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Effects of hybrid forecasting on revenue development within the airline industry – a simulated analysis

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I. INTRODUCTION

I.1. Revenue Management

Ever since, the main objective of Revenue Management (RM) is to maximize revenue. Within a competitive environment Revenue Management Systems (RMS) are getting more and more important and are mainly applied in industries that have a high ratio of fixed to variable costs like in energy, railway, shipping and lately even smaller service provider sectors. But within the airline branch, RM certainly has its longest tradition, highest level of complexity and most sophisticated approaches. Originally, RM started with overbooking, i.e. selling beyond its capacity in order to compensate no-shows[1] and cancellations on short notice, thus, avoiding empty seats when departing. Over time, RM in the aviation sector developed more different tools such as forecast, seat allocation and pricing models in order to maximize revenues. In the main parts of this thesis focus on demand forecast and seat allocation while overbooking models or pricing strategies will not be discussed here.

Given a fixed capacity, that equals the number of seats on a certain flight, the science of RM is maximizing expected revenues through market demand forecasting and the mathematical optimization of price and availability of these seats. Thus, seat allocation optimization or seat inventory control is the process of limiting the number of seats sold at different price levels, basically managing the tradeoff between yield and spoilage.

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[1] A „No-Show" refers to a passenger who has a valid booking for a specific flight but does not show up at the departure, e.g. due to misconnex.

The forthcoming subchapters will briefly explain the general development of RM, both, prior and after worldwide deregulation in the aviation sector that had a huge impact on RM.

I.1.1. The Impact of Deregulation on Airline RM

The deregulation in the United States as well as in Europe within the aviation sector changed this industry dramatically. Before the U.S. airline deregulation in 1978 there almost was no such thing as RM in the airline industry. U.S. airlines had no freedom to set the level of their airfares themselves; tariffs were rather determined by the Civil Aeronautics Board (CAB) on a price-per-miles basis, i.e. there was one single price per compartment flying from a certain point A to B, mainly depending on the distance between the two points and regardless of the time of travel or the time of (advanced) booking. Airlines' requests to increase or decrease their fares were mostly denied and increases were only allowed in case of losses in order to compensate the costs. Prices were comparably high to today's tariffs which resulted in both, poor loads and poor revenues. From today's RM point of view that focuses on revenue maximization this situation can be described as overprotection, capturing revenue from passengers who could afford it with their high willingness to pay only (see Chapter I.1.2, Figure 1.1: Overprotection and Dilution).

The development of airline RM in Europe was not much different than the one in the United States and lead to similar consequences. After the Second World War each European nation had its own national "flag carrier", in each case fully or partly owned by the respective government. European Nation's governments negotiated mutually about frequencies and tariffs between the gateways in their two countries. Similar as in the United States, the airfares in these bilateral agreements were

determined according to the suggestion done by the IATA, the International Air Transport Association (IATA) which was founded in 1945[2].

Due to the fact that each national carrier was owned by its nation there was practically no space for any competition to arise. Moreover, the national airlines were often highly subsidized which created no incentive to change their inefficient cost or pricing behavior. But after the successful development in the U.S. aviation industry during the 1980s, the first measures towards deregulation in the Europe airline industry were triggered by the European Council in 1987. This process was finally completed in 1997.

The first steps to a more dynamic pricing and revenue management – then still known as yield management – were taken in the United States in the early 1970s when airlines started offering discounted fares within the same compartment combined with certain restrictions. For example, British Airlines, which was still known as BOAC in that time, offered a lower fare to passengers who purchased their ticket at least 21 days before departure in order to attract passengers with a lower willingness to pay (WTP) and, thus, trying to sell more seats that may have been empty otherwise at the time of departure[3]. But selling all the fixed capacity, i.e. the number of seats in the aircraft on the certain departure date, at the lower fare is also not the optimal choice (see following Chapter I.1.2).

