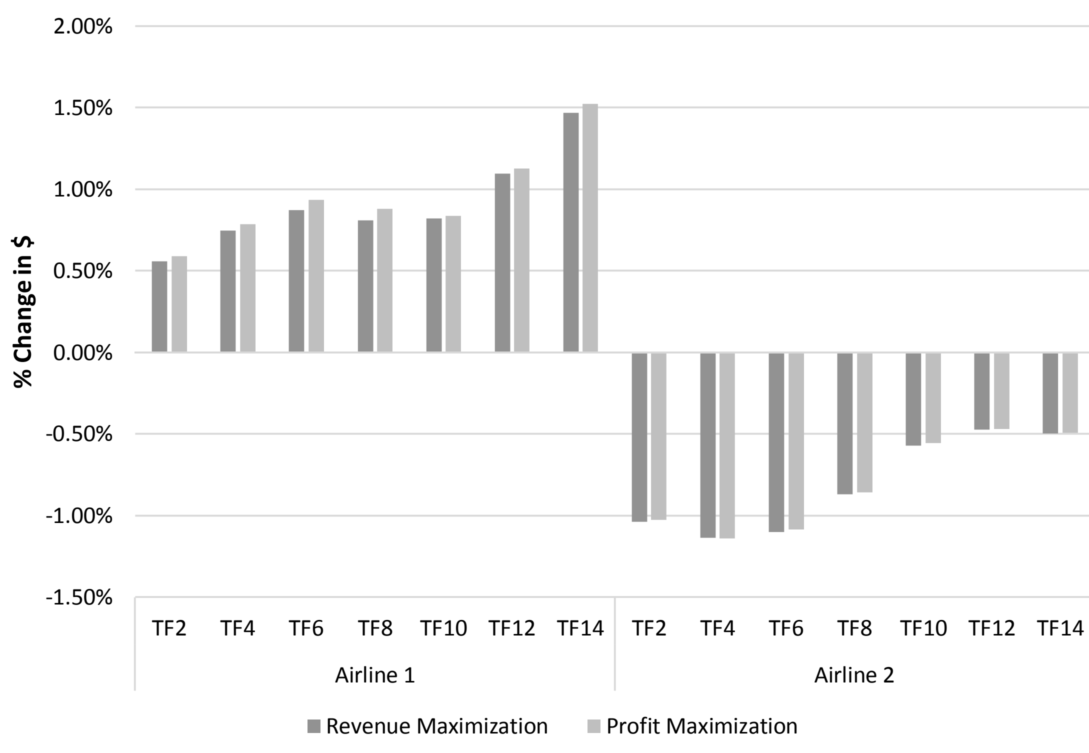

Figure 51: Changes in Operating Profit, Optimized D^3 with EMSRb

Figure 51 shows the changes in operating profit for Airline 1 and Airline 2 when demand driven dispatch is implemented at each TF. For each TF, the first bar shows the results of D^3 with the revenue-maximizing objective function and the second bar shows the results of D^3 with the operating profit-maximizing objective function. Note that there is no clear difference between the effects of D^3 on Airline 2 given the objective function. However, note that the operating profit-maximizing objective function uniformly produces better results for Airline 1 than the revenue-maximizing objective function. The incremental gains of using an operating profit-maximizing objective function over the revenue-maximizing objective function is small, ranging from 0.02% to 0.07%, but statistically significant.

The operating profit of Airline 1 increases between 0.56% and 1.52% depending on the objective function and TF. As stated above, the operating profit-maximizing objective function uniformly performs better. With this objective function, the gains for Airline 1 peak in two places: TF6 at 0.93% and TF14 at 1.52%. This distribution mimics the revenue results of D^3 with the bookings-based swapping. The distribution is in fact largely driven by changes in revenue, and these changes also mimic the results of bookings-based swapping. Figure 52 displays the changes in revenue.

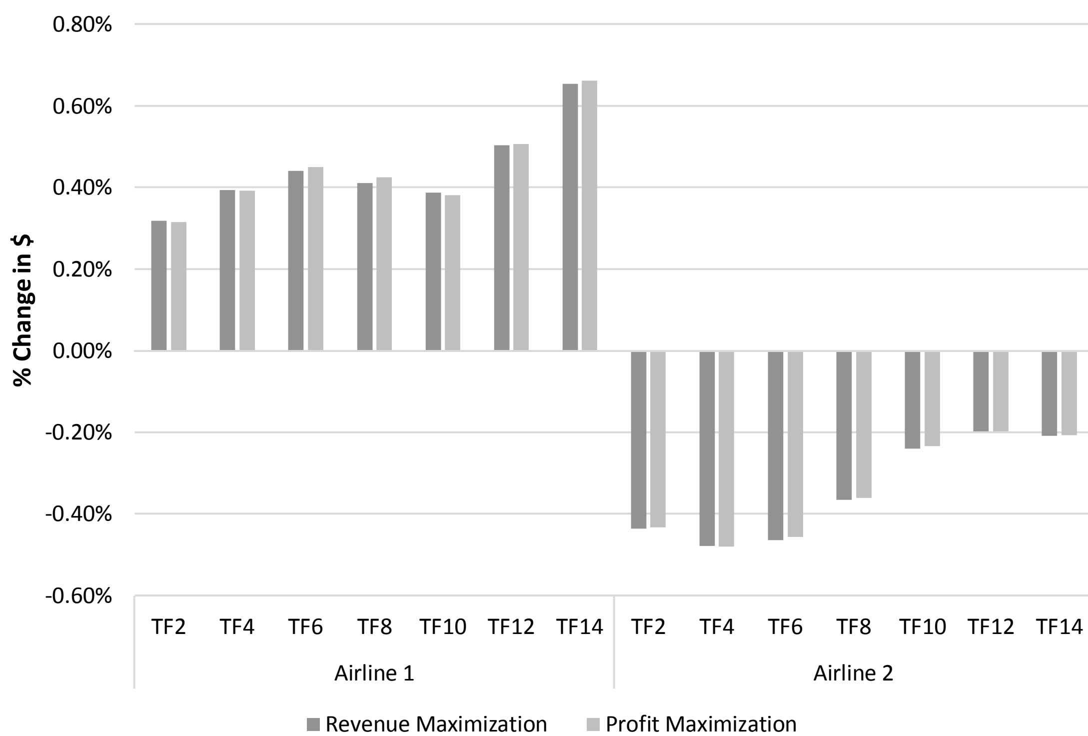

Figure 52: Changes in Revenue, Optimized D^3 with EMSRb

Airline 1's changes in revenue are similar in magnitude to those from bookings-based swapping until later TFs when optimized fleet assignment begins to outpace bookings-based swapping significantly. In TF2, Airline 1 sees a revenue gain of 0.31% or 0.32%. Revenue-maximization performs better. At TF14, Airline 1 sees a revenue gain of 0.65% or 0.66%, with operating profit-maximization performing better. The revenue gain of 0.66% in TF14 is greater than its bookings-based swapping counterpart at 0.54%. In fact, at all TFs, the optimized fleet assignment with either objective function increases revenues more than bookings-based swapping.

As was the case with bookings-based swapping, revenue gains and hence operating profit gains have a bimodal distribution peaking at TF6 and TF14. TF6 benefits from Fare Class 6 still being available and from being timed such that plenty of demand has not yet arrived and can take advantage of the lowest fare class but not so much so that dilution overcomes increases in bookings. Thus, as D^3 is implemented approaching TF8, it is still possible for additional capacity to be sold in large numbers to price-sensitive passengers. Dilution occurs but large increases in bookings offset this dilution. After FC6 is closed by AP rules, the gains of D^3 can no longer include the additional revenue from this large increase in lower fare class bookings. However, as more AP restrictions set in, revenue gains increase dramatically. The greatest increase in revenue is in TF14. At this point, the vast majority of demand has already booked or declined to book. Yet, by increasing capacity on high demand flights and thereby allowing just a few more bookings in the highest fare classes, these high yield bookings result in a greater revenue benefit than all earlier implementations of D^3.

Note another important result of these experiments when contrasting the revenue results of revenue-maximization and operating profit-maximization: both have very close results, in several cases being within 0.01%pts of each other. One might expect that the operating profit-maximizing objective function would compromise revenue gains in order lower operating costs. This is not the case, however. It is not clear as to which increases revenue more. As will be shown with changes in RPMs and yield, profit-maximizing swaps result in slightly fewer additional RPMs and slightly less of a decline in yield. In the base case, Airline 1 benefits from less low fare availability and therefore not allocating as much additional capacity to some high demand flights may prevent dilution and therefore result in uncompromised revenue gains. It is also the case that both types of optimization objective result in similar swap decisions—especially with the double counting of revenue inherent in giving each leg full network contribution, revenue maximization overrules cost-minimization.

Finally, the results shown in Figure 51 and Figure 52, changes in operating profit and revenue respectively, uncover another interesting result. In later implementations, Airline 1 gains significantly for both revenue and operating profit. Airline 2 loses approximately one third as much as Airline 1 gains in percentage terms. In TF14 with operating profit-maximizing D^3, the two airlines combined see a 0.55% increase in operating profits. In early timeframes, however, Airline 2 loses more than Airline 1 gains. For example, in TF4 with operating profit-maximizing D^3, the two airlines combined see a *decrease* in operating profits of 0.14%. When D^3 is implemented early and Airline 1 captures additional demand at the expense of yield, Airline 1 sees significant benefits but the industry actually sees *losses* due to the implementation of demand driven dispatch.

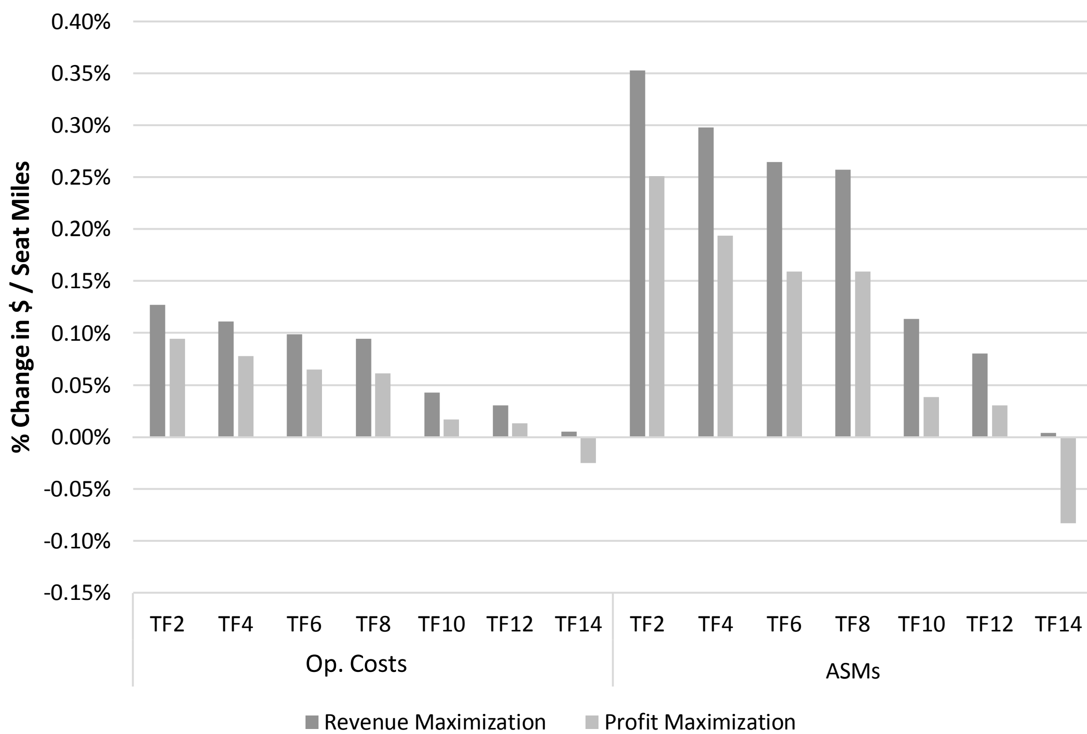

Figure 53: Changes in Op. Costs and ASMs, Optimized D^3 with EMSRb

Having looked at changes in revenue, the other component to changes in operating profit is changes in block hour costs. Figure 53 shows changes in block hour costs as well as changes in ASMs for Airline 1. Airline 2 sees no changes, as its fleet assignment is static. Note the direct relationship between changes in ASMs and changes in block hour costs. When larger aircraft fly longer distances, total block hour costs and ASMs increase. This is what happened in all but TF14. The increases in ASMs and block hour costs are to be expected, especially in the early time frames—longer routes have higher fares and therefore more incremental revenue potential. In later TFs, forecasted bookings to come often drop below capacity and therefore the incremental gains of up-gauging become zero or negative in the case of operating profit-optimization. Hence, in TF14 with operating profit-maximization, ASMs and block hour costs drop.

Figure 53 also shows another important result. Comparing the changes in ASMs and block hour costs between revenue-maximizing D³ and operating profit-maximizing D³, operating profit-maximizing D³ uniformly increases ASMs less than its counterpart by approximately 0.10%. This is because recognizing the costs of more ASMs causes the fleet assignment component of D³ to be more judicious when up-gauging. However, in the early time frames, operating profit-maximizing D³ still increases ASMs by as much as 0.25%, meaning that the fleet assignment model is consistently considering revenue potential from up-gauges to be greater than cost increases. This is the case until TF14, when forecasted bookings to come are low and ASMs decrease by 0.08%, block hour costs by 0.02%.

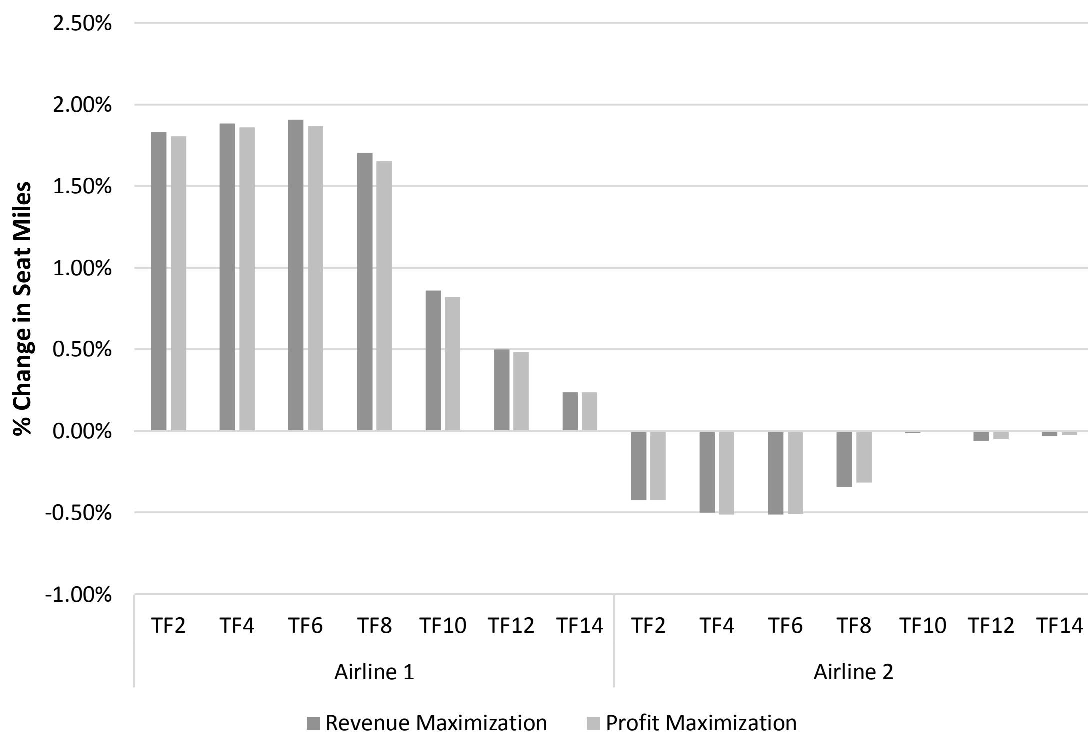

Figure 54: Changes in RPMs, Optimized D³ with EMSRb

Changes in RPMs are the counterpart to changes in ASMs. While Airline 1's ASMs increased by as much as 0.35%, RPMs increased by as much as 1.91% in TF6, as shown in Figure 54. This implies an increase in load factor (1.28 % pts) but also a significant increase in captured demand. Airline 2 sees modest decreases in RPMs in the early TFs of about

0.5% while Airline 1's gains in RPMs are near 2%. Therefore, most of the additional bookings are not taken from Airline 2 but are rather passengers who previously did not fly. The later the implementation of D^3, the less of an increase in RPMs Airline 1 experiences and the less of a decrease Airline 2 experiences. In TF 14 with operating profit-maximizing D^3, Airline 1's ASMs decrease by 0.08% but its RPMs still increase by 0.24%.

These changes in RPMs and ASMs result in large increases in load factor, as shown in Figure 55. Between TFs 2 and 8, load factor increases by about 1.2 to 1.4 percentage points. These increases are notably less from TF10 on as demand has already been rejected and AP restrictions have set in. As Airline 2's ASMs did not change, its changes in LF are a scalar function of its changes in RPMs. Also note that, as operating profit-maximizing D^3 resulted in slightly smaller increases in RPMs but significantly smaller increases in ASMs, load factor increases are larger with operating profit-maximizing D^3.

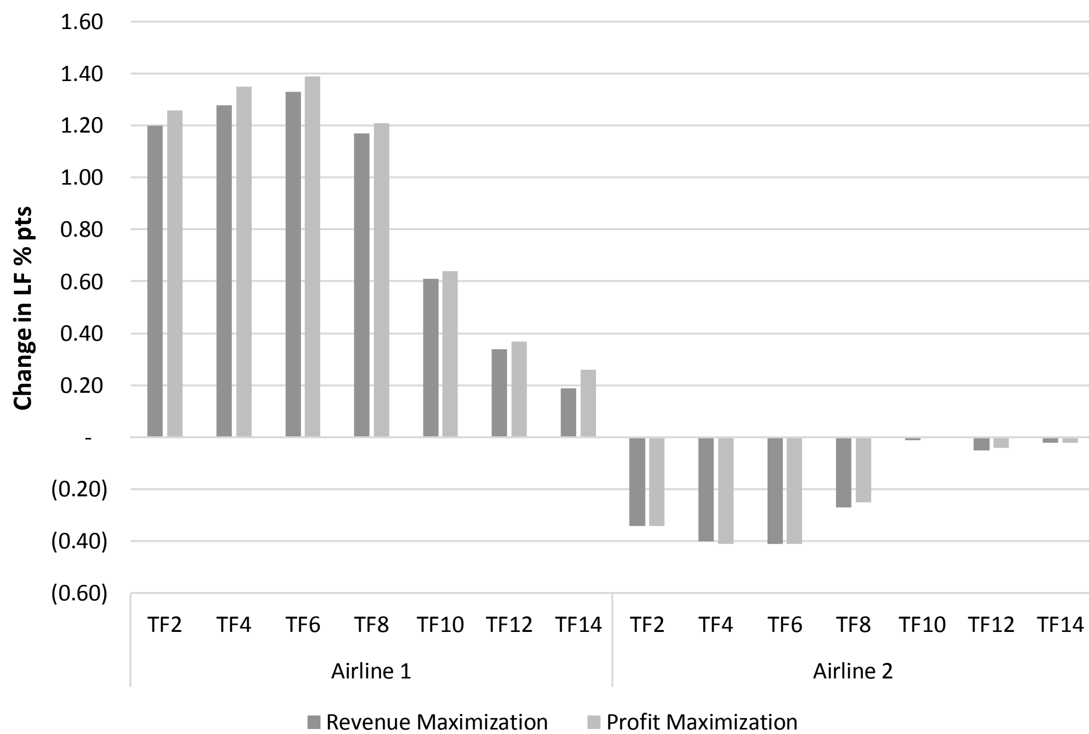

Figure 55: Changes in LF % pts, Optimized D with EMSRb

As was the case with bookings-based swapping, however, the large increases in RPMs and load factor in the early time frames comes at a cost. Yield decreases substantially as the additional capacity added to high demand flights increases availability and bookings in the lowest fare classes.

Figure 56 displays changes in yield for Airline 1 and Airline 2 as Airline implements demand driven dispatch at each time frame. With the exception of TF6, there is virtually no difference in changes in yield between revenue-maximizing D^3 and operating profit-maximizing D^3. Therefore, while the revenue-maximizing objective function for D^3 results in a slightly larger increase in RPMs, it does not have a notably different effect on yield as compared with operating profit-maximization.

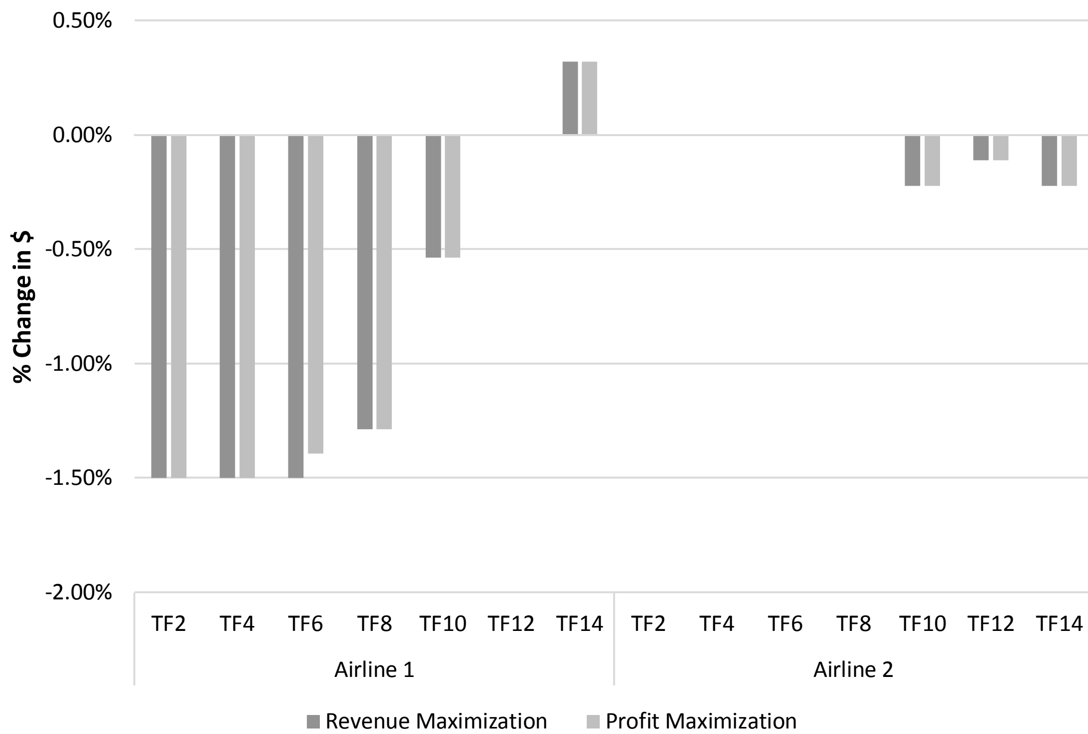

Figure 56: Changes in Yield, Optimized D^3 with EMSRb

As expected, Airline 1's yield declines significantly in the earliest TFs and then begins to decrease less, especially after TF 8 when AP restrictions set in. In TF 14, just as with bookings-based swapping, yield actually increases. This again illustrates the importance of considering pricing and RM and how they interact with demand driven dispatch.