After deregulation in both areas, North Atlantic and Europe, the airlines entered a more competitive environment as suddenly all airlines were free to choose their airfares themselves. The need for the right seat allocation as described above and, hence, the need for a RM system that maximizes revenue was becoming more obvious and needed.

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[2] Burghouwt, G., M. Huys. 2003. Deregulation and the Consequences for Airport Planning in Europe. *DISP* Volume 154, p. 37.
[3] McGill, G.I., G.J. van Ryzin. 1999. Revenue management: research overview and prospects. *Transportation Science.* Volume 33, Issue 2, pp. 233-256.

I.1.2. Further Development of Airline RM

The product an airline is the flight transportation service from a certain point A to another point B on a specified future date. As described earlier, before deregulation there was one single price for this service regardless of other preconditions like demand, competition or the time of booking prior departure.

As an airline can set prices by itself since the deregulation the question raises what is the right price. If the price is set too high the airline will eventually produce a suboptimal output in terms of revenue maximization. Assuming a certain demand curve, this high price captures the revenue that results from high price and low quantity – only passengers with a willingness to pay equal or greater than the full fare will be affected. Hence, the airline has a lot of unused seats at the time of departure; lost revenue that could have been gained through selling the rest of the capacity offered at a lower price than the full fare. Even when today's pricing structures are different and more complex than before the deregulation the problem of overprotection remains the same.

However, if the price is set at a lower level, meaning that most passengers' willingness to pay exceeds the (discounted) fare, the total capacity can be sold most of the time. Consequently, passengers enjoy a great consumer surplus, especially high yield customers. From those high yield passengers airlines usually expect strong revenue streams, however, with this pricing strategy expected high revenues are diluted with low fares.

Hence, the airlines have developed strategies over time in order to maximize revenues by charging not only one price for the flight from A to B but offering several pricing levels depending on certain conditions such as time of booking prior departure, lengths of stay, the possibility to refund the ticket and others. With these conditions airlines were able to distinguish between the passenger types and their willingness to pay, thus, inventing different "products" fitting each passenger type. In general, two types of passengers can be distinguished: leisure and business

travelers. Referring to the first one, leisure passengers, they have the following main characteristics: a comparable low willingness to pay (as many other costs have to be beard next to the flight, as for example accommodations) and an early booking behavior as they tend to fix their holiday somewhat in advance. Moreover, leisure travelers usually stay at least some days or over the weekend and their holidays are rarely rescheduled. In contrast, business passengers often need to fly on very short notice, they might need to rebook or even refund their booked flight when, for instance, a meeting is rescheduled or cancelled. Business travelers usually stay only one or two days never using their spare time staying over the weekend. In order to have this flexibility they are willing to pay a higher price than leisure passengers.
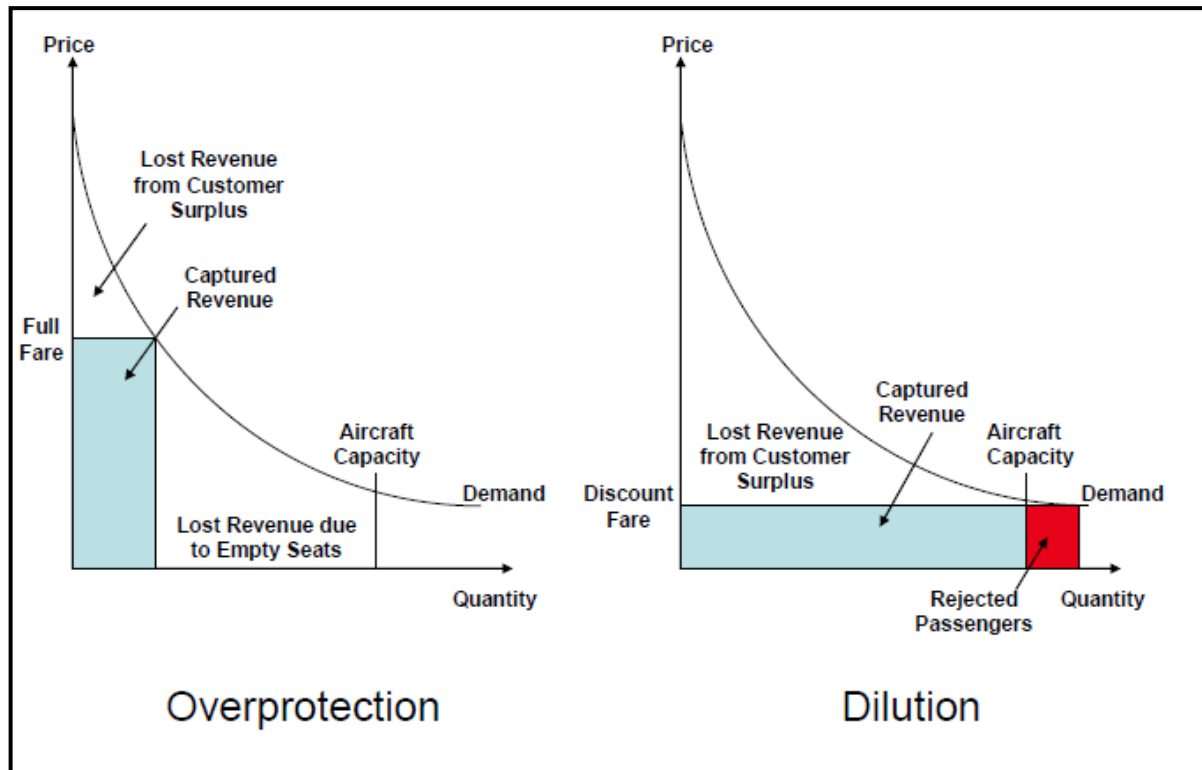
Figure 1.1: Overprotection and Dilution, reproduced from Keyser[4]