Also note in Figure 56 that Airline 2's yield does not change until the implementation of demand driven dispatch by Airline 1 in the latest time frames. This is in contrast to bookings-based swapping where Airline 2 experienced relatively constant decreases in yield when Airline 1 engaged in D^3 at any time frame. It is also notable that Airline 2 does not experience declines in its yield in the earlier time frames despite these earlier time frames being when it sees the greatest decrease in its revenue and operating profits. Therefore, the decreases in revenue and operating profit for Airline 2 in the earliest TFs can be attributed solely to lost RPMs (or market share) while the decreases in revenue and operating profit in the later time frames can be attributed more so to decreased yield.

This also suggests that while Airline 1 sees significant dilution from gaining many low fare bookings, what bookings Airline 1 is taking away from Airline 2 are coming from all fare classes in Airline 2, such that Airline 2's yield changes very little. Thus as some high yield passengers from Airline 2 are purchasing low fare tickets on Airline 1 instead, this explains why in the earliest time frames demand driven dispatch can lower the overall industry revenue and operating profit while benefiting the airline implementing D³.

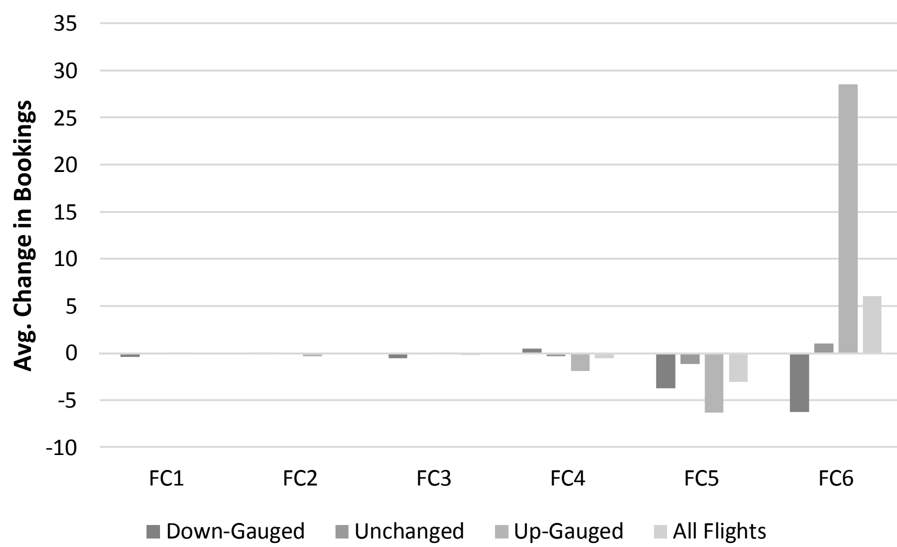

Figure 57: Changes in Bookings by FC, Optimized D³ with EMSRb at TF6

Figure 57 shows Airline 1's changes in bookings by fare class depending on swap type when Airline 1 implements operating profit-maximizing D³ at TF 6, the pre-AP restriction peak 31 days prior to departure. The average up-gauged flight sees an increase of roughly 28.6 bookings in FC6. The average up-gauge is by 27.2 seats. How is the average increase in FC6 bookings greater than the average increase in seats? Just as with bookings-based swapping (see page 56), early implementation of D³ result in spiral down. Note that while up-gauged flights see large increases in FC6 bookings, they also see notable decreases in FC4 and FC5 bookings. As the availability for FC6 is increased, passenger who would have otherwise sold up to FCs 4 and 5 are able to purchase the cheaper FC6 itineraries. Meanwhile, the higher fare classes are almost unchanged by the implementation of demand driven dispatch.

Also note in Figure 57 the continuing theme that up-gauging flights has a much larger impact on changes in bookings than down-gauging flights. Down-gauged flights lose approximately 10.5 bookings across all fare classes as compared to the base case. Compare this to the approximate increase of 20.2 bookings across all fare classes for up-gauged flights. Hence, demand driven dispatch drives large increases in load factor and it remains the case that the probability of causing spill by down-gauging low demand flights is by far trumped by the potential to decrease spill by up-gauging high demand flights.

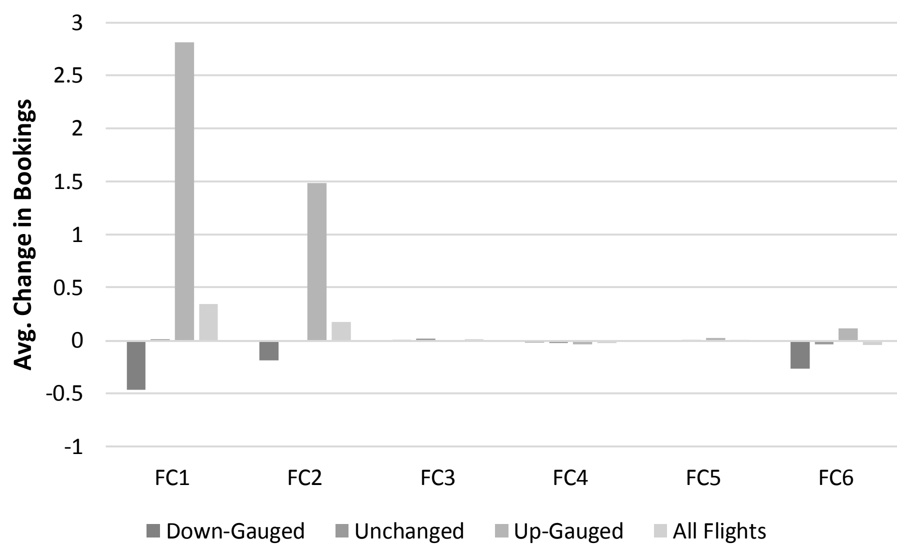

Figure 58: Changes in Bookings by FC, Optimized D³ with EMSRb at TF14

Figure 58 also shows Airline 1's average changes in bookings by fare class and by type of gauge-change when operating profit-maximizing demand driven dispatch is implemented by Airline 1, although now demand driven dispatch is implemented at TF14. TF14 is the best performing time to implement D³ and is only 5 days prior to departure. The same patterns emerge as with bookings-based swapping—down-gauging has little effect on bookings while up-gauging causes increased bookings in FC1 and FC2, the only open fare classes 5 days prior to departure and on. Rather than a very large increase in bookings as was the case in TF 6, however, the largest increase is only roughly 2.82 bookings in FC1 on up-gauged flights, about one tenth the increase in bookings in FC6 in TF6. Yet, the higher fares in FC1 and FC2 mean that even with far fewer additional bookings, the revenue increase and therefore operating profit increases are much greater for Airline 1 with TF14 implementation of D³.

In conclusion, testing demand driven dispatch with an EMSRb-based RM optimization and standard forecasting at different time frames results in very consistent findings.

Both revenue-maximizing and operating profit-maximizing fleet assignment uniformly outperform bookings-based swapping. Profit-maximizing fleet assignment uniformly outperforms revenue-maximizing fleet assignment.

The operating profit-maximizing objective function doesn't lead to compromised revenue results while it does result in lower operating costs and therefore higher operating profits. Across the time frames, revenue-maximization overwhelms cost reduction, however, as evidenced by both objective functions in the fleet assignment process leading to increases in ASMs and block hour costs in the earlier time frames when lots of additional demand can be captured by re-allocating demand.

As was the case with bookings-based swapping, up-gauging results in much larger increases in bookings than down-gauging leads to decreases in bookings. In the early time frames, increases in bookings are almost entirely in FC6 and spiral down occurs. In the later time frames, AP restrictions force all increases in bookings to accrue to FC 1 and FC 2, resulting in fewer additional bookings but more additional revenue and operating profit.

Operating profit increases between 0.56% and 1.52%. Revenue increases between 0.31% and 0.66%. Block hour costs change from between -0.02% and 0.13%. Thus, even though Berge and Hopperstad (1993) suggested that a large proportion of the gains of D^3 comes from cost reduction, these simulations suggest that in fact the vast majority of gains are revenue gains, albeit this is highly dependent on the RM system used, network structure and competition, and the typical system load factor.

6.1.2. Timing Swaps with DAVN

Section 6.1.2 follows the same format as Section 6.1.1. The same experiments are run, testing the implementation of revenue-maximizing and operating profit-maximizing demand driven dispatch at various time frames, except that rather than using EMSRb-based optimization for RM both Airline 1 and Airline 2 use DAVN with standard path class forecasting for their RM systems. The fundamental difference is that both airlines now control their availability by OD rather than by leg. DAVN subtracts displacement costs from each connecting itinerary and then maps said itineraries to virtual buckets that are controlled by leg. Further details and references can be found in Section 2.2.2.

Again, the base case is that neither airline engages in demand driven dispatch. In the alternate cases, Airline 1 alone implements demand driven dispatch at one of seven time frames: TF2, TF4, TF6, TF8, TF10, TF12, and TF14. These correspond to 42, 31, 24, 17, 10, and 5 days prior to departure, respectively. The first results from implementing demand driven dispatch with optimized fleet assignment and DAVN are in Table 6.

Table 6: Percentage of Swappable Flights that Experienced Swaps, DAVN

	TF2	TF4	TF6	TF8	TF10	TF12	TF14
Revenue-Max.	51.83%	51.19%	48.75%	45.12%	27.56%	23.04%	26.79%
Profit-Max.	51.18%	50.64%	48.52%	44.58%	27.27%	22.36%	24.82%

The results are similar to those when EMSRb-base optimization was used by both airlines. More swaps take place in the earliest timeframes and then the number of swaps drops dramatically after TF8 when AP restrictions set in. At the outset, more swaps take place with DAVN as opposed to previously with EMSRb. Finally, the pattern holds that operating profit-maximizing demand driven dispatch uniformly results in slightly fewer swaps at all time frames.

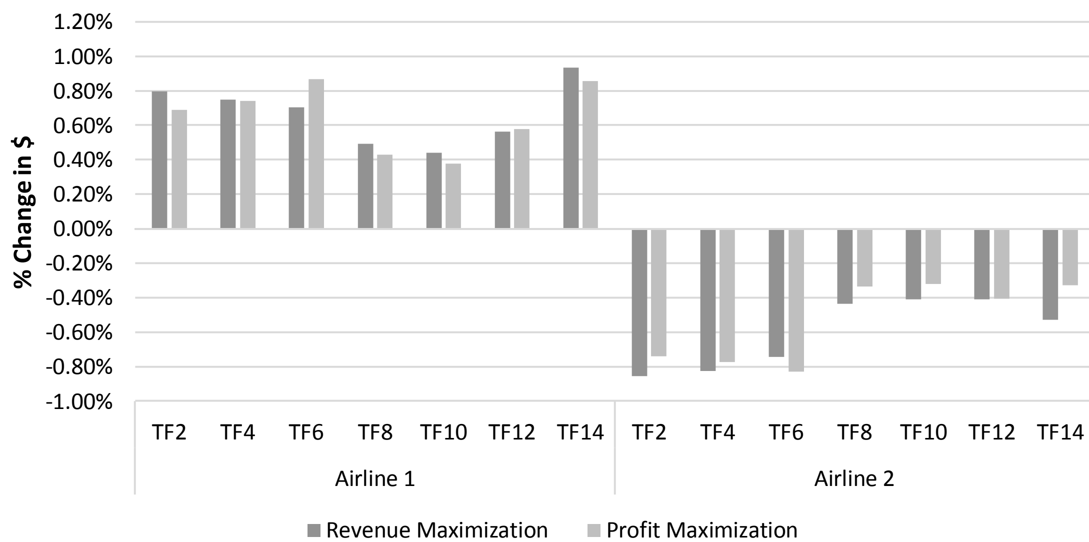

Figure 59: Changes in Operating Profit, Optimized D³ with DAVN

Figure 59 shows the changes in operating profits for Airline 1 and Airline 2. Again, there is a bimodal distribution of operating profit gains for Airline 1 with peaks at TF6 and TF14. However, TF6 and TF14 now perform similarly rather than TF14 being far superior, as was the case with EMSRb. This suggests that DAVN is doing a better job of reserving seats for higher fare classes as compared to EMSRb or doing a poorer job of capturing high FC demand at the end, diminishing the gains of demand driven dispatch at the latest time frame. The gains in the earliest time frame are still as high as with EMSRb, however. Therefore, the conclusion is more nuanced than "better RM" diminishes the gains of D^3.

It is again the case that, specifically in the earliest time frames, demand driven dispatch causes Airline 2's operating profits to decrease by as much as Airline 1's improves in percentage terms. This highlights the importance of considering demand driven dispatch as a competitive action.

Interestingly, it is no longer the case that operating profit-maximizing D^3 performs better than revenue-maximization in all cases for improving operating profits. The difference is that with DAVN as the underlying RM system, the revenue results are no longer as close as they were with EMSRb. Figure 60 shows the changes in revenue from implementing demand driven dispatch. Note that with EMSRb the revenue results were consistently very close between revenue maximization and profit maximization at all time frames. Now, revenue-maximization is more effective than operating profit-maximization, with the exception of TF6, at increasing revenues. This is to be expected. Connecting itineraries now have their revenue value deducted by displacement costs—estimates of incremental revenue to come are systematically lower with DAVN than with EMSRb. Hence, incremental costs have a larger impact on the fleet assignment and operating cost-minimization ultimately *does* compromise revenue gains, as opposed to with EMSRb where it did not.

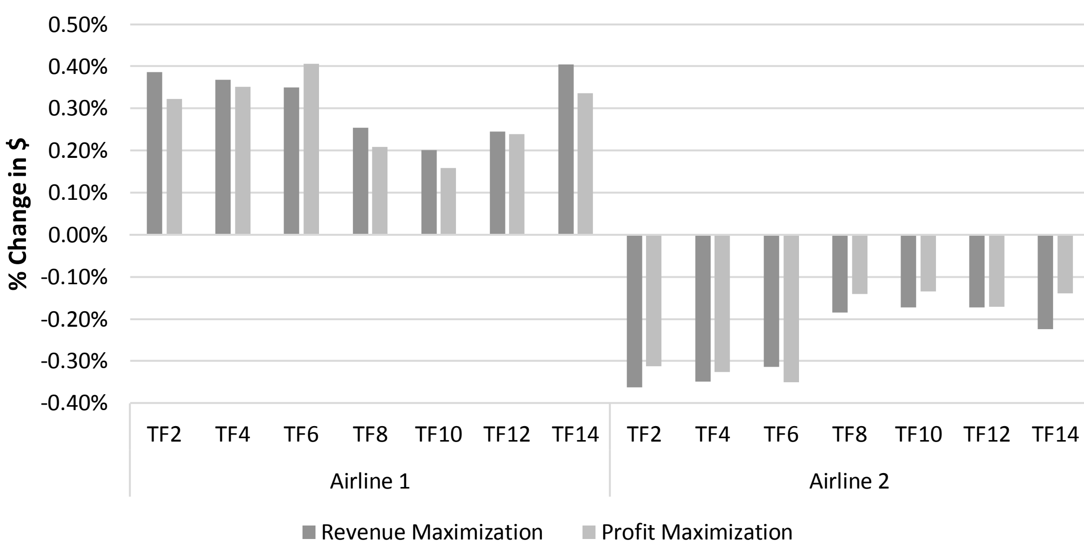

Figure 60: Changes in Revenue, Optimized D^3 with DAVN

Also in Figure 60, revenue gains in TFs 2, 4, and 6 are approximately the same as with EMSRb. Revenue gains are lower in TF14, however. This matches the results with changes in operating profits. Consistent with previous findings, Airline 2's revenue decreases by about the same as Airline 1's increases in the earliest time frames and by less in the latest time frames. This suggests that in the earliest time frames Airline 1 benefits significantly from taking demand from Airline 2 but in the latter timeframes more so from sell-up.

Figure 61 shows changes in block hour costs and ASMs. With EMSRb, only the last time frame saw decreases in block hour costs and ASMs. With DAVN, decreases begin with operating profit-maximization in TF10, 17 days prior to departure as opposed to only 5 days prior to departure. The decreases are also much larger, as much as -0.09% and -027% for block hour costs and ASMs respectively in TF14.

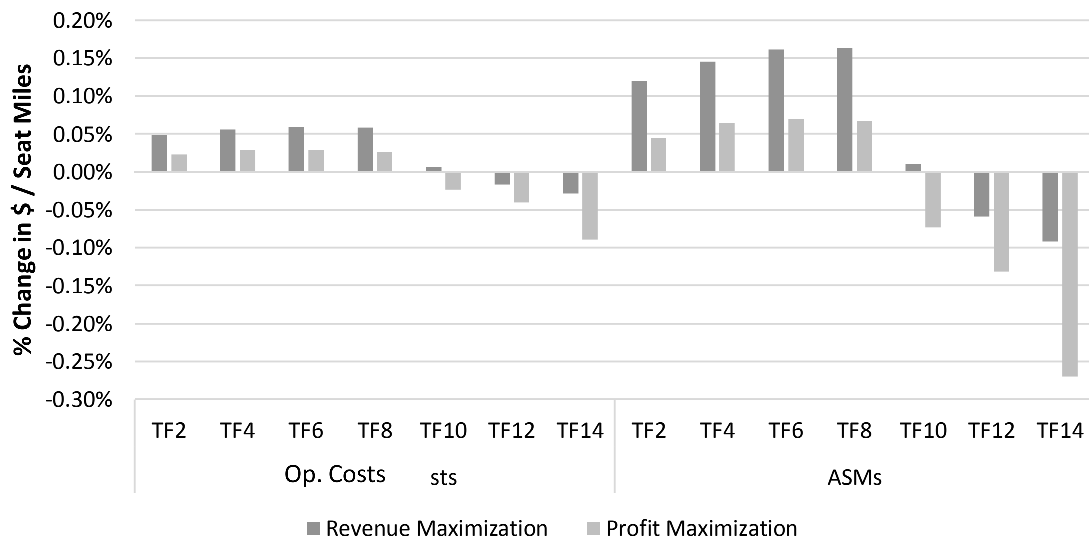

Figure 61: Changes in Op. Costs and ASMs, Optimized D³ with DAVN

As was evident with changes in revenue, cost reduction now plays a larger role in the fleet assignment. Hence, with DAVN, the difference in changes in ASMs and block hour costs between revenue-maximizing and operation-profiting maximizing D³ are larger than with EMSRb and the total reductions of both with operating profit-maximizing D³ are larger. Increases in ASMs in the earlier TF with either revenue or operating profit-maximization is predicted—longer routes have higher fares and therefore offer more incremental revenue for larger capacities.

Thus, the relationship between revenue maximization and operating cost minimization is visible in operating-profit maximization, as is the importance of the composition of the revenue estimates for each leg. Of course, the base cases of either EMSRb or DAVN have many differences, but the effect of subtracting displacement costs from the full network contribution of connecting fares on each leg is visible in differences in changes in ASMs and block hour costs.

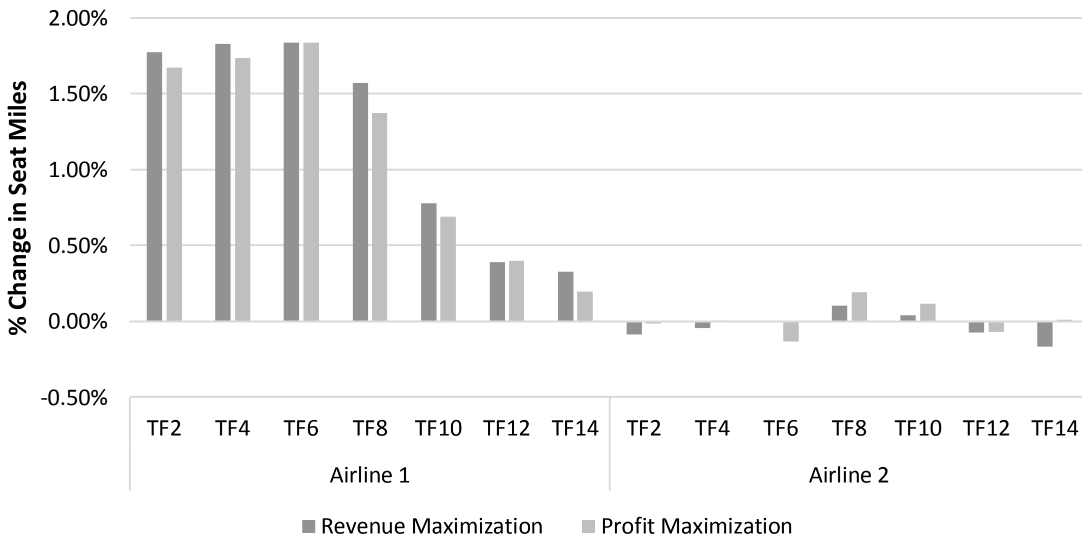

Figure 62: Changes in RPMs, Optimized D^3 with DAVN

Figure 62 shows changes in RPMs and Figure 63 shows changes in LF %pts, which are very similar given the comparatively small changes in ASMs for Airline 1 and no changes in ASMs for Airline 2.

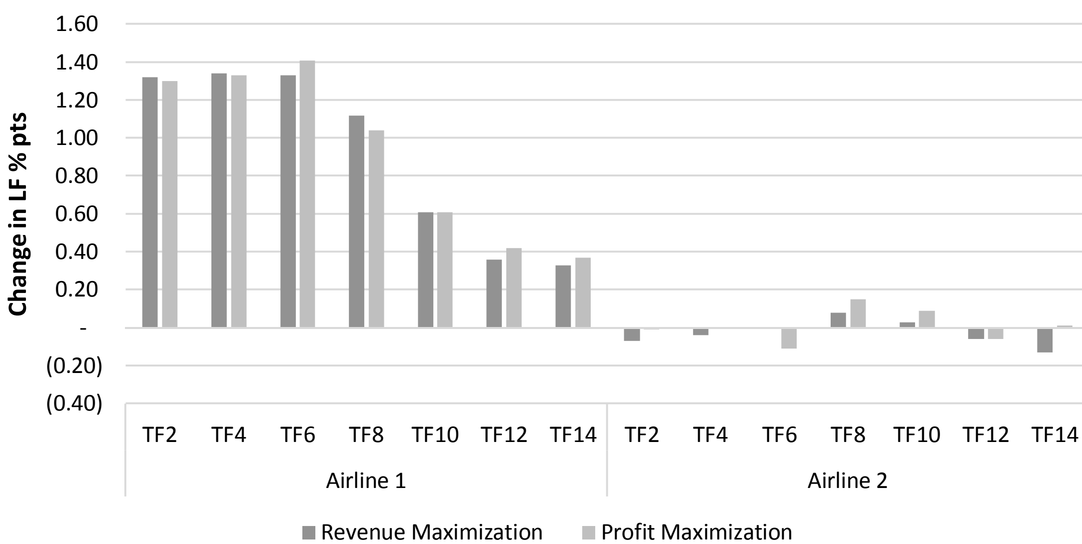

Figure 63: Changes in LF % pts, Optimized D^3 with DAVN

Changes in load factor, shown in Figure 63, and changes in RPMs, shown in Figure 62, display very similar changes for Airline 1 from D^3 with EMSRb. Increases in load factor of about 1.3 %pts occur for Airline 1 in the earliest time frames. These increases in passengers drop precipitously after TF8 when AP restrictions set in. Note, however, that Airline 1 now sees greater increases in load factor from operating profit-maximizing D^3 rather than with revenue-maximizing D^3. This is because of the larger decreases in ASMs.

The most notable difference of D^3's effects on RPMs and load factor with DAVN as compared with EMSRb is with Airline 2's results. Airline 2 is also using DAVN rather than EMSRb. With EMSRb, Airline 1's implementation of D^3 caused significant decreases in Airline 2's RPMs and load factor and left yield largely unchanged. Now with DAVN, Airline 2's RPMs and load factor are largely unchanged and instead its yield decreases, as shown in Figure 64. It would seem that the use of DAVN for Airline 2's RM system changes the nature of how Airline 1's D^3 implementation affects Airline 2's revenue. Again, the interaction of D^3 and RM is not trivial.

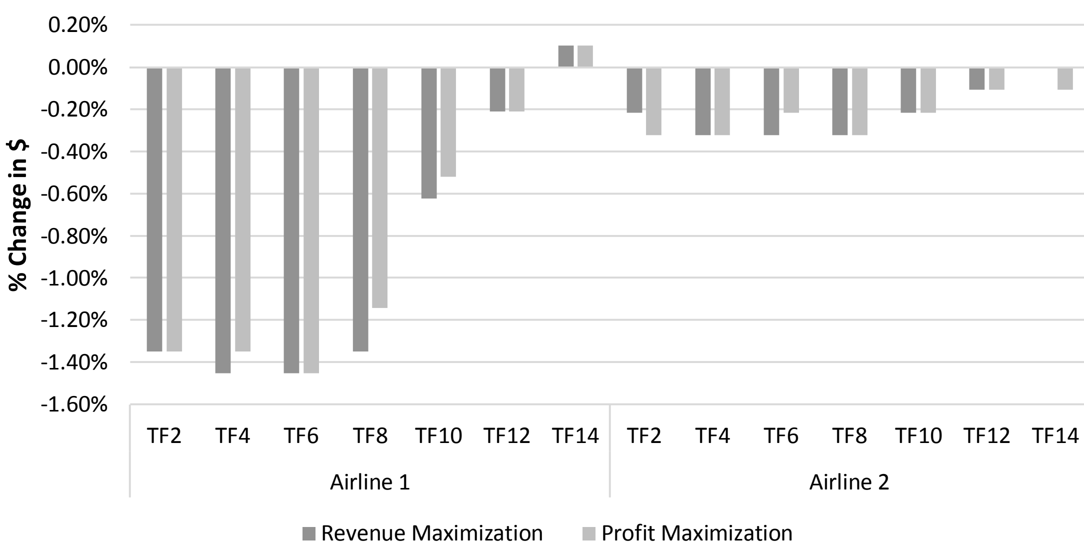

Figure 64: Changes in Yield, Optimized D^3 with DAVN

The changes in yield for Airline 1 are on the other hand very similar to those with EMSRb. The earliest implementations of demand driven dispatch result in large decreases in yield. After TF8, when AP restrictions set in, yield does not decrease as much and finally increases in TF14. Generally, operating profit-maximizing D^3 results in smaller decreases in yield as compared to its revenue-maximizing counterpart. With EMSRb, yield changes were almost identical. Now, as cost reduction plays a larger role in the fleet assignment for operating profit-maximizing D³, the differences in yield changes are more pronounced between revenue-maximizing D³ and operating profit-maximizing D³.

Underlying these changes in yield and RPMs are the same patterns in changes in bookings by swap type, as shown in Figure 65 (swaps in TF6) and Figure 66 (swaps in TF14).

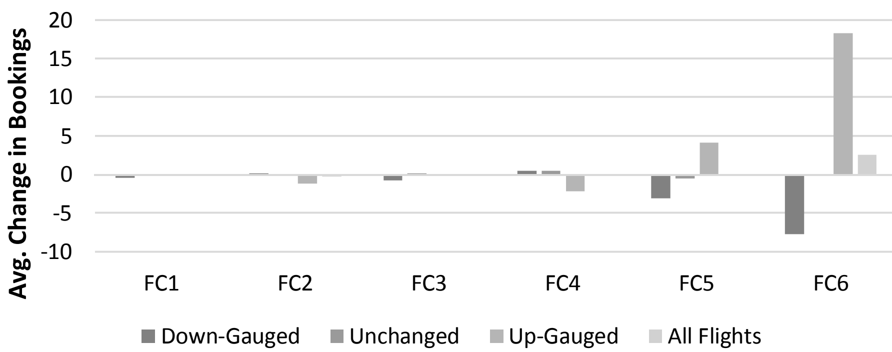

Figure 65: Changes in Bookings by FC, Optimized D³ with DAVN at TF6

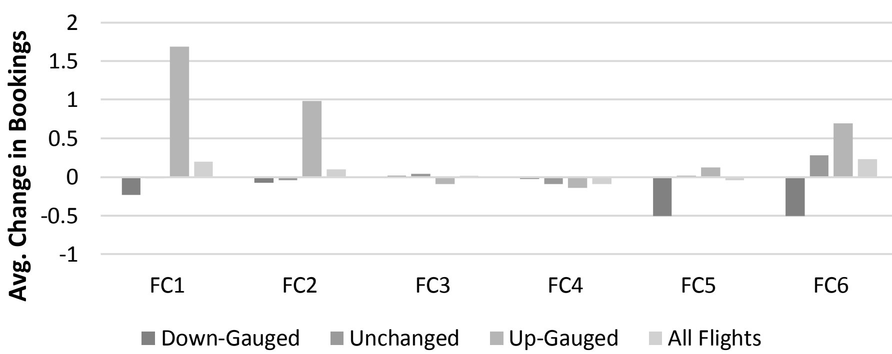

Figure 66: Changes in Bookings by FC, Optimized D³ with DAVN at TF14

As was the case with EMSRb, demand driven dispatch in TF6 results in mostly additional bookings in FC6 when flights are up-gauged. Unlike with EMSRb, rather than spiral down from FC5, FC5 bookings increase as well, signaling that again DAVN is protecting availability differently. In TF14, increases in bookings are mostly in FC2 and FC1 with up-gauged flights, leading to higher yield. These changes, however, are only one tenth the magnitude of those in Time Frame 6, as was the case with EMSRb. Some additional bookings also occur in FC6 from feedback effects (the AP restrictions prevent them from being a direct effect). The same feedback effects were present with EMSRb but there they were much smaller.

How is it that FC6 sees increases in bookings, especially on up-gauged flights, when the up-gauging takes place 5 days prior to departure when FC6 is not available? This question led to an investigation of when FC6 sees increases in bookings; as necessary, the increases in FC6 bookings take place before 21 days prior to departure. By TF8, 24 days prior to departure, on average Airline 1 has taken an additional 17.23 bookings in FC6. As a majority of these increased bookings take place on up-gauged flights, up-gauged flights must have more availability prior to TF14. Figure 67 shows the changes in the average displacement costs for the top quartile of Airline 1's fullest flights. Note that as capacity is added to the fullest flights at TF14, the average displacement cost suddenly drops. This is intuitive and explains additional bookings in FC1 and FC2 as full flights are given additional seats; it does not explain additional bookings in FC6.

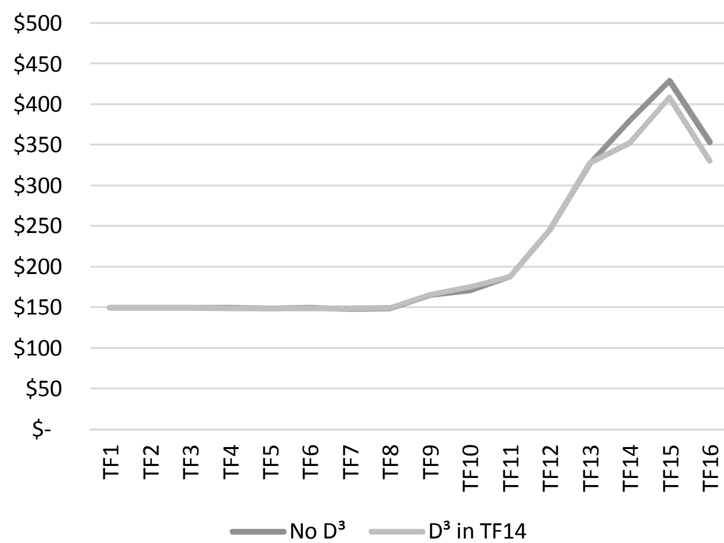

Figure 67: Change in DCs in Top Quartile of Fullest Flights from D^3 at TF14

However, the answer can be found in displacement costs in the third quartile of Airline 1's fullest flights. These flights have enough forecasted bookings to come to be on the border of DAVN's availability control closing the lowest virtual buckets, those most likely to contain FC6 itineraries. Changes in displacements costs in the third quartile of fullest flights from D^3 at TF14 are shown in Figure 68. As can be seen, these displacement costs are on average lower at the outset of the booking period. While DAVN does not use bid price control, the lower average displacement costs indicates that capacity is not, on average, as constrained, meaning the EMSRb leg-control applied within DAVN would be less likely to close the lowest virtual buckets. Lower displacement costs also imply that FC6 connecting itineraries are more likely to be mapped to a higher virtual fare class, and therefore more likely to be available.

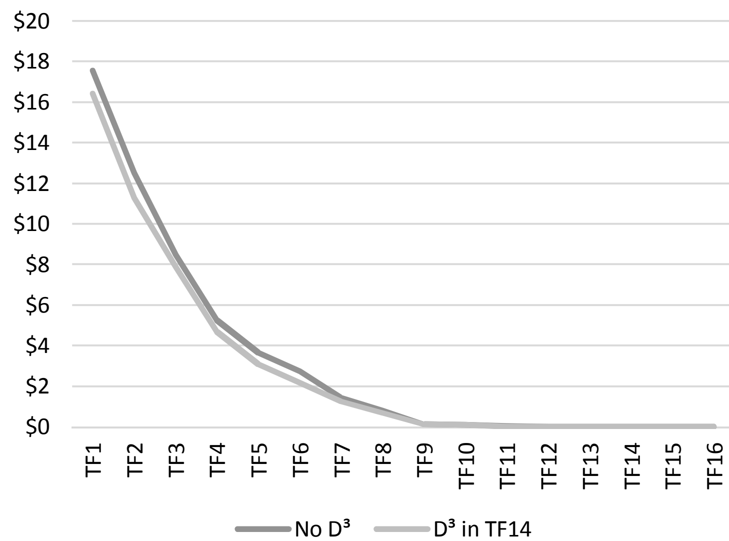

Figure 68: Change in DCs in Third Quartile of Fullest Flights from D^3 at TF14

This slight change in displacement costs explains the increase in FC6 bookings. It also explains why it predominantly occurs on unchanged and up-gauged flights—unchanged and up-gauged flights that were on the edge of being assigned larger aircraft are precisely those flights that would be most likely to fall into this quartile of flights.

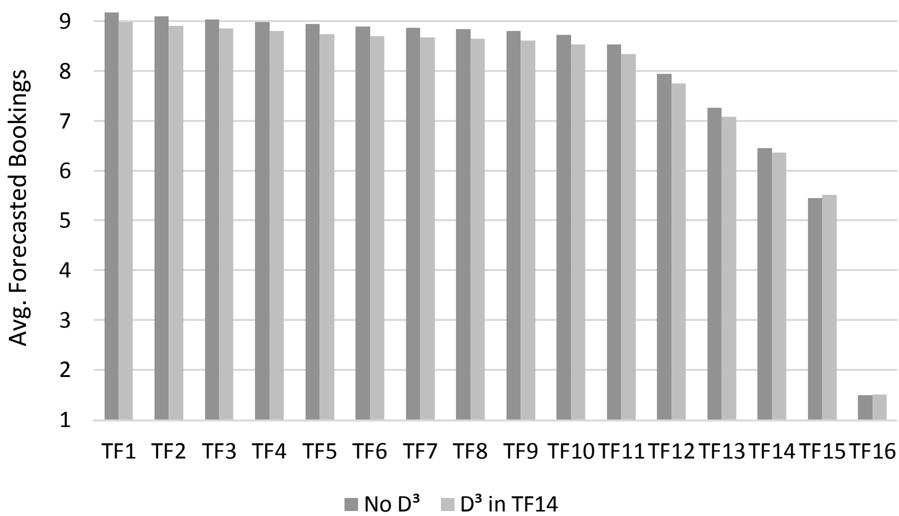

Figure 69: Changes in Forecasted BTC for FC1 with D^3 at TF14

The remaining question is why implementing demand driven dispatch would result in lower displacement costs at the beginning of the booking period. To answer this question, see forecasted bookings to come in FC1 with and without the implementation of D^3 at TF14, shown in Figure 69. It should be expected that because overall bookings in FC1 increased with the implementation of D^3, the forecasted bookings to come for FC1 should increase. This is predictably the case after TF14, when up-gauging occurs. It is *not* the case beforehand, however. Instead, the forecasted bookings to come are systematically lower.

Table 7: % Chg. in Forecasted BTC in TF1 by FC, from D^3 in TF14

FC1	FC2	FC3	FC4	FC5	FC6
-2.18%	-0.27%	-1.01%	-6.81%	-3.17%	-0.49%

The lower forecasts, while easier to see in absolute terms in FC1 due to the lower absolute forecasts themselves, are present in all six fare classes, as shown in percentage terms in Table 7. It is likely that the additional capacity added to the highest demand flights, while increasing total observed bookings, is actually inadvertently lowering forecasts for future flights. The most plausible mechanism is via unconstraining. If additional capacity is added to high demand flights in the last time frames, the affected itineraries are no longer constrained by capacity and therefore no longer subject to unconstraining. Hence, the forecasts, while made larger by more observed bookings, would ultimately be lower due to no unconstraining. Again, this highlights the (sometimes) unexpected interactions between demand driven dispatch and revenue management.

In summary, repeating the tests of timing demand driven dispatch with DAVN as the underlying RM system for both airlines confirmed the trends from tests with EMSRb. Operating profits increased from 0.38% to 0.93%. Revenues increased from 0.16% to 0.41%. Operating costs changed from between -0.09% and 0.06%. Again, revenue increases drive the operating profit increases, as was the case with D^3 with EMSRb.

There are subtle differences, however, highlighting the intricate interactions between RM and D^3. For example, while revenue and operating profit changes for Airline 1 are similar in the first TFs, in the last TFs after AP restrictions take effect there are smaller gains when Airline 1 uses DAVN as the RM system. Airline 2 loses revenue and operating profit with almost exactly the same magnitudes has it had when EMSRb was used in the RM system but through losses in yield rather than losses in RPMs. Therefore, RM systems not only effect how an airline responds to D^3 when it implements it itself, but also when a competitor implements it.

With DAVN applying displacement costs to connecting itineraries and thereby reducing the double counting of network contribution on leg revenue, cost reduction plays a larger role in fleet assignment as compared to with EMSRb. Hence, with DAVN as the RM system at both airlines, operating profit-maximizing D^3 results in less of an increase in RPMs and revenue but larger decreases in ASMs and block hour costs. This highlights the importance of carefully considering how revenue estimates are composed for D^3 (and fleet assignment in general), as when paired with costs the relative magnitude of incremental revenues and incremental costs alters the dynamic between revenue-maximization and cost-minimization.

6.2. Competitive Demand Driven Dispatch

Section 6.2 contains the results of both Airline 1 and Airline 2 implementing demand driven dispatch in competition with one another. As was seen in bookings-based swapping, the fundamental results of demand driven dispatch do not change when competition is integrated into the experiment, but changes in the magnitudes of shifts in yield and RPMs can alter the revenue and profit outcomes of implementing demand driven dispatch. Thus, demand driven dispatch is tested with both Airline 1 and Airline 2 and also at both TF6 and TF14, peak D^3 implementation times in previous tests.

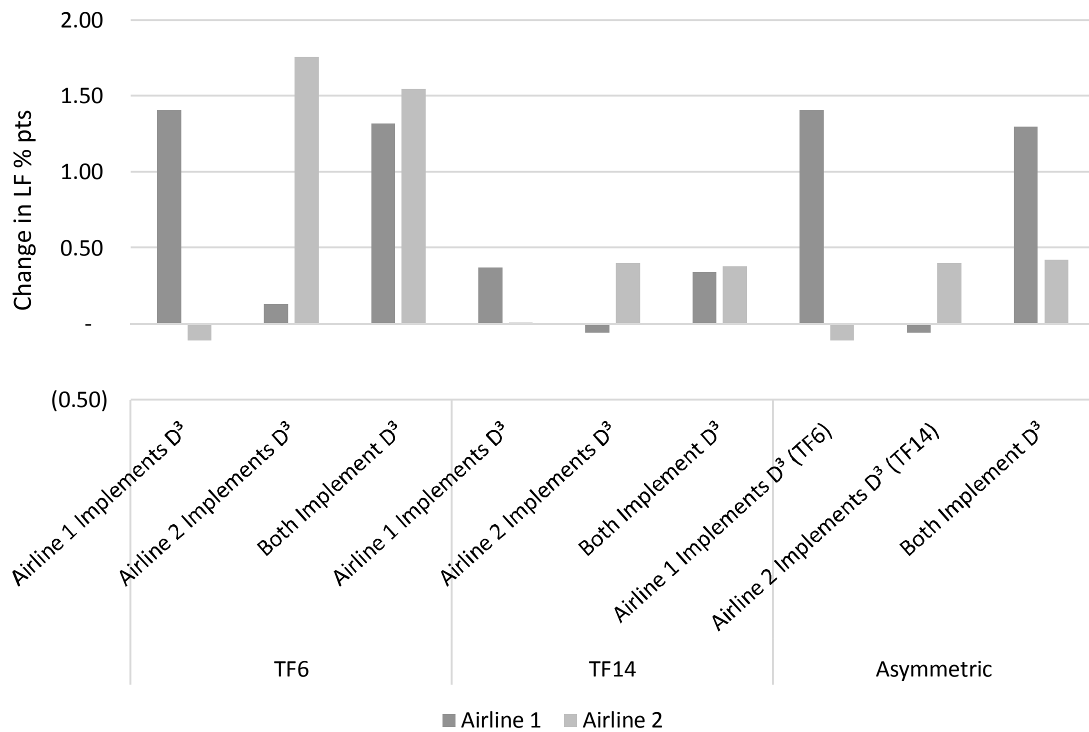

Figure 70: Changes in LF % pts with Competitive D^3

Figure 70 displays changes in load factor based on the scenarios being tested: Airline 1 implementing demand driven dispatch at TF6, Airline 2 implementing D^3 at TF6, or both implementing D^3 at TF6, the same three scenarios at TF14, and then the results when Airline 1 implements at TF6 and Airline 2 implements afterwards at TF14. In all tests, the base case is with both airlines using DAVN with standard path class forecasting and no demand driven dispatch. Then, in the alternate case, either one or both airlines implements demand driven dispatch with an operating profit-maximizing objective function at the stipulated time frames.

Patterns in load factor changes are similar for Airline 2 as they have been for Airline 1 at different time frames. When Airline 2 implements D^3 in TF6, it has a large increase in LF (+1.76%pts). When it implements D^3 in TF14, it has a smaller increase in LF (+0.40%pts). Airline 1 exhibits the same results (identical to the results of Section 6.1.2 with op. profit-maximization). Examining changes in load factor also reveals several other interesting patterns that introduce the competitive dynamics of demand driven dispatch. When Airline 1 alone implements D^3, Airline 2 sees decreases in load factor but not nearly as large in magnitude as Airline 1's increases. This is true in either TF6 or TF14. When Airline 2 alone implements demand driven dispatch, it sees even larger increases in load factor and in this case Airline 1 sees a slight increase in LF in TF6 and a slight decrease in TF14. When both implement D^3, the magnitude of LF change for both is slightly less as when they implemented D^3 alone. As seen in the previous section, demand driven dispatch implemented at one airline typically hurts the revenue and hence profits of the competitor—if LF is not highly affected, this suggests that with DAVN as the RM system what harm the D^3-implementing airline does to its competitor is via yield reductions.

To further explore the competitive dynamics of demand driven dispatch, one or both airlines implementing demand driven dispatch at TF6, at TF14, or asymmetrically at both TF6 and TF14 are tested. For all of these cases, changes in ASMs, RPMs, and yield are analyzed, providing insight into how each of the airline's implementation of demand driven dispatch affects the other. Then, the resulting changes in revenue, operating costs, and operating profit will be shown. Finally, changes in operating profit for each airline in each scenario will be placed in a game theoretic framework for a brief analysis of the competitive implications of demand driven dispatch given that airlines have flexibility in when in the booking period they would implement D^3, should they choose to do so.

6.2.1. Competitive D^3 at Time Frame 6

The first set of experiments take place in TF6 (31 days prior to departure). Recall that in TF6 Airline 1 saw its largest increase in operating profit with D^3 implemented with an operating profit-maximizing objective function. 31 days prior to departure, advanced purchase restrictions do not apply to any of the fare products and up-gauges in capacity on high demand flights lead to large increases in Fare Class 6 and some Fare Class 5 bookings. This drastically decreases yield but increases RPMs more for the implementing airline, leading to revenue increases and hence operating profit increases. The same principles hold for Airline 2 when it implements D^3 in TF6.