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[4] Keyser, M. R. 2008. RM Methods for Multiple Fare Structure Environments. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA. pp. 15-16

Knowing these characteristics one can use certain practices in order to separate these target groups, thus, being able to reflect the true demand and true willingness to pay for each group maximizing revenue, respectively minimizing the revenue losses through overprotection and dilution (see Figure 1.1). Lowest fares are combined with restrictions that hinder business travelers of purchasing them such as advanced purchase, minimum stays and Saturday/Sunday rules. Advance purchase implicates that a fare is purchasable only until a fixed period prior departure, e.g. 21 days. Minimum stay refers to a certain period of days the passenger has to stay between departure and return. Whereas, meeting the Saturday/Sunday rule the passenger needs to stay over the weekend in order for this fare to be applicable. Furthermore, low fares are often neither rebookable nor refundable. The smaller the discounts from the full fare – actually the original and highest fare within a compartment – the more flexible the products become. The full fare has no restrictions at all. If one of these restrictions is violated the higher fare is applicable where all demanded conditions are met. In other words, different pricing levels in combination with certain restrictions are used for market segmentation and to allocate the correct price to each travel type, i.e. the price that equals the passenger's willingness to pay (see Figure 1.2).
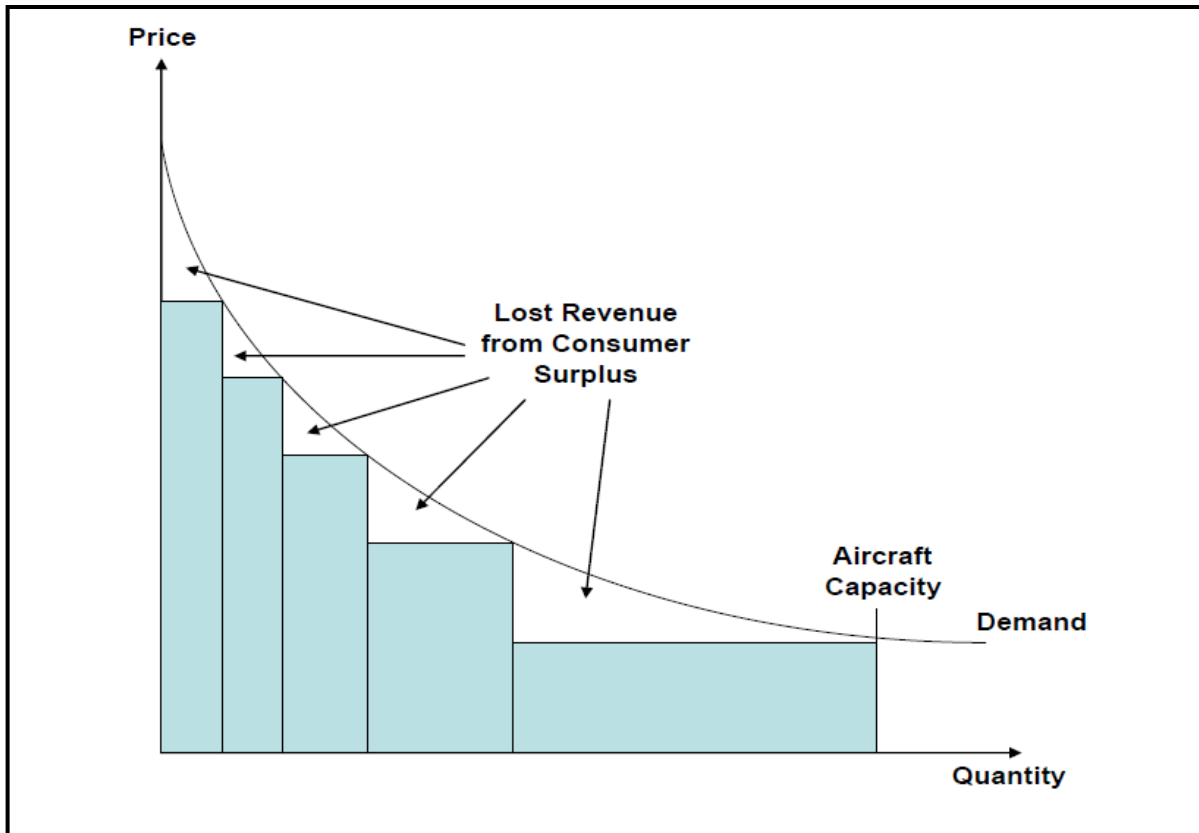
Figure 1.2: Dynamic Pricing, reproduced from Keyser [4]