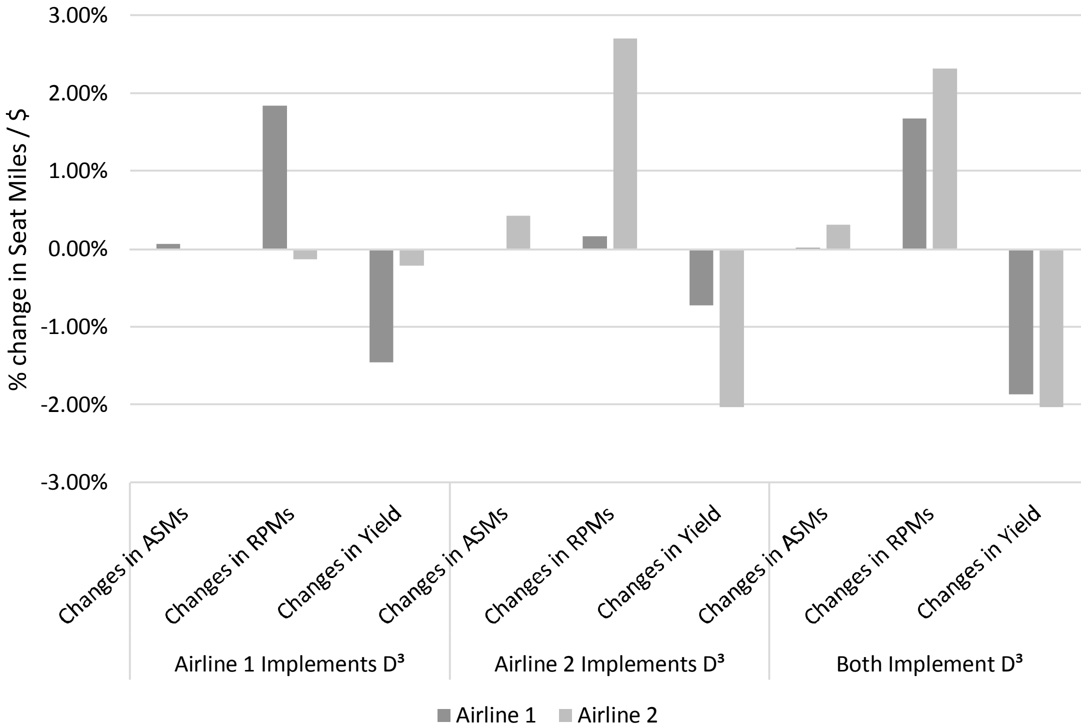

Figure 71: Changes in ASMs, RPMs, and Yield When D^3 is Implemented at TF6

Figure 71 shows these changes in RPMs and yield, as well as ASMs. When Airline 1 implements demand driven dispatch in TF6, it has a 0.07% increase in ASMs. When Airline 2 implements D^3, its ASMs increase by 0.43%. This is very similar to the results of competitive D^3 with bookings-based swapping—Airline 2's initial fleet assignment promotes more up-gauging regardless of variation in demand. When both implement D^3, Airline 1 has virtually no change in ASMs and Airline 2 has a slightly smaller increase.

Changes in RPMs are consistent: Airline 1's increase by 1.84% when it implements D^3 and Airline 2's increase by 2.71% when it implements D^3. When both implement D^3, Airline 1's RPMs increase by 1.68% and Airline 2's by 2.32%, in both cases less than when they were alone in implementing D^3 but more when summed together. It is also the product of the same phenomenon seen with bookings-based swapping—both airlines are increasing capacity on the same high demand flights and are therefore competing for the same low fare passengers.

As such, yield decreases. Almost all of the new bookings on up-gauged flights are made in Fare Class 6 (the lowest), increasing RPMs but decreasing yield. As shown in Figure 71, Airline 1's yield decreases by 1.45% when it implements D^3 and Airline 2's by

2.03% when it implements D³. Also, when either airline implements D³, it not only decreases its yield but also the yield of its competitor, more so than it affects its competitors RPMs. Hence, when both airlines implement demand driven dispatch, their yields decrease by as much or more as when one airline does, with Airline 1's decreasing by 1.87% and Airline 2's by 2.03%. Still, increases in RPMs outpace decreases in yield and revenue increases.

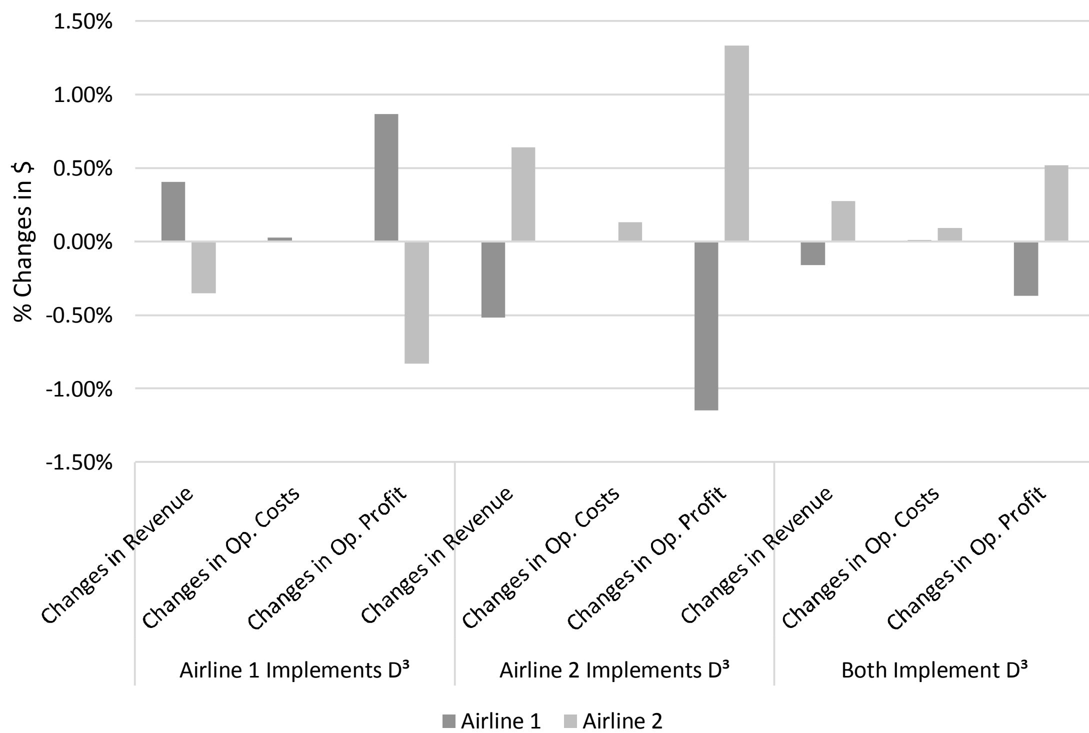

Figure 72: Changes in Revenue, Op. Costs, and Op. Profits When D³ is Implemented at TF6

Figure 72 shows the changes in revenue, operating costs, and operating profit when Airline 1, Airline 2, or both implement demand driven dispatch in TF6. The results are as expected given the changes in ASMs, RPMs and yield. When Airline 1 implements demand driven dispatch it has a large increase in RPMs and a smaller decrease in yield, leading to an increase in revenue of 0.41%. Airline 2, whose RPMs decrease and yield decreases more, sees a decrease in revenue of 0.35%. Airline 1 has an increase in ASMs and therefore a slight increase in operating costs (0.03%). The scenario is reversed when Airline 2 alone implements demand driven dispatch at TF6. Its revenue increases by 0.64% and Airline 1's decreases by 0.52%. Airline 2's operating costs increase more (0.13%) than Airline 1's, as its ASMs increased more. In either scenario, the airline that implements demand driven dispatch sees a large increase in operating profit—0.87% for Airline 1 and 1.33% for Airline 2.

The story becomes more complicated when both airlines implement demand driven dispatch. As shown in Figure 72, when one airline implements demand driven dispatch, the other airline loses almost as much revenue as the implementing airline gains. Thus, when both airlines implement demand driven dispatch, their operating profit results are mixed. In fact, if one takes the operating profit gains of each airline when they alone implemented D^3 and subtract the losses when they did not but the competitor did, the results are roughly those of both airlines implementing demand driven dispatch: operating profit losses of 0.37% for Airline 1 and gains of 0.52% for Airline 2. Thus, while Airline 1 would be better off if neither airline engaged in demand driven dispatch, the Nash Equilibrium is again, as it was with bookings-based swapping, for both airlines to implement D^3.

This outcome for changes in operating profit is by definition the result of changes in revenue and operating costs. For both airlines, the magnitude of the increases in operating costs are slightly smaller. However, revenue does not increase for either airline as much as it did when they were alone in implementing D^3. As both airlines offer increased availability to the same low-yield passengers, further dilution reduces revenues, especially for Airline 1.

6.2.2. Competitive D^3 at Time Frame 14

In this section, the competitive tests of D^3 are repeated except that demand driven dispatch is implemented in TF14 rather than TF6. TF14 was also a peak implementation time for Airline 1 in earlier time frame tests with DAVN and a profit-maximizing objective function for D^3, increasing operating profits for Airline 1 by 0.86%, as compared to the increase of 0.87% at TF6. Although the operating profit gains of demand driven dispatch are very similar at TF6 and TF14, there are significant qualitative differences in how the implementation of D^3 at these time frames increases the operating profit of the implementing airline.

At TF14, only 5 days prior to departure, advance purchase restrictions prevent the sale of all but Fare Classes 1 and 2, the highest fare classes. Thus, any up-gauging of flights primarily results in increases in bookings the highest fare classes (excluding feedback effects as discussed at the end of Section 6.1.2) and leads to only modest decreases in yield or even increases in yield, as compared to D^3 in TF6 which causes large decreases in yield. Another important qualitative outcome of demand driven dispatch in TF14 is that the large number of bookings already accepted limits the ability to perform swaps (avoiding denied boardings) and also limits the ability for additional seats on up-gauged flights to be sold, as very little time remains.

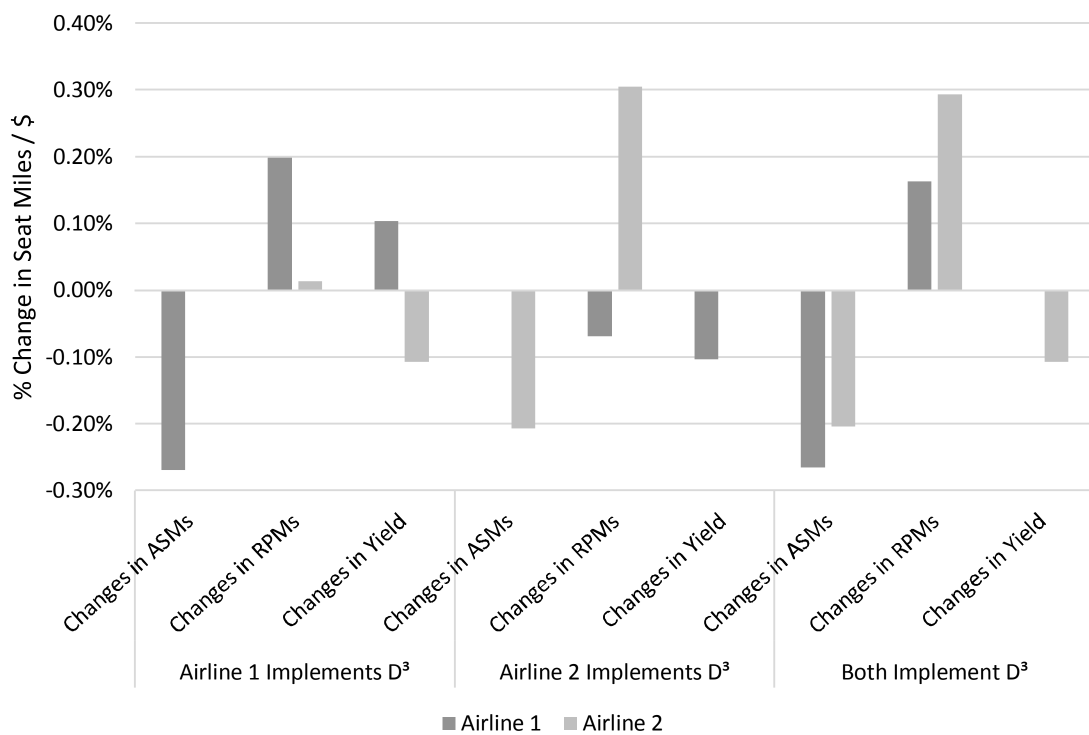

Figure 73: Changes in ASMs, RPMs, and Yield When D^3 is Implemented at TF14

Figure 73 shows the changes in ASMs, RPMs, and yield from one or both airlines implementing demand driven dispatch at TF14. Note that there are significant differences in the outcomes. Instead of minute increases in ASMs, ASMs decline for the airline implementing demand driven dispatch alone, by 0.27% for Airline 1 and by 0.21% for Airline 2. When both airlines implement demand driven dispatch, changes in ASMs are similar: Airline 1's decrease by 0.26% and Airline 2's by 0.20%. Why do ASMs decrease so much? Only 5 days prior to departure, there are very few forecasted bookings to come, and therefore incremental revenue forecasts are quite small. Meanwhile, incremental costs are of the same magnitude as at all time frames. Therefore, the relative magnitude of incremental cost savings has a larger influence on the objective function of demand driven dispatch and D^3 pursues more down-gauges on long flights than in earlier time frames.

In line with previous tests of later implementations of D^3, RPMs increase for the implementing airline by much less than when implemented at TF6. Airline 1's RPMs only increase by 0.20%, as compared to 1.84% in TF6. However, rather than suffering large-scale dilution, yield actually increases by 0.10% when Airline 1 alone implements demand driven dispatch. Thus, even with far fewer additional bookings, revenue increases by almost as much. The same holds for Airline 2's RPM and yield changes.

Competitively, demand driven dispatch in TF14 largely harms the "other" airline's yield, not RPMs. This is consistent with D^3 in TF6, but more pronounced in TF14. These results occur because up-gauging a very constrained flight in the last days before departure does not drastically change the absolute number of bookings by either airline, but it does determine which airline sells more bookings to the few, but highest-paying, business passengers who arrive late in the booking period. When both airlines implement demand driven dispatch at TF14, changes in ASMs, RPMs, and yield are again moderated as compared to when only one airline implements D^3, being roughly a combination of the results of when only they implemented D^3 and when only their competitor implemented D^3.

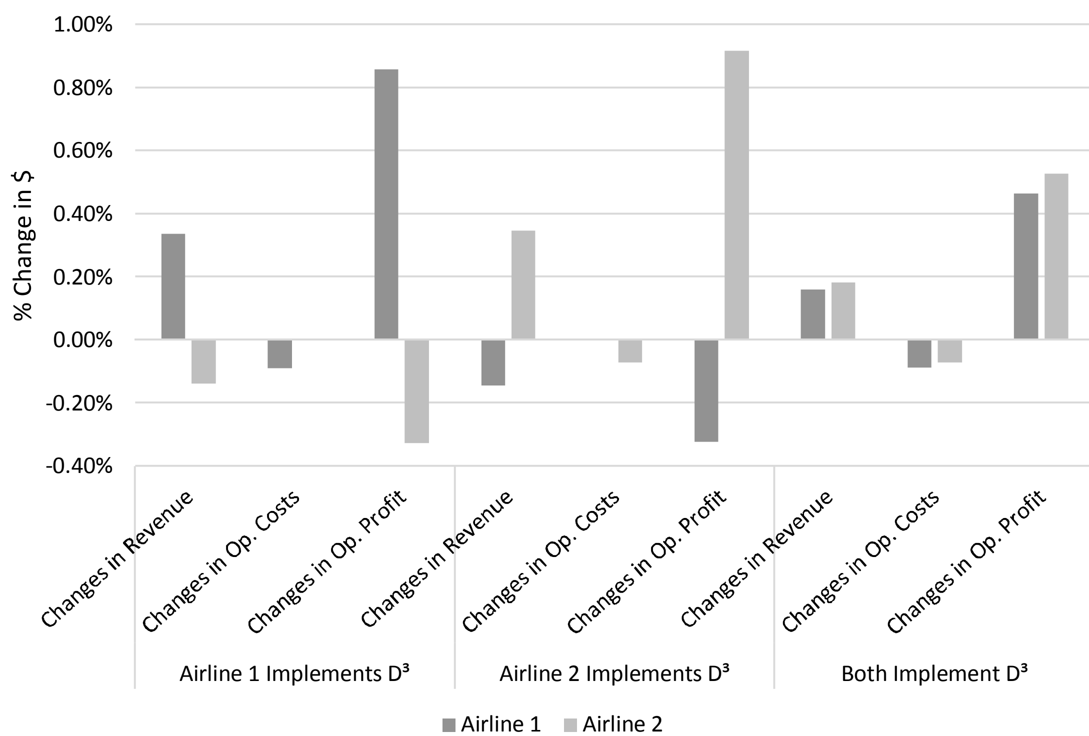

Figure 74: Changes in Revenue, Op. Costs, and Op. Profit When D^3 is Implemented at TF14

Figure 74 displays the changes in revenue, operating costs, and operating profit when one or both airlines implements D^3 at TF14. The results are quite symmetric between the two cases where only one airline implements demand driven dispatch. The results are also symmetric in the third case where both airlines implement D^3. The implementing airlines see increases in revenue: 0.16% for Airline 1 and 0.18% for Airline 2. Both see decreases in operating costs from decreases in ASMs: 0.09% for Airline 1 and 0.07% for Airline 2.

Changes in Operating profit are also symmetric between airlines: 0.46% for Airline 1 and 0.53% for Airline 2. This is in contrast to tests in TF6 where Airline 1 lost operating profits when both airlines implemented demand driven dispatch. Thus, again in TF14 with DAVN and an operating profit-maximizing objective function for D^3, the Nash Equilibrium is for both airlines to implement demand driven dispatch.

6.2.3. Asymmetric Competitive D^3

The final section on the competitive dynamics of demand driven dispatch contains the test where Airline 1 implements demand driven dispatch at TF6 and Airline 2 implement D^3 at TF14. As has been shown, demand driven dispatch at TF6 and TF14 result in similar results in changes in operating profit for one airline implementing but arrive at those profit results in significantly different ways.

When both airlines implement, both the magnitudes of TF14 operating profit results and the underlying processes by which operating profit increases differ. Thus, it is worth investigating what happens when one airline implements D^3 at TF6 and the other at TF14. Two competitive dynamics are at play. First, Airline 1 at TF6 is targeting low-yield demand with up-gauges early in the booking period while Airline 2 at TF14 is targeting high-yield demand. Their up-gauges do not directly affect the same potential passengers, although feedback effects from both airlines do. Second, Airline 1 is implementing D^3 "first," a possible advantage.

Figure 75 shows the changes in ASMs, RPMs, and yield when demand driven dispatch is implemented at one or both airlines at these asymmetric time frames, TF6 and TF14. Note that the results of Airline 1 alone implementing D^3 at TF6 and Airline 2 alone implementing D^3 at TF14 are identical to their counterparts in the previous two sections, 6.2.1 and 6.2.2. The third set of results, however, are new. With Airline 1 implementing D^3 at TF6 and Airline 2 at TF14, Airline 1 sees an increase in ASMs of 0.7% while Airline 2's ASMs decrease by 0.20%. These changes are consistent—Airline 1's forecasted incremental revenues are larger than Airline 2's, meaning that Airline 1's D^3 is more influenced by revenue-maximization and has more up-gauges on long-haul (higher fare) flights. Meanwhile, Airline 2's D^3 is more influenced by cost-minimization and therefore has more up-gauges on short-haul (and lower fare) flights.

These differences in ASM changes based on time frame of implementation mimic those of how revenue is accounted for in the assigner—with or without displacement costs. The exact results of fleet assignment in general and in these cases demand driven dispatch are highly dependent on the precise definitions of leg-profitability used. Balancing the relative magnitudes of incremental revenue gains and incremental cost reductions makes the difference between increases or decreases in system ASMs as a result of demand driven dispatch. Furthermore, the magnitudes of incremental revenues are affects by a variety of highly variable parameters including demand levels, relative fare ratios between fare classes, time of swapping in the booking period, etc.

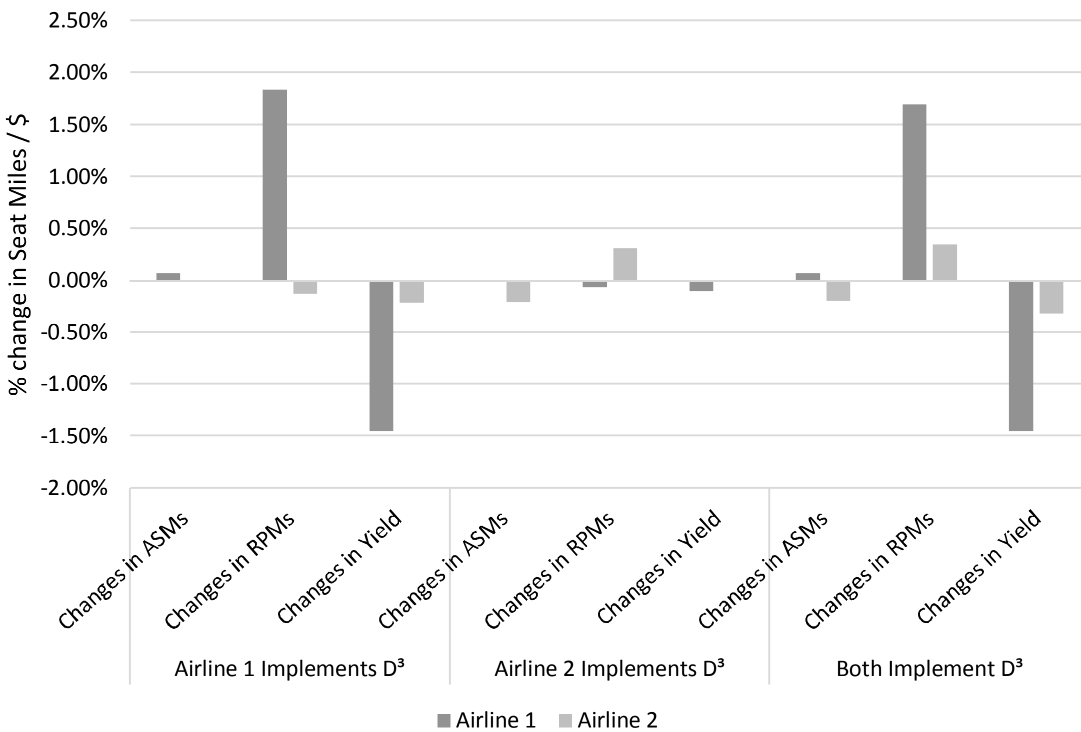

Figure 75: Changes in ASMs, RPMs, and Yield When D^3 is Implemented Asymmetrically

Airline 1's RPMs increase by 1.70% when it implements D^3 at TF6 while Airline 2 implements at TF14. Interestingly, Airline 2's RPMs also increase, in this case by 0.35%. This is a larger increase in RPMs than when Airline 2 alone implements D^3 at TF14. Why is Airline 2's RPM increase assisted by Airline 1's implementation of demand driven dispatch at an earlier time frame? The answer is partially given in changes to Airline 2's yield. Airline 1's yield decreases quite a bit—to be expected with early implementation of D^3. However, Airline 2's yield decreases, as well. When it alone implements D^3 at TF14, its yield is virtually unchanged, but when Airline 1 implements D^3 at TF6 Airline 2's yield drops 0.32%.

The answer is straightforward—when Airline 1 increases availability on high demand flights early in the booking period it causes spiral down for itself and, by capturing Airline

2's previous higher class bookings in its now open FC6, causes spiral down for Airline 2 as well. Airline 2 enjoys more bookings in higher fare classes due to its D^3 at TF14, but still suffers from dilution due to Airline 1's D^3 at TF6.

Figure 76 shows the changes in revenue, operating costs, and operating profits from the asymmetric implementation of D^3 by Airline 1 and Airline 2 at TF6 and TF14, respectively. Changes in revenue, etc. are identical to previous tests for each airline implementing D^3 alone. The airline that implements demand driven dispatch sees large increases in revenue, small increases or decreases in operating costs depending on the timing of D^3, and large increases in operating profit.

When both airlines implement demand driven dispatch, however, the results are less symmetric as compared to when both airlines implemented D^3 at the same time. For the first time, when both airlines implement D^3, Airline 1 has a larger increase in operating profit than Airline 2 (0.41% versus 0.17%).

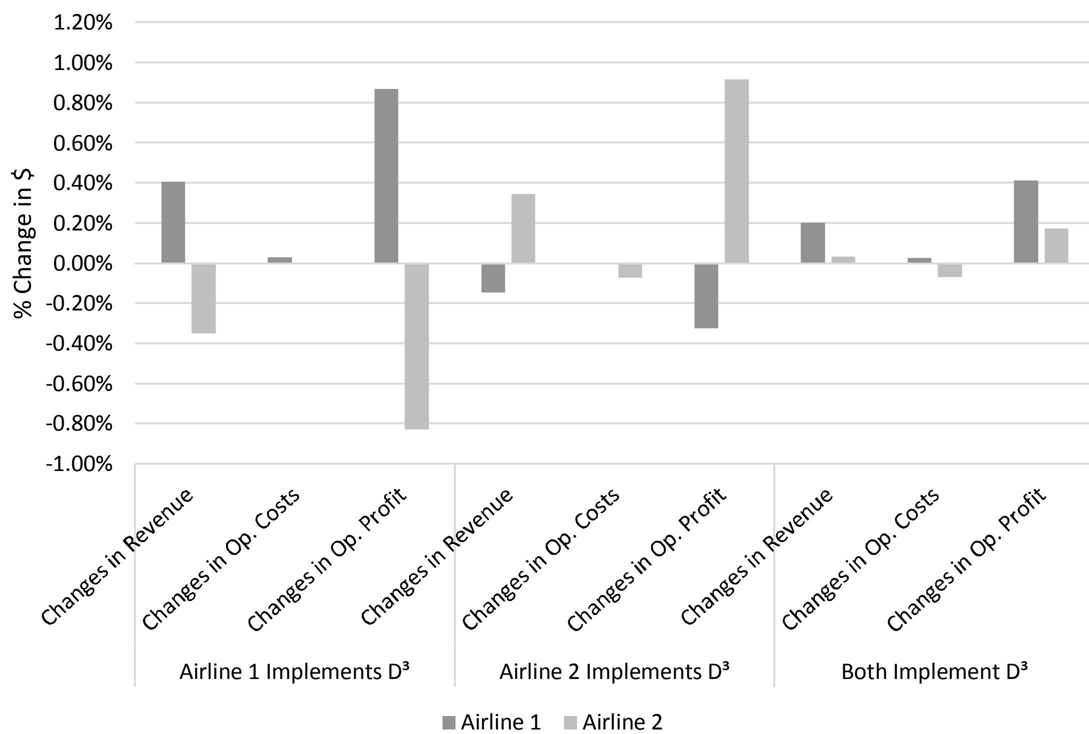

Figure 76: Chgs in Rev., Op. Costs, and Op. Profits When D^3 is Implemented Asymmetrically

This phenomenon is the result of Airline 1 causing the dilution of Airline 2's bookings with its implementation of D^3 in TF6. Note that Airline 2's revenue benefit from D^3 in TF14 drops from 0.35% to only 0.03% when Airline 1 implements D^3 at TF6. This is a direct result of Airline 1's loss of yield. What operating profit cost improvements Airline 2 experiences are as more a result of the -0.07% decrease in operating costs through reductions in ASMs as the 0.03% increase in revenues. Charts of the same experiment with Airline 2 implementing at TF6 and Airline 1 at TF14 can be found in the appendix.

From the results in Figure 76 and also those of Airline 1 implementing D^3 at TF14 and Airline 2 at TF6 (shown in the appendix), it is the case that when both airlines implement D^3, whichever airline implements at an earlier time frame benefits more from demand driven dispatch. This can also be seen in Figure 77.

		Airline 1		
		No D^3	D^3 at TF6	D^3 at TF14
Airline 2	No D^3	AL1: 0.00% AL2: 0.00%	AL1: +0.87% AL2: -0.83%	AL1: +0.86% AL2: -0.33%
	D^3 at TF6	AL1: -1.14% AL2: +1.33%	AL1: -0.37% AL2: +0.52%	AL1: -0.34% AL2: +1.09%
	D^3 at TF14	AL1: -0.32% AL2: +0.92%	AL1: +0.41% AL2: +0.17%	AL1: +0.46% AL2: +0.53%

Figure 77: Game Theory Grid of Op. Profit Outcomes from D^3

Figure 77 is a game theoretical grid showing the changes in operating profits for Airline 1 and Airline 2 when they individually choose one of three strategies: no D^3, D^3 at TF6, or D^3 at TF14. The resulting changes in operating profit are a result of both their own decisions and the decisions of their competitor. In the four cells in the bottom right, where both airlines implement D^3, there is advantage to implementing D^3 in an earlier time frame than the competitor.

However, this benefit does not extend evenly or linearly. In fact, the only Nash Equilibrium in the matrix, the highlighted grid on the right, is where Airline 1 implements at TF14 and Airline 2 implements at TF6. Note that when either airline is engaging in D^3 alone, it is to its advantage to implement at TF6. Once both airlines implement, the advantage persists for Airline 2 but does not persist for Airline 1. This is likely due to the greater magnitudes at which Airline 2 benefits from D^3 in all scenarios, and therefore adversely affects Airline 1. By moving its D^3 to TF14, Airline 1 is in some ways insulating itself from the full adverse effects of Airline 2 implementing D^3 at TF6. Rather than competing with Airline 2, which swaps more aggressively given its static fleet assignment, for low-yield passengers at TF6, Airline 1 does better (although it is still hurt) to up-gauge later to capture different, high-yield passengers.

6.3. Conclusions from Optimized Swapping

Tests of demand driven dispatch using a network optimization technique with revenue or operating profit-maximizing objective functions both reaffirmed conclusions from Chapter 4 and illustrated new patterns. First, timing swaps, especially in relation to the pricing structures in place in the affected markets, critically affects the outcome of demand driven dispatch as well as how that outcome is achieved. Early swaps result in substantial increases in RPMs and load factor with large decreases in yield—dilution. Late swaps result in little increase in RPMs and load factor but also increase yield. Thus, the revenue and operating profit outcome of demand driven dispatch is typically bimodal depending on the time of implementation, with the peaks in operating profit benefits being 5-10 days prior to the first AP restrictions and 5 days prior to departure.

Both revenue-maximizing and operating profit-maximizing demand driven dispatch, using revenue estimates from the output of the RM systems (both from EMSRb and DAVN), outperform the simpler bookings-based swapping throughout the bookings period. This is to be expected, as these methods reference the estimated relative revenue value of additional seats given demand and, in the case of operating profit-maximization, take into account the additional costs of flying larger aircraft longer distances. When only one airline implements demand driven dispatch, revenue gains range from gains of 0.16% to 0.66%. Operating cost changes range from -0.09% to 0.13%. Operating profit gains range from 0.38% to 1.52%.

With EMSRb-based revenue management, operating profit-maximizing demand driven dispatch does not compromise revenue results and uniformly provides larger operating profit increases than its revenue-maximizing counterpart. With DAVN as the revenue management system, it is no longer clear throughout the time frames if operating profit-maximization results in better outcomes—as displacement adjusted revenue gives cost-minimization more influence over the fleet assignment, revenue outcomes become compromised when down-gauging occurs on longer stage length, higher revenue flights, to decrease operating costs. Unlike previous studies such as Berge and Hopperstad (1993), revenue improvements, not cost reductions, have driven the majority of operating profit increases with only a few exceptions. This is likely due to higher load factors as compared to previous studies.

One such exception is when both airlines implement demand driven dispatch. Dilution results in meager revenue increases, and thus cost reductions become a greater proportion of the operating profit increases. The competitive dynamics of demand driven dispatch suggest that there are benefits from implementing demand driven dispatch at an earlier point than one's competitor. It also remains the case that the Nash Equilibrium always involves both airlines implementing D^3. In early time frames, significant dilution results in neutralized revenue benefits for the competing airlines. The same occurs in later time frames but to a lesser extent. When both airlines implement demand driven dispatch, operating income changes range from -0.37% to 0.92%. It is always the case, however, that an airline's operating profits improve when it implements demand driven dispatch, given that it was not previously doing so and regardless of if its competitor is doing so.

7. Chapter 7: Sensitivity Analysis

Chapter 7 focuses on the robustness of the results of Chapter 6. Several important variables have been assumed in previous simulations that can affect the magnitudes of outcomes of demand driven dispatch. First, demand levels were held constant in Chapter 6, with the base case load factor for both Airline 1 and Airline 2 being approximately 80%. However, demand levels and the resulting average system load factors are important for the efficacy of demand driven dispatch. At very high demand levels, swaps become increasingly difficult as a proportion of flights are no longer eligible for down-gauging, limiting the number of flights that can be swapped in general. Furthermore, at high demand levels, revenue-maximization dominates the objective of the fleet assignment while at low demands, where most flights are predicted to have low load factors, cost minimization becomes more important.

Second, the gains of demand driven dispatch are largely dependent on the quality of the underlying static fleet assignment. As was seen in Chapter 4 and Chapter 6, Airline 2's inferior static fleet assignment led to it consistently benefiting much more from demand driven dispatch, which uniformly had a more positive effect on Airline 2's ASMs than on Airline 1's. In order to test the significance of the static fleet assignment on the benefits of D^3, again the focus is on the performance of Airline 1. The static fleet assignment for Airline 1 is updated to be a better fleet assignment, one whose origin is in fleet assignment optimization with an operating profit-maximizing objective function. Then, demand driven dispatch is tested again, with the new gains being incremental above those of simply improving the static fleet assignment.

Third, variability of the demand in PODS is varied. Demand driven dispatch, as described in the introduction, is not only highly dependent on the variability of demand but a direct response to it. Therefore, presumably the greater the variability of demand, the greater the benefits of demand driven dispatch. The lesser the variability of demand, the lesser the benefits of demand driven dispatch. Therefore, the last set of sensitivity tests include raised and lowered variabilities of demand and the resulting changes in operating profits, revenues, costs, etc. due to the implementation of demand driven dispatch.

7.1. Varying Demand Levels

This section contains tests of demand driven dispatch at various demand levels. As mentioned previously, demand levels and the average system load factors prior to the implementation of demand driven dispatch affect both the ability of demand driven dispatch to operate and the results of its operation. At higher demand levels, flights fill much faster, preventing down-gauging so as to prevent denied boardings. As a result, fewer swaps are possible. When swapping is possible, the profit-maximizing objective function of demand driven dispatch is more likely to favor revenue-maximization over cost-minimization as increased forecasts of bookings to come will increase the relative magnitude of incremental revenue forecasts from swapping.

At lower demand levels, and especially at very low demand levels, demand driven dispatch is easier to implement—nearly all flights are eligible for down-gauging as fewer bookings have been taken. However, incremental revenue forecasts from swapping may be very low or even zero. If none of the flights in a swappable set are projected to book up to the lowest available capacity, there would be no forecasted revenue benefit for any swap. Potential for cost reductions remain, however. Thus, at lower demand levels, swapping is primarily driven by the goals of operating cost-minimization.

To illustrate these points, demand driven dispatch was tested at nine demand levels, the middle of which (Demand Level 5 in Figure 78) has an identical demand level to all tests in Chapter 6. Figure 78 shows the base case load factors for Airline 1 at each of these nine demand levels, ranging from a system load factor of 64.17% at the lowest demand level to 87.76% at the highest demand level.

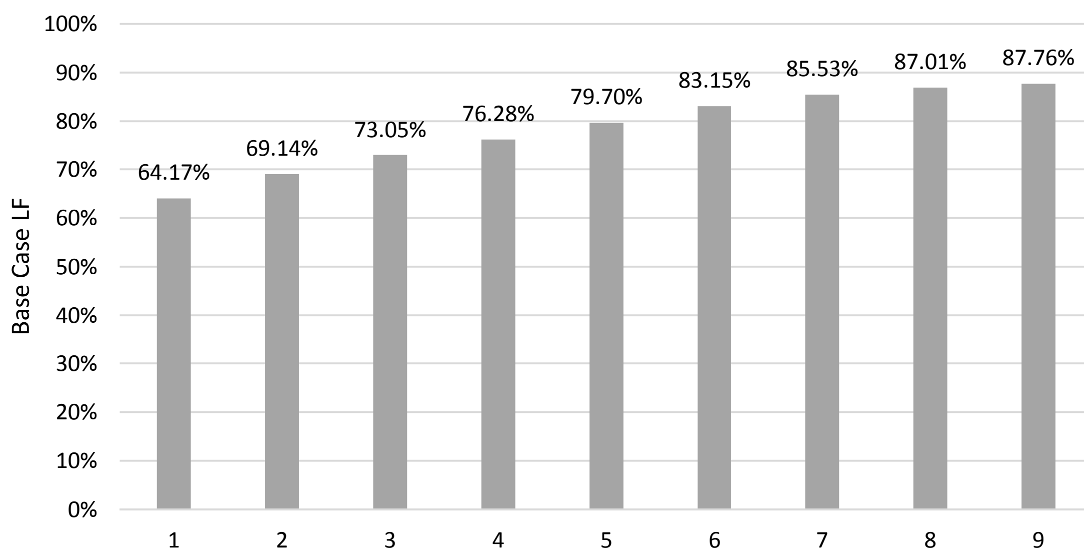

Figure 78: Airline 1 Base Case Load Factors for Sensitivity Analysis

In the base cases, both Airline 1 and Airline 2 use DAVN with standard path class forecasting for their RM systems. Neither airline uses demand driven dispatch. Then, in all of the alternate cases, Airline 1 implements demand driven dispatch at TF6 with the fleet assignment objective of maximizing operating profit. Thus, the results of Demand Level 5 are identical to previous tests of demand driven dispatch at TF6 with DAVN and an operating profit-maximizing objective function in Chapter 6.

Note that the average system load factors can be misleading—even with low system load factors many flights can be capacity constrained and with high system load factors many flights can depart with many empty seats. Figure 79 shows the load factor distributions for all flight departures at the highest and lowest demand level settings. Note the differences in average load factors that in both cases, full and low load factor flight departure occur.

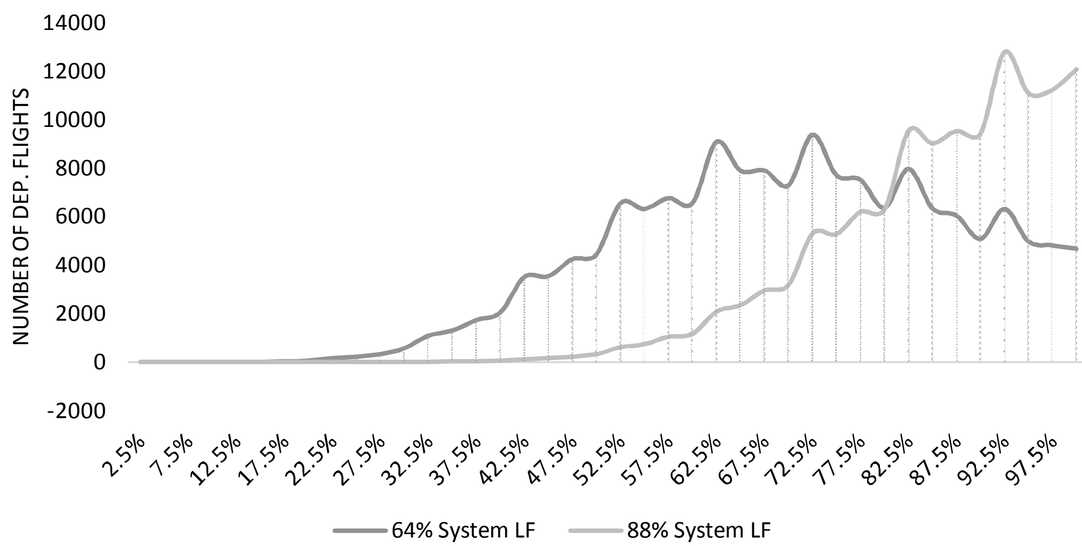

Figure 79: LF Distributions for Highest and Lowest Demand Levels

As demand levels and average system load factors rise, it is apparent that finding feasible swaps becomes more challenging—any swap requires a down-gauge, and feasible down-gauges are more difficult to find when load factors are higher. Thus, it is expected that as base load factors climb, the percentage of flights in the swappable set that are actually swapped decrease. However, given the load factor distributions in Figure 79, while finding feasibly swaps become more difficult, it is not drastically so. Figure 80 shows this relationship.

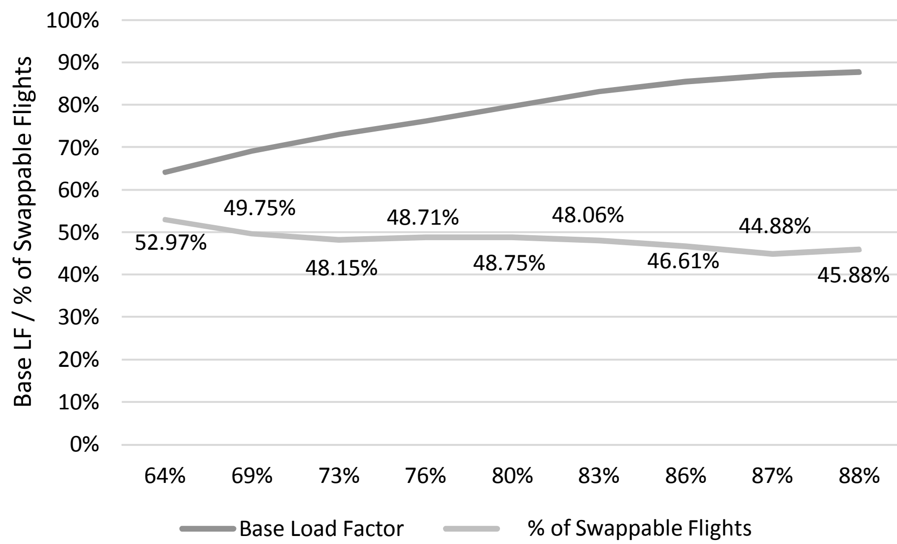

Figure 80: % of Swappable Flights Swapped from D³, Varying Demand Levels

Note that while the decrease in the percentage of swappable flights that are actually swapped is present, this decrease is not dramatic, nor even monotonic. The feasibility of swaps is not the only, nor the primary, determinate of whether or not the assigner changes the fleet assignment. With bookings-based swapping, the motivation for swapping was simple: the largest aircraft fly the flights with the largest forecasts. With a fleet assignment based on optimizing expected operating profits, many more factors are at play.

In determining how many swaps take place, and which aircraft are assigned to which flights, revenue and cost are now the driving factors. Cost is dependent only on stage length and the size of the aircraft. Revenue, however, is highly dependent on demand levels. When most flights are at very low load factors, gauge-changes become far less relevant for revenue as even the smallest aircraft may be able to accommodate the demand on the busiest flight. Thus incremental revenue projections will be small. At very high demand levels, any up-gauges will require down-gauges that will likely result in spilled demand, such that even though demand driven dispatch increases RPMs, the trade-off between flights lessens these increases in RPMs. At middle demand levels, incremental revenue estimates from swapping are likely to be highest, as flexibility remains to down-gauge low demand flights without spilling demand while high demand flights still benefit substantially from additional capacity.

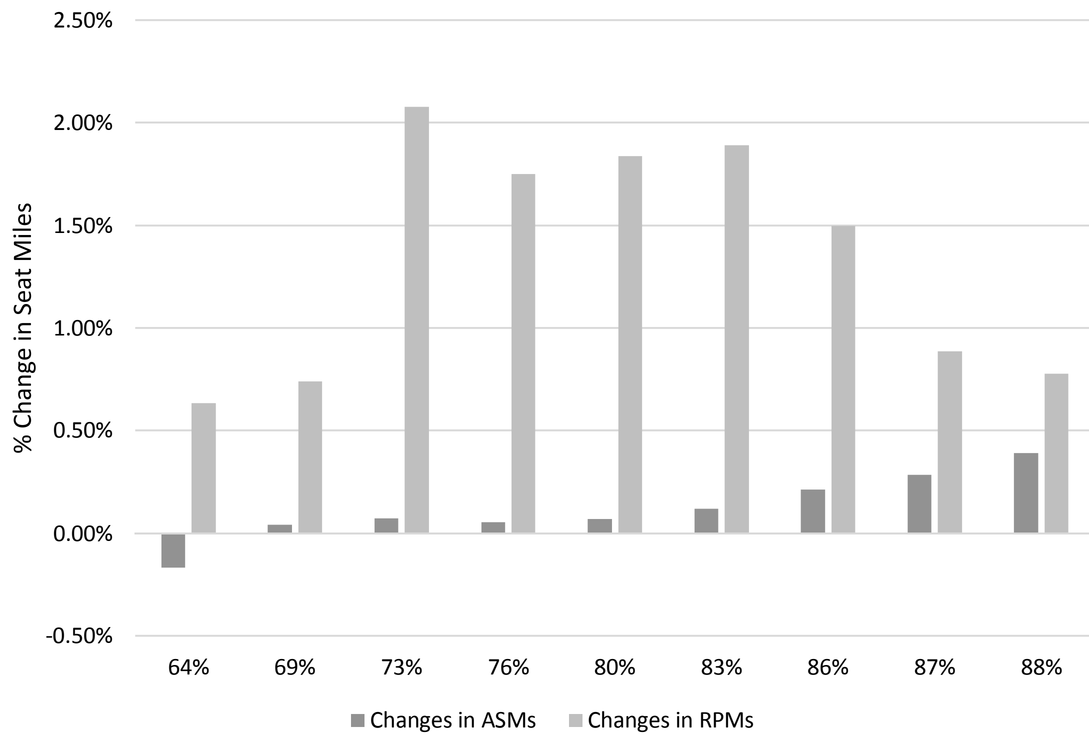

Figure 81: Changes in ASMs and RPMs from D^3, Varying Demand Levels

Figure 81 displays exactly these relationships. At very low base load factors, such as 64% and 69%, RPM increases are much smaller, 0.63% and 0.74% respectively. At a base load factor of 64%, ASMs decrease by 0.17%. At these low demand levels, revenue benefits from up-gauging high demand flights are limited. System averages can be deceptive, and some high demand flights still benefit greatly from up-gauges, but it is worth noting that at a base load factor 64%, the typical flight has 96 passengers, far fewer than 130 which is the capacity of the smallest aircraft. Still, cost reductions are not only as effective but are also more feasible with low load factors. Thus, at the low base load factors of 64% and 69% ASM changes are between -0.17% and 0.04%, far lower than with higher demand levels.