However, with this new innovation of dynamic pricing consequently a problem arose: how many seats per flight should be sold at a lower fare and how much of the fixed capacity should be protected for late high yield bookings? A brief overview about the traditional tools that were developed as a response to this question will be given in Chapter II.1. Later on, an explanation about the RM Tools of the new environment will follow as well.

I.2. Objective of the Thesis

For each sophisticated RM system an accurate forecast for future demand is a crucial factor influencing the outcome of revenue maximization process essentially. Traditional network carrier (NWC) used to separate and forecast passenger demand through certain restrictions. However, through the emergence of the low cost carrier (LCC) the traditional RM systems using this separation became invalid; especially a correct forecasting process was not possible anymore after the removal of the separating restrictions. Traditional RMS used by NWC had – and still have – great difficulties in classifying business and leisure demand in this new semi- or unrestricted market environment where fare structures are indifferent except for the price level. This resulted in the development of new RM methods eventually. Hybrid Forest is one method of this "new generation" of RM systems generating two separate forecasts for two different passenger demand types: yieldable and priceable demand. Priceable demand refers to price-sensitive customers who strive to buy the cheapest available fare only whereas yieldable demand represents passengers who buy a fare because of its characteristic, for example the possibility to rebook or refund the fare. As these two demand types vary in their booking behavior two different forecasting methods apply too. Both forecasts of yieldable and priceable demand are then taken together to a total "hybrid" forecast model.