At middle demand levels, from about 73% to 83% in Figure 81, ASM increases range between 0.07% and 0.12%. RPM increases, however, are much larger, ranging from 1.75% to 2.08%. Why such large increases in RPMs at these middle demand levels? First, enough demand exists in the system for up-gauges on high demand flights to result in large increases in bookings and thus RPMs. Second, demand is not so high that up-gauging flights means causing spilled demand on the down-gauged flights. Thus, at middle demand levels up-gauging flights reaps the benefits of additional bookings from up-gauging without the cost of spill from the associated down-gauging. Third, as demand levels increase so do the forecasted bookings to come, and therefore the expected incremental revenues of up-gauging flights (such as longer stage length, higher fare flights) becomes larger and has more influence over the assigner's fleet assignment. This is evidenced by the consistently larger increases in ASMs. Fourth, swapping aircraft is still relatively easy at medium demand levels.

At high demand levels, in Figure 81 base load factors of 86% and above, demand driven dispatch enters its third phase in relation to demand levels. RPM increases begin to decline precipitously, from 1.50% to 0.78%. Meanwhile, ASM increases become larger, from 0.21% to 0.39%. In this phase, up-gauging the highest demand flights requires down-gauging flights that do result in spilled demand. Thus, total RPM increases decline. The assigner chooses to spill demand on shorter flights that have lower fares. Thus, shorter flights get down-gauged and increasingly longer flights get up-gauged, leading to ASM increases.

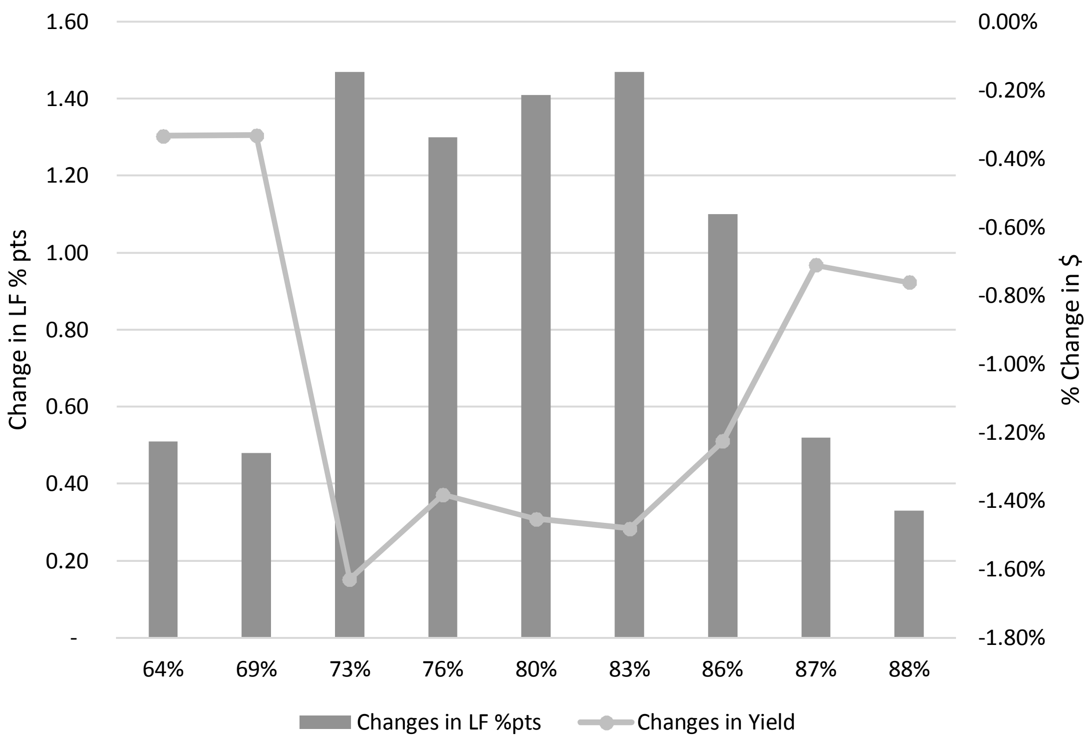

Figure 82: Changes in LF %pts and Yield from D^3, Varying Demand Levels

Figure 82 shows changes in load factor and yield from implementing demand driven dispatch at TF6 with different demand levels. The changes in load factor are the outcome of the large increases in RPMs and the smaller changes in ASMs, ranging from a -0.17% at the lowest demand level to a 0.39% increase at the highest demand level. The largest increases in RPMs are at middle demand levels, and therefore middle demand levels see the largest increase in load factor, as well.

Figure 82 also illustrates the trademark relationship between load factor changes and yield changes, specifically when demand driven dispatch is implemented at TF6. The larger the increase in RPMs, the greater the decrease in yield, with yield decreasing as much as 1.63% at a base load factor of 73%. Again, at TF6, before AP restrictions apply, up-gauging high demand flights results in increases in bookings for the lowest fare classes only due to the nature of revenue management.

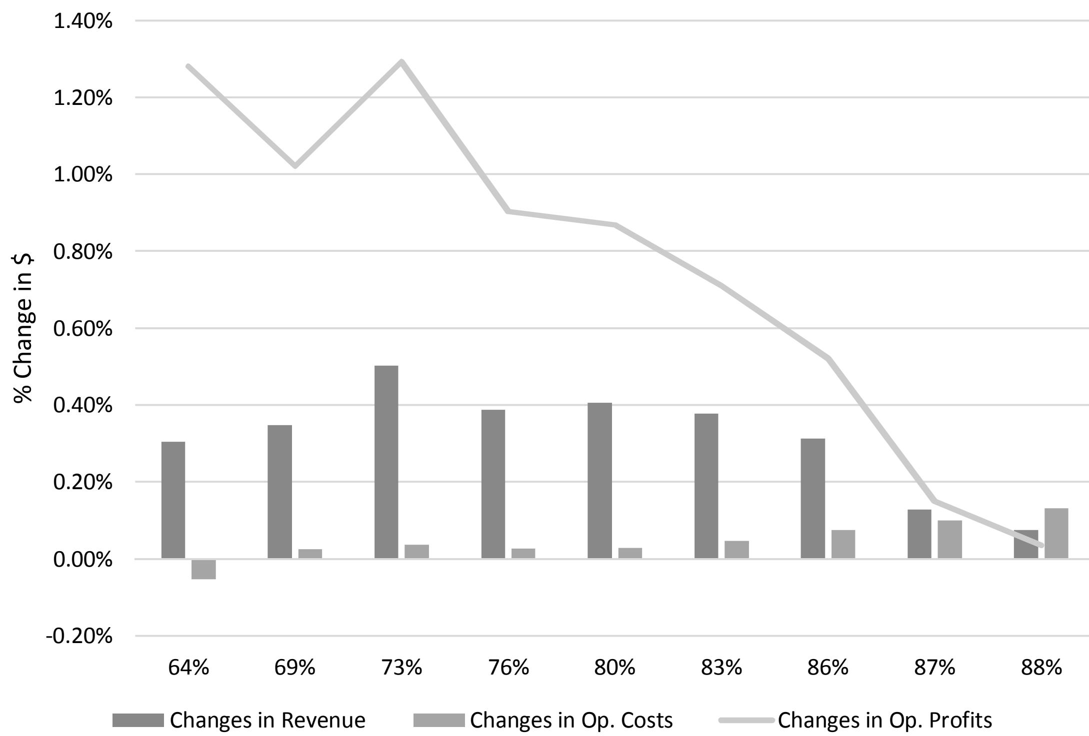

Figure 83: Changes in Revenue, Op. Costs, and Op. Profits from D³, Varying Demand Levels

Figure 83 shows the changes in revenue, operating costs, and operating profits as a result of implementing demand driven dispatch at various demand levels. As was predicted in previous studies, such as Cots (1999), demand driven dispatch's benefits decrease as demand levels increase. This pattern is certainly confirmed by this sensitivity analysis, albeit the underlying reasons are more complicated than merely the ability to execute fewer possible swaps. As was seen in Figure 79, the decrease in the number of flights experiencing swaps is not dramatic as demand levels increase. Yet, the decline in the operating profit results of demand driven dispatch are dramatic, falling from a high of 1.29% to only 0.04% at a base load factor of 88%.

Changes in revenue are at their greatest in the middle demand levels, peaking at 0.50% and reaching their minimum of 0.08% at the highest demand level. This mimics the increases in RPMs observed in Figure 80. It follows that when bookings increase the most, revenue will increase more. However, note that revenue increases more at the lowest demand levels than it does at the highest, despite increases in RPMs being lower at lower demand levels. This is due to lower yield. As mentioned previously, up-gauges at the highest demand levels are primarily on longer flights—longer flights have lower yield. The decline in yield at the highest demand levels compared to those at the lowest demand levels results in revenue increases being higher for the lower demand levels, despite lower increases in RPMs. This again emphasizes the importance of yield, in this case over load factor, in driving improvements in revenue.

Changes in operating costs are simple to explain. At the lowest demand levels, when ASMs decrease, operating costs decrease. As demand levels climb and ASMs increase by more, operating costs increase more, as well. At the highest demand level, operating costs actually increase more, in percentage terms, than revenue. However, as revenue in absolute terms is greater than operating costs, the change in operating profits is still positive.

In summary, the result of the profit-maximizing objective of demand driven dispatch at different system demand levels confirms previous findings that the gains of demand driven dispatch decline as system demand levels increase. However, they also reveal important nuances. These include the unique ability of profit-maximizing D^3 to reduce operating costs at the lowest demand levels, for D^3 to substantially increase revenue and bookings in middle demand levels, and the stagnation of revenue increases at high demand levels due to trade-offs between capturing some spilled demand only to spill other demand. As was the case with bookings-based swapping, demand driven dispatch has fewer returns at higher demand levels, but an inability to find feasible swaps is not the dominant reason for this phenomenon.

7.2. Optimizing Airline 1's Fleet Assignment

As shown in previous tests when comparing the results of D^3 for Airline 1 and Airline 2, the underlying, static fleet assignment plays a role in determining the gains of D^3. The better the underlying fleet assignment, the lower the gains from demand driven dispatch one would expect. This is primarily because, while demand driven dispatch is conceptually a response to the variability and uncertainty of demand, it is also capable of "fixing" a poor original fleet assignment. The fleet assignment portion of demand driven dispatch operates in much the same was a typical fleet assignment process for a static assignment with the exception that it is intended to be used dynamically during the booking period of the affected flights. It is a signal that the original fleet assignment is inadequate if demand driven dispatch is routinely performing the same swaps for particular flights on every departure day—it would be much more efficient for the results of these swaps to have been the original fleet assignment.

What then are the gains of demand driven dispatch with an improved fleet assignment? In order to answer this question, Airline 1's static fleet assignment is updated and improved and demand driven dispatch is then tested again with the base case without demand driven dispatch but with the improved original fleet assignment. The results of demand driven dispatch given the improved original fleet assignment can then be considered the "incremental" benefits of demand driven dispatch above those attainable from a static fleet assignment created prior to the booking period, or, more simply, the gains of D^3 that come only from responding to the variability of demand.

The goal of improving the static fleet assignment of Airline 1 is not to find and implement the "optimal" fleet assignment, but instead implement the fleet assignment that would be used if the same fleet assignment process used in D^3 was used for the static assignment. In other words, if the most common final fleet assignment as created by demand driven dispatch was the static fleet assignment, then the gains of implementing D^3 thereafter would represent the realistic gains possible only from responding to the variation in demand, not from performing the same swaps regardless of variation in demand. Table 8 shows the probabilities of each aircraft being assigned to each leg-pair, where Leg 1 and Leg 2 columns contain the matched legs in each leg-pair. For example, Leg 85 and Leg 169 are two legs in a leg-pair from and back to the hub. The static fleet assignment is indicated by the grey highlight—the original fleet assignment has a 150-seat aircraft scheduled. With D^3 in TF2, these leg-pairs are actually operated by a 150-seat aircraft on 63.20% of departures.

Table 8: Most Common Aircraft Assignments, D^3 in TF2 with DAVN

Leg 1	Leg 2	130-Seats	150-Seats	170-Seats
85	169	36.45%	63.20%	0.35%
86	170	0.00%	0.00%	100.00%
87	171	24.60%	71.95%	3.45%
88	172	2.45%	82.40%	15.15%
89	173	0.00%	16.90%	83.10%
90	174	0.00%	0.00%	100.00%
91	175	37.05%	61.85%	1.10%

92	176	0.00%	0.00%	100.00%
93	177	99.80%	0.20%	0.00%
94	178	2.60%	69.20%	28.20%
95	179	0.00%	0.00%	100.00%
96	180	18.75%	77.80%	3.45%
97	181	0.25%	40.25%	59.50%
98	182	8.95%	78.60%	12.45%
99	183	39.35%	60.50%	0.15%
100	184	100.00%	0.00%	0.00%
101	185	100.00%	0.00%	0.00%
102	186	72.80%	27.10%	0.10%
103	187	99.70%	0.30%	0.00%
104	188	0.00%	7.05%	92.95%
105	189	57.25%	42.70%	0.05%
127	211	0.10%	50.30%	49.60%
128	212	0.00%	0.00%	100.00%
129	213	0.05%	66.55%	33.40%
130	214	100.00%	0.00%	0.00%
131	215	2.35%	96.45%	1.20%
132	216	84.60%	15.40%	0.00%
133	217	94.50%	5.50%	0.00%
134	218	100.00%	0.00%	0.00%
135	219	0.00%	0.00%	100.00%
136	220	0.00%	0.00%	100.00%
137	221	8.00%	89.75%	2.25%
138	222	0.00%	0.00%	100.00%
139	223	24.25%	75.00%	0.75%
140	224	0.00%	0.00%	100.00%
141	225	71.10%	28.90%	0.00%
142	226	0.00%	0.00%	100.00%
143	227	1.40%	94.10%	4.50%
144	228	5.60%	86.70%	7.70%
145	229	99.55%	0.45%	0.00%
146	230	100.00%	0.00%	0.00%
147	231	8.50%	90.90%	0.60%

Again, table 8 shows the probabilities of each leg-pair being assigned one of the three aircraft sizes when D^3 is implemented. Airline 1 is using DAVN as its RM system and profit-maximizing demand driven dispatch is implemented at TF2. With DAVN the assigner subtracts the previous time frame's displacement costs from OD itineraries—therefore TF2 is the earliest D^3 can be implemented (thereby approximating the static fleet assignment which takes place prior to the booking period beginning). The highlighted cells in Table 8 display which aircraft was assigned to these legs in Airline 1's original base case fleet assignment.

As can be seen in Table 8, the original fleet assignment contains some poor matches between demand and capacity. For example, Legs 95 and 179 are assigned a 130-seat aircraft, the smallest, but the assigner for demand driven dispatch assigned a 170-seat aircraft on every departure day in every trial. Hence, the gains have little to do with D^3 responding to variations in demand but rather are the result of "fixing" the static fleet assignment. The process for improving Airline 1's static fleet assignment is straightforward: using the above probabilities, Airline 1's static fleet assignment is updated so that it matches the most likely fleet assignment post-D^3 in TF2 with an operating profit-maximizing objective function. Hence, the static fleet assignment for Airline 1 is now optimized with the same techniques as those used in D^3, and the remaining gains of D^3 can be attributed principally to D^3's response to variations in demand.

Table 9: Primary Base Results with Original Static Fleet Assignment

Al 1	ASMs	RPMs	LF	Yield	Revenue	Op. Costs	Op. Profit
1	24,589,596	19,597,736	79.70%	$0.0964	$1,888,849	$1,038,409	$850,440
2	25,365,524	19,710,632	77.71%	$0.0936	$1,845,116	$1,065,245	$779,871

Table 9 shows the primary base case results of the original static fleet assignment. Both airlines had similar system load factors, yield levels, and operating profit levels. The original static fleet assignments were made to create a realistic load factor distribution, an important factor for testing the efficacy of revenue management techniques. However, these original static fleet assignments were also therefore not "optimized" for expected operating profit. Table 10 shows the primary base case results of the new base case where Airline 1's static fleet assignment is matched to the most common fleet assignment resulting from D^3 at TF2, optimizing expected operating profit.

Table 10: Primary Base Results with Optimized Static Fleet Assignment

Al 1	ASMs	RPMs	LF	Yield	Revenue	Op. Costs	Op. Profit
1	24,596,116	19,998,415	81.31%	$0.0949	$1,897,425	$1,038,578	$858,847
2	25,365,524	19,660,079	77.51%	$0.0935	$1,837,280	$1,065,245	$772,035

Table 11: Changes in Primary Results from Optimizing Static Fleet Assignment

Al 1	ASMs	RPMs	LF	Yield	Revenue	Op. Costs	Op. Profit
1	0.03%	2.04%	1.61	-1.56%	0.45%	0.02%	0.99%
2	0.00%	-0.26%	(0.20)	-0.11%	-0.42%	0.00%	-1.00%

Table 11 shows the changes in base case primary results from the original static fleet assignment for Airline 1 to the optimized static fleet assignment for Airline 1. Note the very significant improvements in primary metrics. ASMs increase slightly (0.03%) but RPMs increase much more (2.04%). Load factor increases by 1.61 pts, accordingly. Yield also decreases by 1.56%. Therefore, the results of replacing the original static fleet assignment are very similar to the results of D^3 at TF2. RPMs increase by a significant amount but this increase in bookings corresponds with significant dilution. Overall, revenue increases by 0.45% and operating costs increase by 0.02%. Operating profit for Airline 1 increases 0.99%, as compared to the gain of 0.69% from operating profit-maximizing D^3 in TF2. Does this mean that demand driven dispatch is inferior to simply attaining a better static fleet assignment? No.

The changes in primary metrics, *over the updated, optimized static fleet assignment*, from implementing demand driven dispatch at TF6 with an operating profit-maximizing objective are shown in Table 12. Demand driven dispatch increases operating profits above and beyond the benefits of the optimized static fleet assignment. Regardless of how well-fitted the static fleet assignment is, the variability of demand in different markets on different departure days means that demand driven dispatch serves the purpose of responding to this variability of demand in a way that static fleet assignments cannot—dynamically.

Table 12: Chgs in Primary Results from D^3 at TF6, Given the Opt. Static Fleet Assignment

Al 1	ASMs	RPMs	LF	Yield	Revenue	Op. Costs	Op. Profit
1	-0.01%	0.03%	0.03	0.00%	0.09%	0.00%	0.20%
2	0.00%	-0.05%	(0.04)	-0.11%	-0.06%	0.00%	-0.15%

With the optimized static fleet assignment, demand driven dispatch performs fewer swaps; only 15.31% of the swappable flights are actually swapped on average (7.65% of *all* flights are swapped). ASMs decrease only slightly and operating costs remain approximately constant. RPMs increase slightly, as does load factor. Yield remains approximately constant. Revenue increases by 0.09% and operating profit increases for Airline 1 by 0.20%. In summary, the gains of demand driven dispatch are not erased or reversed when the static fleet assignment undergoes some form of improved optimization. Rather, there is less low-hanging fruit and demand driven dispatch's benefits retain the same patterns but at a smaller magnitude. These benefits of demand driven dispatch reflect the magnitudes of gains to be had when D^3 is responding principally to variation in demand.

7.3. D^3 with Demand Variability and the New Fleet Assignment

As demand driven dispatch is typically understood as the integration of revenue management and fleet assignment to address the variability of demand, the final section of sensitivity tests contains the results of implementing demand driven dispatch at a variety of levels of demand variability. The expected outcome is straightforward: as demand driven dispatch is meant to address the variability of demand, the higher the variability of demand the greater the benefits of demand driven dispatch should be.

Demand is stochastic in PODS, as described in Chapter 3. Demand varies by departure day, with some days having higher demand than others as determined by random draws with a Gaussian distribution. Demand in OD markets also varies by random draws with a Gaussian distribution. Finally, demand varies stochastically as PODS randomly generates different numbers of business versus leisure passengers, and each of these passengers in turn is generated with a random set of disutilities for various fare restrictions, travel times, etc. For testing demand driven dispatch at different levels of demand variability, the variability of demand for OD markets is changed.

A K-factor of 0.20 has been used in all previous tests for the variability of demand by OD market. Demand driven dispatch is also tested at all of the K-factors shown in Table 13 for variability of demand by OD market. In empirical studies, estimates of demand K-factors on flights have been estimated to be between 0.20 and 0.40 (Belobaba, 2006). For sensitivity testing, D^3 is tested with the new, optimized fleet assignment for Airlie 1 and K-factors ranging from 0.15 to 0.45 at 0.05 increments.

K-factors of demand for flights is not the same as demand for OD Markets. The "demand" for flights in PODS would be a combination of all of the variability by day, OD markets, passenger types, and preferences. However, as described in Swan (2002), combining demand by OD markets in on a single flight, as is done in PODS with the use of connecting hubs, actual variation of demand by flight will be less than the variation of demand by OD market as a statistical property of combining distributions. Hence, the OD market demand K-factors from 0.15 to 0.45 combined with the other dimensions of demand stochasticity represent a reasonable range for modeling variability of demand.

For each level of demand variability, the changes in primary metrics for Airline 1 due to the implementation of demand driven dispatch are shown. The base case is both airlines using DAVN with standard path-class forecasting and no demand driven dispatch. The alternate cases have Airline 1 implementing demand driven dispatch at TF6 with a profit-maximizing objective function.

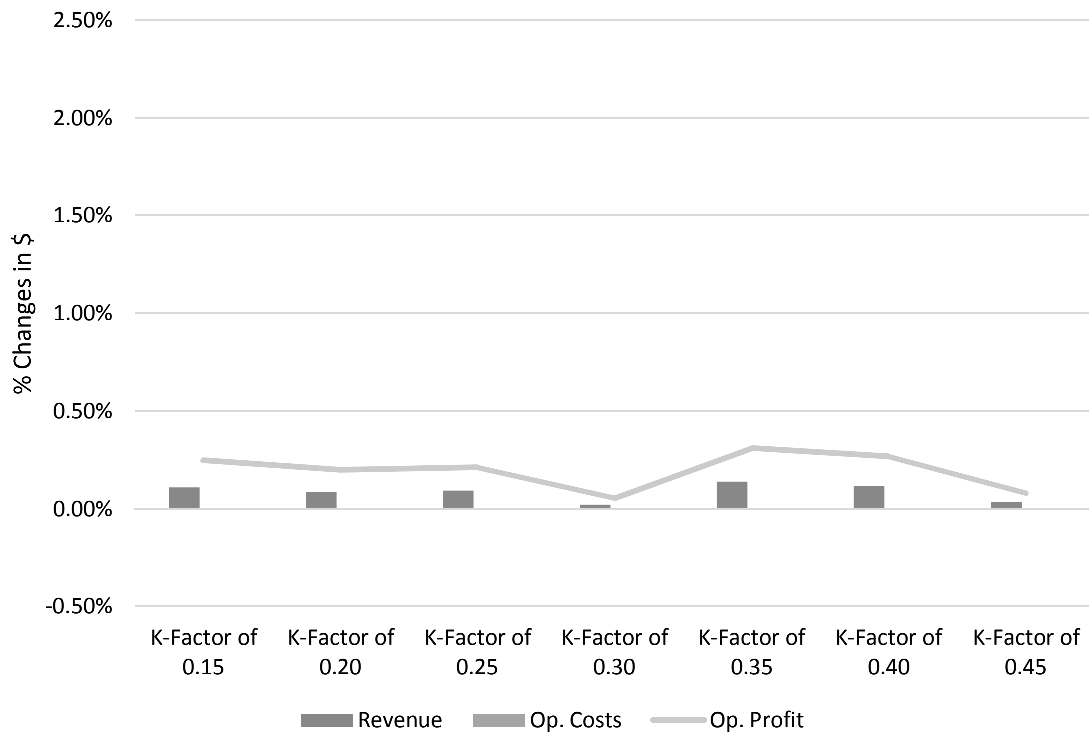

Figure 84: Chgs in Revenue, Op. Costs, and Op. Profit from D³ at TF6 with Diff. K-Factors

Figure 84 shows the changes in revenue, operating costs, and operating profit at each of the tested K-factors for OD market demand (with the scale matched to the changes when D³ is implemented in TF14). Despite the intuition that the operating profit gains of demand driven dispatch should increase as the variability in demand increases, this is not the case. In fact, the linear trend is very ambiguous and at all levels of demand variability the gains of D³ at TF6, with the new, optimized fleet assignment, are low and inconsistent.

Some consistency remains, however. As was the case in all previous tests at of D³ at TF6, the vast majority of the gains of demand driven dispatch are the result of increases in revenue, not reductions in operating costs. This is, again, in contrast with previous studies but consistent with the tests presented in this thesis. Whether or not demand driven dispatch causes larger increases in revenue or decreases in costs actually depends largely on demand levels, the timing of swaps, the relative cost structures, and the type of allocation of revenue to legs.

Why do changes in operating profit (mostly driven by changes in revenue) behave so inconsistently across demand variability levels, and why is the trend not clearly positive?

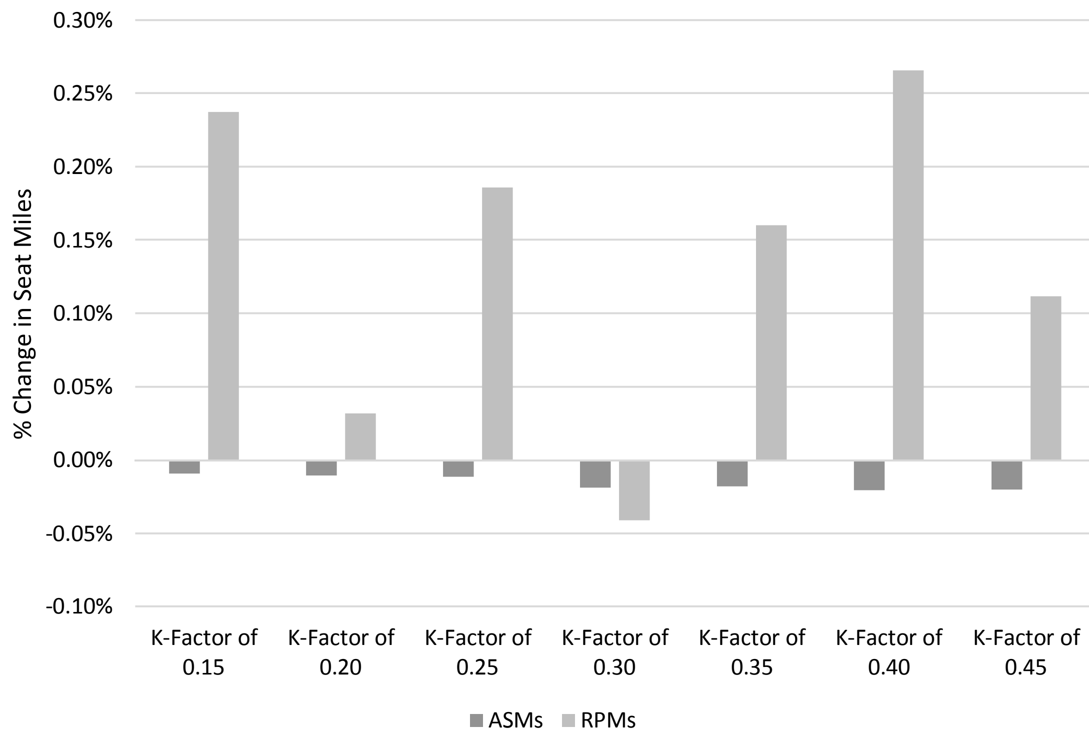

Figure 85: Changes in ASMs and RPMs from D³ at TF6 with Different K-Factors

Figure 85 shows changes in ASMs and RPMs due to the implementation of D³ at TF6 and at each level of demand variability. Decreases in ASMs are fairly consistent across demand levels, suggesting that cost minimization is not a large factor in determining fleet. However, RPM changes are relatively larger and much less consistent. Cost minimization across demand variability levels is not driving significant differences in swaps at different levels of demand variability, but changes in forecasted demand are. At all levels of demand variability, the percentage of flights swapped ranged from 7.57% to 8.05%. The percentage of flights swapped is relatively stable and cannot be the cause of the inconsistent and small gains from D³ at TF6 with the new, optimized fleet assignment. The culprit is not the quantity of swaps but shifting swapping decisions chasing forecasted demand.

It is a false assumption that demand driven dispatch, because it is designed to respond to the variability of demand, is immune to it. One interpretation of these results is that variations in demand can confuse the assignment process in demand driven dispatch.

Multiple explanations exist for this confusion in the assigner that results in low and inconsistent gains from D³ at TF6. However, most importantly, demand driven dispatch relies on the exact same forecasts as the revenue management system. As the variability of

OD market demand changes, this directly impacts the forecasts that demand driven dispatch uses for its assigner—D^3, although it is meant to address variability of demand, is ultimately directly affected by the variability of demand. By the end of TF6, 31 days prior to departure, roughly 56% of demand as arrived. The assigner, using *estimated* incremental revenue gains from expected bookings to come, is entirely dependent on forecasted bookings to come and remaining capacity. Despite the variability in demand, and even the variability in bookings in hand from one departure day to the next, the forecast will be relatively stable as a result of how it is constructed (as a function of past departure days), although the standard deviation will grow with the variability of demand. Simply put, at 31 days prior to departure the demand forecast is not capable of predicting the variability of demand as reliably as D^3 requires for strong improvements in profitability.

This interaction between the variability of demand and the forecasts has direct impacts on the revenue management system employed. For example, EMSRb-based optimization used in a leg-based RM system or at the end of DAVN uses the standard deviation of the forecast as an input. This alters booking limits irrespective of demand driven dispatch. Then, with demand driven dispatch being implemented using revenue estimates derived from the RM system's EMSR curves, the interaction is further complicated.

Demand driven dispatch cannot be made immune to the variability of demand. However, D^3 can be performed in such a way that it is more resilient to the variability of demand. If D^3 is performed at the other peak time, TF14 at 5 days prior to departure, cost-minimization plays a larger role in fleet assignment and incremental revenue estimates are based more so remaining capacity than on bookings to come. In other words, the operation of D^3 at TF14 should be much more resilient to and independent of the variability of demand while the gains of D^3 at this time frame remain subject to the variability of demand. If D^3 at TF14 is tested at differing levels of OD market variability it should be expected that the results show a much more consistent reflection of the hypothesis that increased variability translates into increased gains for demand driven dispatch.

To test this hypothesis, demand driven dispatch was again implemented at each of the above seven levels of OD market variability with the objective function of the assigner being to maximize operating profits. However, in these tests demand driven dispatch is implemented at TF14 rather than TF6, or 5 days prior to departure instead of 31 days prior to departure. Figure 86 shows the changes in revenue, operating costs, and operating profits at each of the levels of variability of OD demand. As can be seen in Figure 87, the changes are very consistent, much higher, and grow as the variability of demand increases—precisely the prediction put forth above.

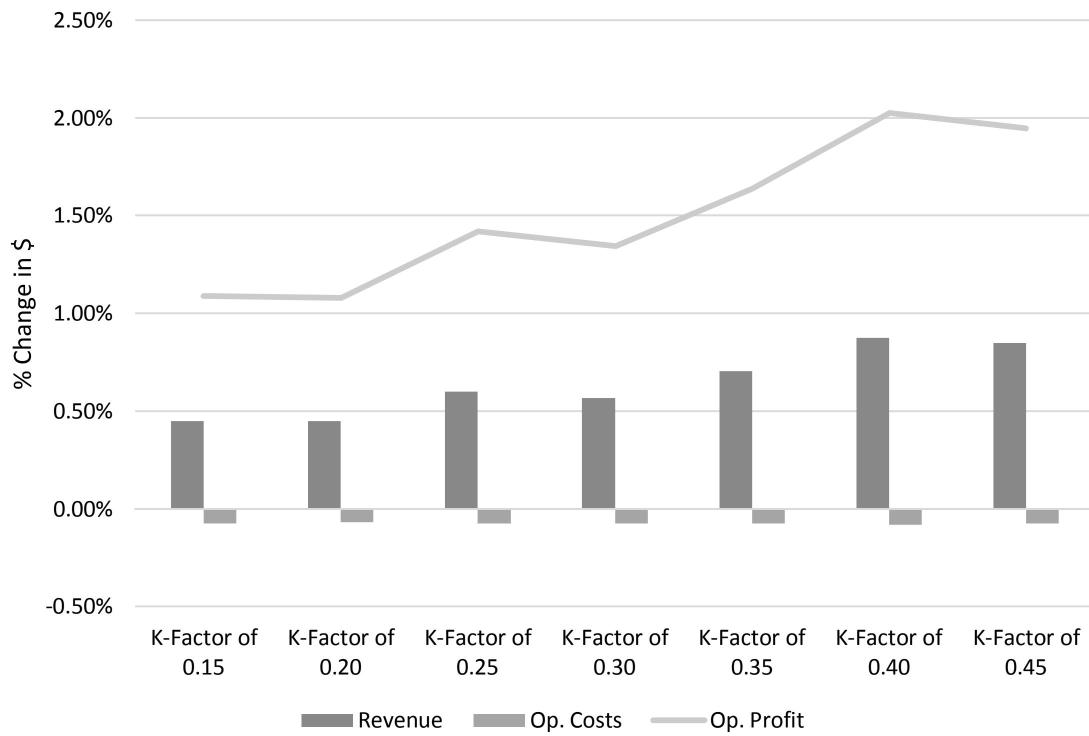

Figure 86: Chgs in Revenue, Op. Costs, and Op. Profit from D^3 at TF14 with Diff. K-Factors

Operating profits increase from as much as 1.08% to 2.03%, even with the base case having an improved, optimized static fleet assignment. Revenues increase from as much as 0.45% to 0.88% and operating costs decrease from as much as 0.07% to 0.08%. The gains from demand driven dispatch are higher and increase (albeit with a step function likely from the capacity "ledges") with increased variability of demand. The increases in operating profit are also consistent with previous tests in Chapter 6, being the sum of large increases in revenue with smaller but significant decreases in operating costs. At TF14, additional capacity on up-gauged flights can only be booked by the two highest fare classes. Thus, increases in RPMs are combined with increases in yield rather than dilution. Demand driven dispatch is also better able to allocate demand with reduced uncertainty, a function of the factors discussed previously. Finally, it is promising that demand driven dispatch has such positive results even on top of an optimized static fleet assignment—revenues increase, costs decrease, and profits increase due to demand driven dispatch's unique ability to respond to the variability of demand as neither RM nor static fleet assignments can.

Meanwhile, as shown in Figure 87, both yield and load factor increase. Not many strategies increase both yield and load factor, but demand driven dispatch implemented late in the booking period accomplishes this. Again, in changes in LF percentage points and yield, the step function is visible as is the increased effects of demand driven dispatch at higher levels of variability of OD market demand.

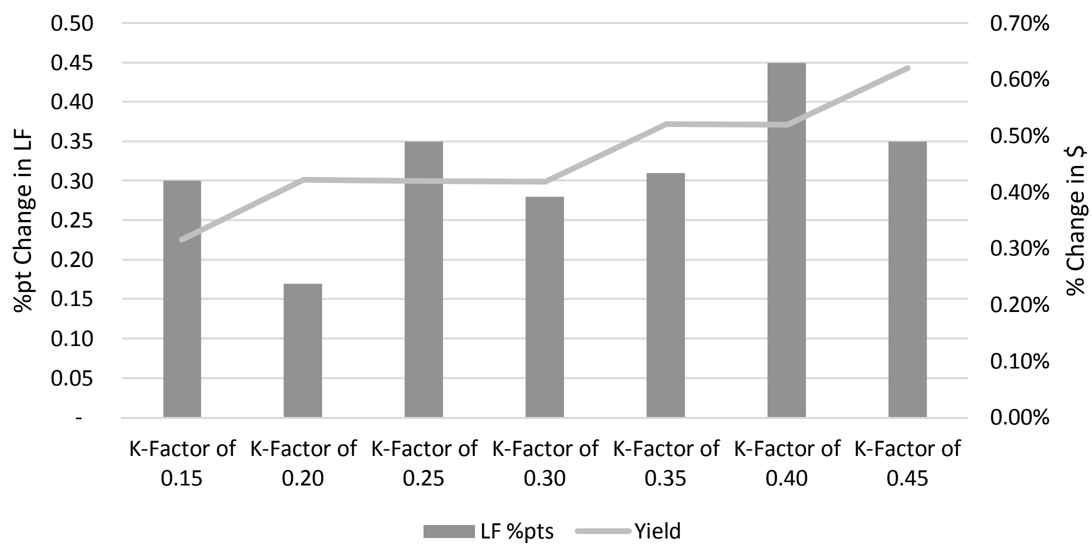

Figure 87: Changes in LF %pts and Yield from D³ at TF14 with Different K-Factors

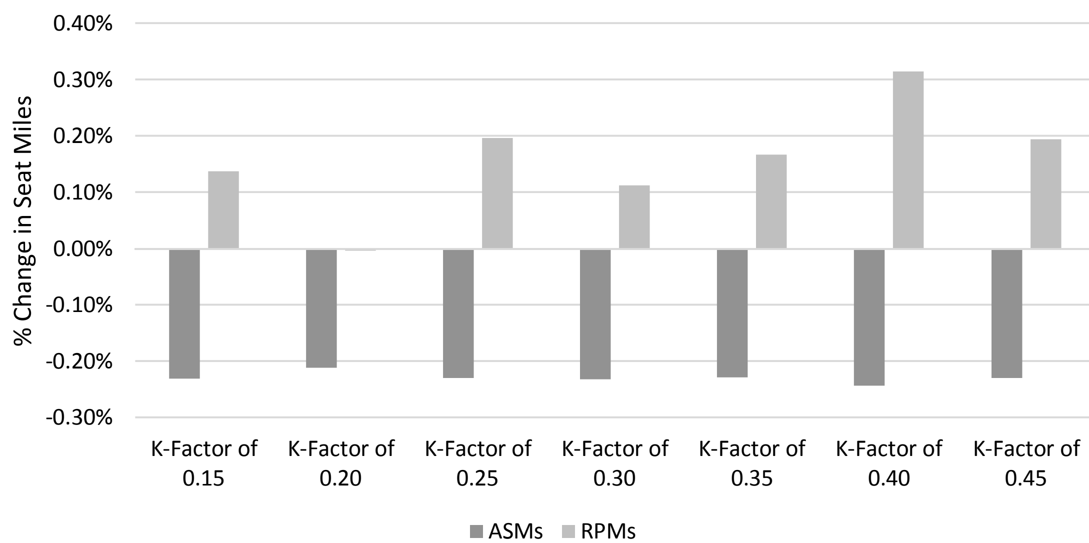

Figure 88: Changes in ASMs and RPMs from D³ at TF14 with Different K-Factors

Figure 88 shows changes in ASMs and RPMs. Increases in RPMs are smaller but significant. As bookings to come are very small 5 days prior to departure, the assigner is more focused on cost-minimization than it would be at TF6. Still, up-gauged flights see increased bookings, and these bookings are high-yield. Meanwhile, cost reduction takes place through the reduction of ASMs by strategically up-gauging shorter stage-length flights. Thus, ASMs decrease by as much as 0.24%.

Several important conclusions come from testing demand driven dispatch at various demand levels. Variability of demand is a very important factor for the efficacy of demand driven dispatch. Not only is demand driven dispatch designed as a response to the variability in demand, its effectiveness is also highly affected by the variability of demand, specifically when D^3 is implemented with swaps early in the booking period. Uncertainty and fluctuations in demand directly impact the demand forecasts (which are by comparison stable) used by both the RM systems and by demand driven dispatch through the RM systems' output. It is incorrect to assume that D^3 is naturally impervious to disruptions from the variability of demand, and therefore incorrect to assume that D^3 necessarily performs better in early time frames when the variability of demand is increased.

If D^3 is implemented at a later time frame, however, such as TF14, the results are very promising and consistent. As the variability of demand increases, because this implementation of D^3 is more resilient to the variability of demand by relying less on expected bookings to come and more on remaining capacity and the observed variability of bookings in hand, the gains of D^3 increase as well. Even with the use of an optimized static fleet assignment in the base cases, demand driven dispatch increase operating profits by as much as 2.03%, revenues by as much as 0.88%, and reduces costs by as much as 0.08%. Demand driven dispatch, therefore, is capable of significantly improving operating profits and revenues even while trimming ASMs (and the associated costs) and increasing both yield and load factor.

8. Chapter 8: Conclusions

The final chapter of the thesis summarizes the concepts of demand driven dispatch and this research. Then, the experiments conducted for this thesis and the findings of the various experiments and sensitivity tests of demand driven dispatch are reviewed. The findings in this thesis represent the first tests of D^3 in a competitive network environment with fully simulated revenue management systems. The conclusions of these tests and their relevance to the practice of both revenue management and demand driven dispatch are outlined. Finally, suggestions for future research are suggested.

8.1. Demand Driven Dispatch

Demand driven dispatch (D^3) is an attempt at integrating airline fleet assignment and revenue management. Its objective is to improve airline operational efficiency and profitability by better matching capacity in an airline network to demand by using demand information from the revenue management system to perform dynamic fleet assignment. Whereas static fleet assignments may be made months prior to the departure date of the flights being assigned aircraft, demand driven dispatch allows these aircraft assignments to be adjusted only days prior to departure.

High demand flights can be up-gauged to capture more revenue. Low demand flights (specifically on longer stage lengths) can be down-gauged to reduce fuel burn and save on operating costs. Demand driven dispatch, also often called dynamic re-fleeting or close-in refleeting, increases the flexibility of the airline planning process to account for the very stochastic nature of demand for air transportation.

However, to date the research in demand driven dispatch has focused almost entirely on improving the optimization methods used in the fleet assignment process for demand driven dispatch. Some research has addressed how revenue management might be adjusted to account for D^3, but this has not been the norm. Also to date, research has not been conducted with demand driven dispatch in a competitive network environment with fully simulated revenue management systems. Thus, the competitive dynamics, network dynamics, and pricing and RM dynamics of D^3 have not been well understood.

In this thesis, demand driven dispatch, using the PODS simulator, is tested with fully simulated revenue management systems and stochastic demand that chooses between two competing airlines, competing paths, and available fare classes. It is tested with competition—PODS Network D^3 has two airlines serving all markets. First, D^3 is tested with a simple bookings-based methodology that assigns the largest aircraft to the flights with the highest forecasted demands. Then, D^3 is tested with either a revenue-maximizing or a profit-maximizing fleet assignment optimizer using the bookings and fare output of the airline's RM system and a minimum-cost flow specification.

Demand driven dispatch is then simulated with swapping implemented throughout the booking period to test the efficacy of swaps given the quality of the forecasts, the pricing structures in the affected markets, and the simultaneous operation of the revenue management system. D^3 also simulated in different competitive scenarios, where one or both airlines implement demand driven dispatch at different times. For sensitivity testing, D^3 with optimized swapping is simulated at different demand levels, with an optimized static fleet assignment, and at different levels of demand variability.

8.2. Insights from Bookings-Based Swapping

The first set of tests in Chapter 4 with bookings-based swapping at different time frames showed that early swapping leads to greater increases in RPMs and greater decreases in yield, while late swapping leads to small increases in RPMs and small decreases to small increases in yield, depending on advance purchase restrictions and fares. The timing of swaps in relation to fare restrictions in the market is critical to the outcome of demand driven dispatch. At all time frames, demand driven dispatch improves the implementing airline's revenues. Table 13 shows revenue changes by TF with bookings-based swapping and a leg-based EMSR revenue management system.

Table 13: Changes in AL1 Revenue, TF Summary, Bookings-Based Swapping

Changes in Airline 1's Revenue from D^3 at Different TFs						
	TF4	**TF6**	**TF8**	**TF10**	**TF12**	**TF14**
Leg RM	0.38%	0.45%	0.44%	0.34%	0.44%	0.54%

The second set of tests, altering the airlines' RM systems and the competitive D^3 environment, showed that the effects demand driven dispatch remain consistent throughout the various scenarios, while the details of the RM system do affect the magnitudes of the changes. When one airline engages in demand driven dispatch, the competitor airline loses revenue. When both airlines engage in demand driven dispatch, revenue changes are very small while both airlines gain RPMs and see decreases in yield. Network RM systems appear to leave fewer gains for D^3 to achieve (with revenue gains of 0.20% to 0.30% rather than 0.44% with leg-based RM). Willingness-to-pay forecasting and fare adjustment successfully prevent some of the dilution from demand driven dispatch and reduce the increase in RPMs (with revenue gains of 0.23% rather than 0.20% without willingness-to-pay forecasting, etc.).

However, willingness-to-pay forecasting fundamentally does not address the reason for dilution in early swaps with D^3—the airline implementing D^3 necessarily opens availability to the lower classes when capacity is increased on high demand flights. When both airlines implement D^3, both airlines increase capacity on high demand flights in pursuit of the same low-yield demand, worsening the dilution.

In all cases where one airline implemented D^3, demand driven dispatch improved revenue with increases of as much as 0.10% to 0.63% depending on the RM system and the quality of the initial fleet assignment. When both airlines implement D^3, up-gauging the same high demand flights in competition for the same low fare class demand, yield decreases as much as or more than RPMs increase, leading to neutral revenue results. In all cases, an airline has better revenue performance when it engages in D^3 regardless of its competitor's actions. Thus, both airlines implementing D^3 is the Nash Equilibrium in this competitive game. It is important to understand the D^3 is a competitive action, and that increasing one's capacity and therefore one's availability has impacts both on one's own bookings and revenue and also on one's competitor's.

The third set of tests in Chapter 4 alters base case demand levels and showed the expected decline in revenue gains from demand driven dispatch at higher demand levels. Changes in revenue are shown in Table 14. However, the results suggest that the primary cause of this decline with bookings-based swapping is greater dilution, not the infeasibility of swapping. Furthermore, the magnitudes of changes in revenue, RPMs, yield, etc. *are* affected by the number of swaps that occur, which are in turn affected by the relationship between initial capacity assignments and their associated forecasted bookings at departure. This relationship is unique to bookings-based swapping, which relies on estimates of expected bookings at departure rather than revenue and cost estimates.

Table 14: Changes in AL1 Revenue, Demand Level Summary, Bookings-Based Swapping

Changes in Airline 1's Revenue from D^3 at Different Demand Levels							
	69% LF	**73% LF**	**76% LF**	**80% LF**	**82% LF**	**84% LF**	**86% LF**
Network RM	0.35%	0.38%	0.22%	0.20%	0.32%	0.18%	0.05%

Bookings-based swapping, which represents a very rudimentary method of engaging in demand driven dispatch, nevertheless illustrates substantial improvements in revenue while also providing important insights in the competitive nature of demand driven dispatch and how it broadly interacts with revenue management and pricing. The timing of demand driven dispatch to correspond with advance restrictions in pricing structures is critical. The implementation of D^3 is a competitive action, in some cases affecting the competitor more than the implementer.

8.3. Insights from Optimized Swapping

Tests of demand driven dispatch using optimized swapping with revenue- or profit-maximizing objective functions further support conclusions from Chapter 4 and showed new patterns and conclusions. Timing swaps in relation to the pricing structures in place critically affects the outcome of demand driven dispatch as well as how that outcome is achieved. Early swaps result in substantial increases in RPMs and load factor with large decreases in yield. In other words, while early swaps improve profitability in these tests, they also result in substantial dilution. In contrast to early swaps, late swaps result in little increase in RPMs and load factor but increase yield, improving revenue and operating profit as much or more than early swaps with far fewer swaps in total. Thus, late swaps pose an operational challenge by swapping so close to departure but also an operational advantage in that relatively few total swaps achieve a significant improvement in profitability. Finally, the outcome of demand driven dispatch is bimodal by time frames, with the peaks in operating profit benefits being 5-10 days prior to the first advance purchase restrictions and 5 days prior to departure.

Both revenue-maximizing and operating profit-maximizing demand driven dispatch, which value the revenue potential of flight legs with estimates from the utilized RM systems, perform better than the simpler bookings-based swapping throughout the booking period but especially in the later time frames when incremental benefits of optimizing the swaps approach 0.15% in magnitude. These methods reference the estimated relative revenue value of additional seats given demand and, in the case of operating profit-maximization, take into account the additional costs of flying larger aircraft longer distances. This is a theoretical and pragmatic improvement over bookings-based swapping. When only one airline implements demand driven dispatch, revenue gains range from gains of 0.16% to 0.66%. Operating cost changes range from -0.09% to 0.13%. Operating profit gains range from 0.38% to 1.52%. Improvement in revenue are the primary driver of improvements in profitability. Changes in operating profit across time frames and with different RM systems and D^3 objectives are shown in Table 15.

Table 15: Changes in AL1 Profit, TF Summary, Optimized Swapping

Changes in Airline 1's Op. Profit from D^3 at Different TFs							
	TF2	**TF4**	**TF6**	**TF8**	**TF10**	**TF12**	**TF14**
Leg RM Rev-Max	0.56%	0.75%	0.87%	0.81%	0.82%	1.10%	1.47%
Leg RM Prof-Max	0.59%	0.79%	0.93%	0.88%	0.84%	1.13%	1.52%
Network RM Rev-Max	0.80%	0.75%	0.70%	0.49%	0.44%	0.56%	0.93%
Network RM Prof-Max	0.69%	0.74%	0.87%	0.43%	0.38%	0.58%	0.86%

With leg-based revenue management, operating profit-maximizing demand driven dispatch does not compromise revenue results and provides larger operating profit increases than its revenue-maximizing counterpart at all time frames. With network RM (DAVN) as the revenue management system, the distinction between the benefits of revenue-maximizing D^3 and profit-maximizing D^3 is no longer clear. However, it is clear that with network RM and profit-maximizing swaps, demand driven dispatch keeps ASMs lower and therefore places more emphasis on minimizing costs. This is due to the deduction of displacement costs from incremental revenue, increasing the relative important of incremental cost savings. It also appears to be the case that as cost-minimization takes on greater importance, improvements in revenue do begin to be compromised as compared to only maximizing revenue with D^3.

The gains of D^3 with network RM (DAVN) are smaller than with leg-based RM. This is persistent across time frames, including in the latest time frames when D^3 is not causing dilution. Therefore, this supports the conclusion that the gains of D^3 are smaller when an airline is using more sophisticated network RM.

In contrast to previous research, revenue improvements, not cost reductions, drive the majority of operating profit increases in almost all of the tests. This is likely due to higher load factors as compared to previous studies, along with a host of other factors including the cost structure employed. Rather than generalizing these findings, one should recognize that the exact results of D^3 rely heavily on the particular environment in which it is used, as is the case with both revenue management and fleet assignment.

When both airlines implement demand driven dispatch, dilution results in only slight revenue increases as both airlines add capacity to high demand flights in the hopes of capturing the same low-yield demand. Cost reductions become a greater proportion of the operating profit increases in these competitive cases. The competitive dynamics of demand driven dispatch also suggest that there are benefits from implementing demand driven dispatch at an earlier point than one's competitor while simply implementing D^3 at a different time frame may insulate (to some degree) competitors from each other's D^3. Demand driven dispatch can harm competitor airlines more than it aids the airline implementing D^3, specifically in early time frames. Still, in all cases the Nash Equilibrium of the competitive game of D^3 always involves both airlines implementing D^3. In early time frames, significant dilution results in neutralized revenue benefits for the competing airlines. The same occurs in later time frames but to a lesser extent. When both airlines implement demand driven dispatch, operating income changes range from -0.37% to 0.92%. However, it is always the case that an airline's operating profits improve when it implements demand driven dispatch regardless of its competitor's actions.

8.4. Insights from Sensitivity Testing

The sensitivity testing of D^3 with optimized swapping also displayed several important conclusions. Testing optimized swapping at various demand levels again resulted in the predicted decreases in the benefits of D^3 at higher demands (shown in Table 16). However, it again was not primarily due to fewer swaps. Rather than the infeasibility of swaps driving changes in the benefits of D^3, the interplay of incremental cost and revenue benefits did. The results of demand driven dispatch can be summarized in three general demand groups. At very low demand levels, cost-minimization plays a key role. As most flights have low load factors, the largest aircraft can be placed on the shortest flights without compromising revenue. Some RPM increases and revenue increases from swapping are realized, as even at low system demand levels some flight departure are still capacity constrained.

Table 16: Changes in AL1 Profit, TF Summary, Optimized Swapping

Changes in Airline 1's Metrics from D^3 at Different Demand Levels									
	64% LF	**69% LF**	**73% LF**	**76% LF**	**80% LF**	**83% LF**	**86% LF**	**87% LF**	**88% LF**
Op. Prof.	1.28%	1.02%	1.29%	0.90%	0.87%	0.71%	0.52%	0.15%	0.04%
Revenue	0.30%	0.35%	0.50%	0.39%	0.41%	0.38%	0.31%	0.13%	0.08%
Op. Costs	-0.05%	0.03%	0.04%	0.03%	0.03%	0.05%	0.08%	0.10%	0.13%

At medium demand levels, cost-minimization no longer significantly contributes to the gains of D^3. Instead, demand levels are at a point where there exists enough demand for very large increases in bookings from swaps. High demand flights can be up-gauged to capture significantly more demand while low demand flights still have little enough demand that being down-gauged does not result in spill. At high demand levels, this is no longer the case—swaps necessarily involve trade-offs as to what demand should be spilled. If incremental revenues are greater than incremental cost savings (as they are in these tests), ASMs increase substantially as the assigner chooses to capture additional long-distance/high fare demand and spill short-distance/low fare demand.

Finally, D^3 is meant primarily to address the variability of demand, not "fix" static fleet assignments. When the static fleet assignment of Airline 1 is optimized using the same assigner as in D^3, the benefits of D^3 are no longer the results of fixing the static fleet assignment but are instead only the results of responding the variability of demand. D^3 remains capable of improving profitability. However, early swaps result in low and inconsistent benefits (with changes in operating profits of between 0.05% and 0.20%). This is because D^3 is relying on the same forecasts as RM and, in the earliest time frames such as 31 days prior to departure, these forecasts are not much better than those used for the static fleet assignment. Early swapping is just as susceptible to error due to the variability of demand as other facets of airline planning. The gains of D^3 with early swapping are low if the static fleet assignment is of high quality.

By comparison, demand driven dispatch with late swapping, even when applied to the optimized static fleet assignment, retains large and consistent benefits. As the variability of demand increases, the gains of D^3 increase as well. Even with the use of an optimized static fleet assignment in the base cases, demand driven dispatch increases operating profits by as much as 2.03%, revenues by as much as 0.88%, and reduces costs by as much as 0.08%. Demand driven dispatch is capable of significantly improving operating profits and revenues even while trimming operating costs. It increases both yield and load factor. Demand driven dispatch, functionally a combination of fleet assignment and revenue management, captures demand and revenues and decreases costs in ways that neither of its components can do alone. Ultimately, demand driven dispatch is a practical way to respond to uncertainty that improves profitability by maintaining aircraft assignment flexibility.

8.5. Suggestions for Future Research

Many avenues exist for continuing research on demand driven dispatch and revenue management. Of course, the tests in this thesis did not complete all the combinatorial options of even the aspects of demand driven dispatch tested. Demand driven dispatch can be tested at different points in the bookings process and at multiple points in the bookings process rather than only swapping at one point. The results of swapping more than once could include incremental benefits from remaining more flexible throughout the bookings process.

For example, a set of early swaps and a set of late swaps could take advantage of the two primary strategies by which demand driven dispatch improves profitability. However, with the sensitivity testing showing mediocre results for early swaps, it may also be the case that only late swaps reliably provide large benefits from D^3 when the static fleet assignment is of a high quality. In this case, swapping more than once in the booking period may not be practical given that early swaps may or may not be helpful. Additionally, capacity changes disrupt the RM system. Swapping numerous times throughout the bookings period may underperform simply swapping once as the incremental benefits of swapping multiple times are undermined by damage to the RM process.

Testing D^3 with a wider variety of revenue management systems is also an avenue for future research. While bookings-based swapping was testing with hybrid forecasting and fare adjustment, optimized D^3 can also be tested with HF/FA. The results are likely highly predictable: as HF/FA significantly decreases the valuation of future bookings in low fare classes and therefore the revenue value of additional capacity on high demand flights, cost-minimization ought to play a much larger role in D^3 with HF/FA. Continuing further down the road of integrating revenue management and fleet assignment, testing D^3 where the fleet assignment process and the network availability optimization process are fully integrated could result in incrementally better results. For example, capacity decisions on each leg can be added directly to the optimization by which DAVN finds network displacement costs.

It is also the case, however, that while these methods are theoretically better, they represent a step that makes implementation of such a D^3 scheme exponentially more difficult. As bookings-based swapping did not perform drastically less well than optimized swapping, the incremental gains of such integrated methods might not be substantial while the difficulty of implementing them could be. Another heuristic that may approach the same incremental gains while maintaining the practicality of implementation would be to continue research into adapting capacity inputs to the revenue management system given D^3.

Further research can also be conducted into the competitive and network natures of D^3. An assigner that takes into account network flows rather than assuming independent leg demand could improve the benefits of D^3. The design of networks and fleets can also drastically change the results of implementing D^3. This represents a very expansive frontier for continuing research into demand driven dispatch, as does increasing the number of competitors and their interactions. With more competitors in a network, the competitive impacts of D^3 may not be as large, for example, when only one airline implements D^3.

In conclusion, the research of demand driven dispatch in a competitive network environment, coupled with full RM systems, resulted in new and important conclusions for the practice of D^3. The benefits of implementing practical demand driven dispatch are substantial, as are the avenues for continuing research on the topic.

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Appendix

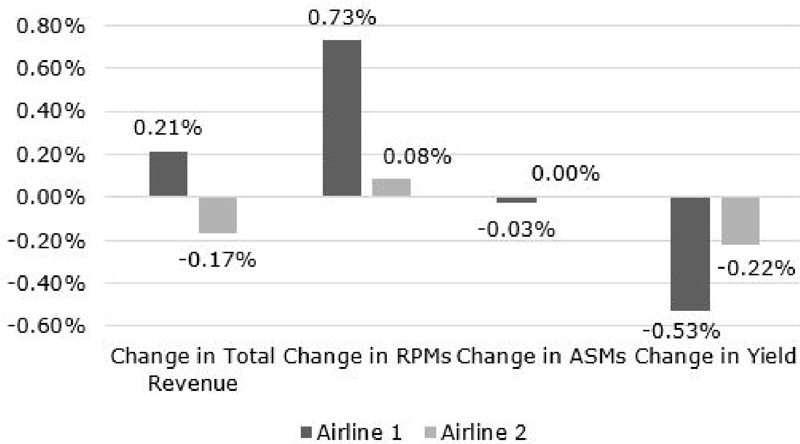

Figure 89: ProBP w/ HF/FA, Airline 1 Uses Bookings-Based D³

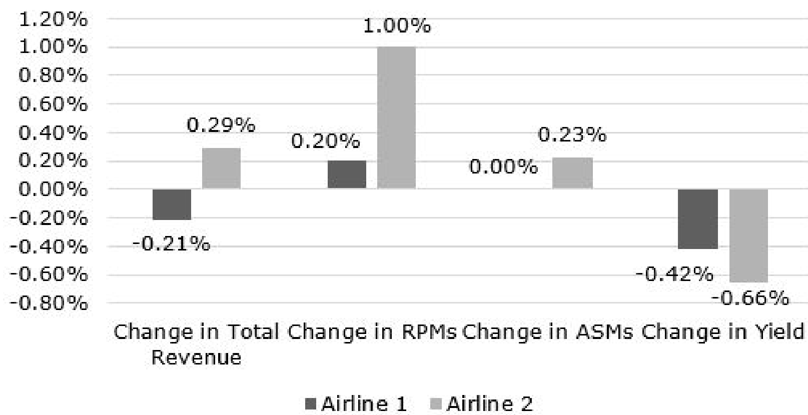

Figure 90: ProBP w/ HF/FA, Airline 2 Uses Bookings-Based D³

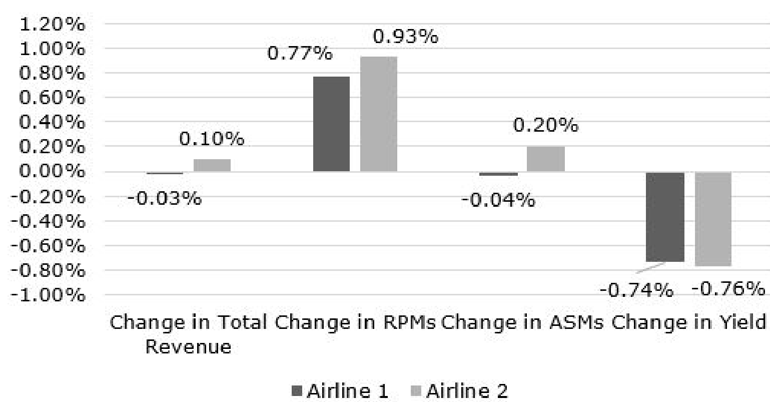

Figure 91: ProBP w/ HF/FA, Both Airlines Use Bookings-Based D³

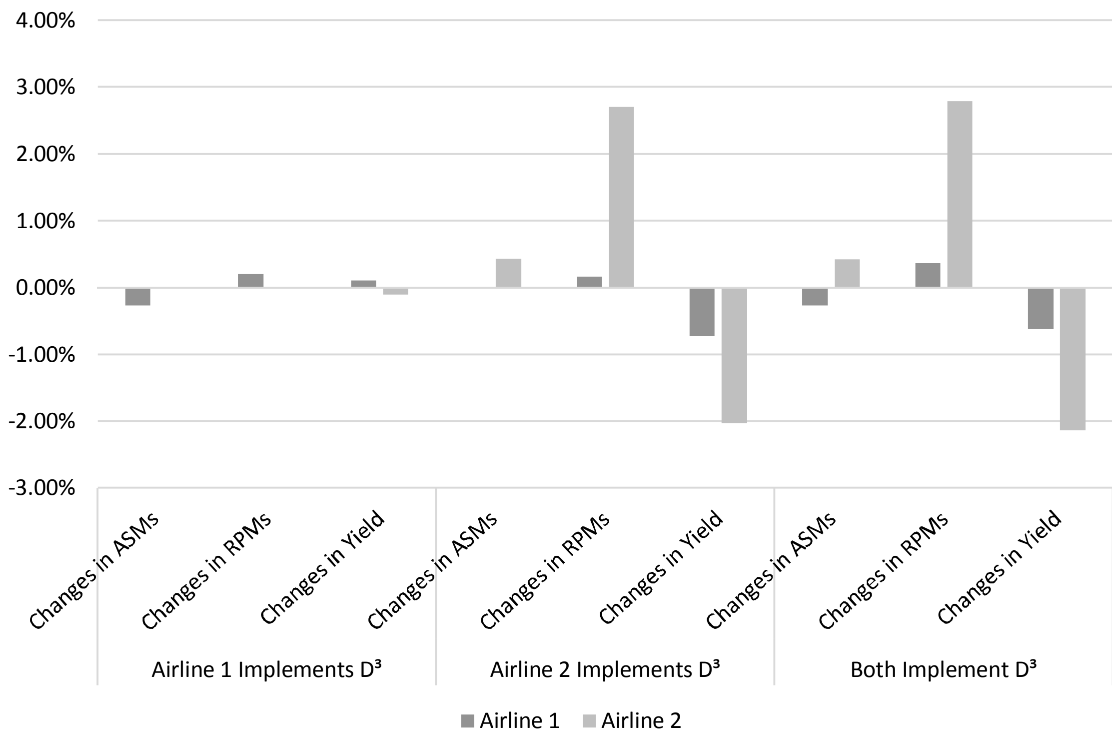

Figure 92: Changes in ASMs, RPMs and Yield, AL1 w/ D^3 at TF14, AL2 at TF6

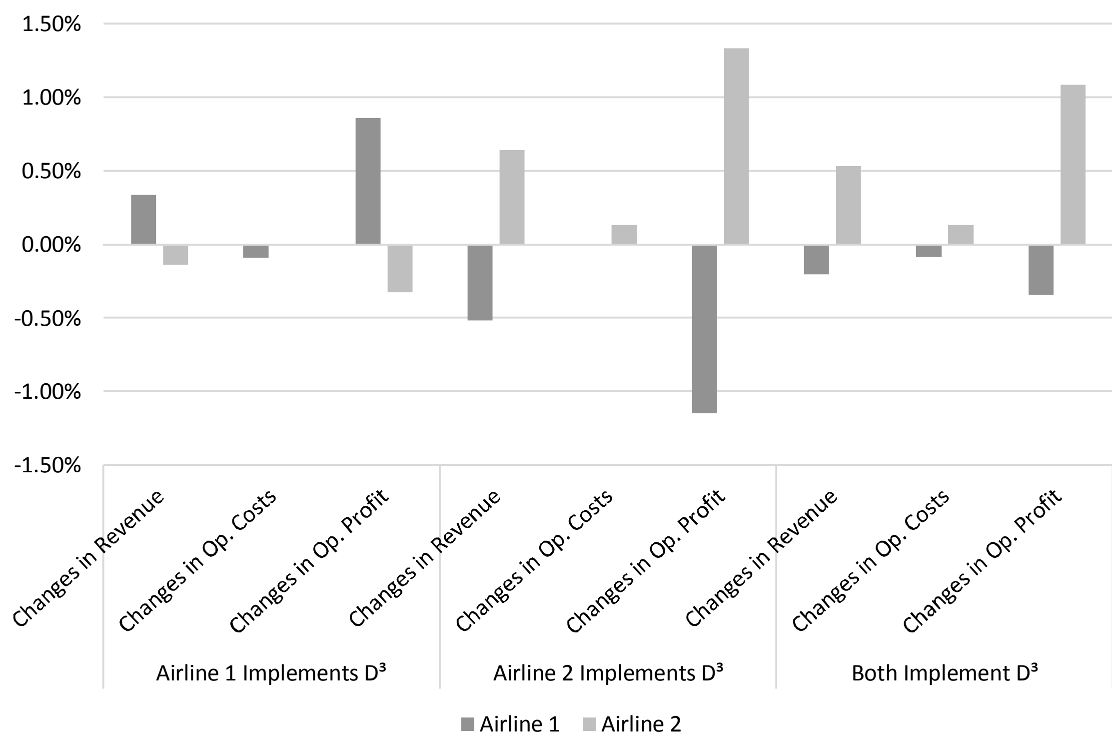

Figure 93: Changes in Rev. Op. Costs, and Op. Profit, AL1 w/ D^3 at TF14, AL2 at TF6