The objective of this thesis is to evaluate the effectiveness of Hybrid Forecasting over other traditional RM methods in unrestricted environments. In order to test this thesis a simulation tool called REMATE is used. REMATE was developed and provided by Deutsche Lufthansa AG together with the University of Berlin. The simulation environment contains of a small network with one hub and three routes where two airlines compete against each other; one LCC and one NWC. The simulation itself offers four different scenarios where the NWC always uses a different RM techniques including first-come-first-serve RM, leg based RM, OD (origin-destination) based RM and, finally, hybrid forecast RM. The results of all

scenarios will be compared and discussed to find an appropriate forecast method for the current aviation environment.

I.3. Structure of the Thesis

This thesis is organized into two three parts: a description about all relevant literature and theory relating to this topic, an overview of the simulation environment used for this thesis and, finally, the presentation and analysis of the simulation results.

Chapter I and II provide insight about the basic theory of airline revenue management presenting the historical development and the most important RM tools applicable. Overbooking, forecasting and inventory control are the topics covered here. Moreover, the low cost carrier business model is discussed.

In Chapter III the problems of today's network carrier are described: the reason for spiral down effect they experienced and the consequential need to evolve traditional RM tools. The hybrid forecast and optimization model which represents one of the new RM tools is also explained in this section.

A detailed introduction of the simulation tool REMATE and the environment that has to be created in order to run a successful realistic simulation is presented in Chapter IV. This includes the development of a network and schedules as well as the demand generation in form of different customer types that reflect the true passenger behavior in a most realistic way.

Chapter V explains the four different simulated scenarios and offers an analysis of all simulation results. The simulation outputs include the airline's revenue, final booked passengers, yield but also the fare class mix and the customer type

distribution. Finally, Chapter VI concludes this thesis with a summary of the findings particularly with regards to the thesis' objection and further research direction is considered.

II. LITERATURE REVIEW

The first literature published about airline RM dates back to the 1960s and focuses on overbooking as the first tool to improve airlines' revenue. After deregulation in the late 1970s the airline environment grew and competition increased leading to greater efforts improving RM quality, and, hence, more papers and thesis about that topic were published. Especially in the last two decades there was another worldwide raise of competition caused by the emergence of low cost carrier which again increased the awareness to enhance airline RM methods. This chapter starts discussing the traditional RM techniques that have been developed before giving an overview about the low cost carrier and the business model they adopt.

II.1. Traditional RM Tools

Soon after the deregulation, airlines realized that each seat on board of their aircrafts is a perishable good, meaning once a seat is left unsold at the time of departure, the chance to sell it is gone forever. So the bottom question was how to optimize those seats most efficiently, in other words, following task should be solved: selling the right seat at the right time to the customer at the right price. When airlines first started to record all bookings in their system they were not able to use this information effectively; not until they could compare the expected booking curve from previous flights with the actual booking curve, thus developing

the first optimization models. Barnhart et al[5] provides insight of the development of airline RM systems from the early 1980s until the "third generation" RM systems were developed, as seen in Figure 2.1. A typical third generation RM model consists of three main components: a forecast model, an overbooking model and a seat optimization model. External inputs needed as a basis are revenue data, e.g. provided from revenue accounting in order to estimate the value of a fare and booking class, actual bookings, collected data from historical booking and no shows for each single flight. Ultimately, this RM component model will output optimal overbooking levels and recommended booking limits in order to maximize overall revenue.

In the following subchapters all three main components will be briefly discussed, overbooking, forecasting and different seat allocation optimization models. More literature about RM systems are provided by McGill and van Ryzin[2] as well as Clarke and Smith[6].

[5] Barnhart, C., P.P. Belobaba, A.R. Odini. 2003. Applications of Operations Research in the Air Transport Industry. *Transportation Science*, Volume 37, Issue 4, pp. 368-391.
[6] Clarke, M., B. Smith. 2004. Impact of Operations Research on the Evolution of the Airline Industry. *Journal of Aircraft*, Volume 41, Issue 1, pp. 62-72.

Reproduced from Barnhart et al.
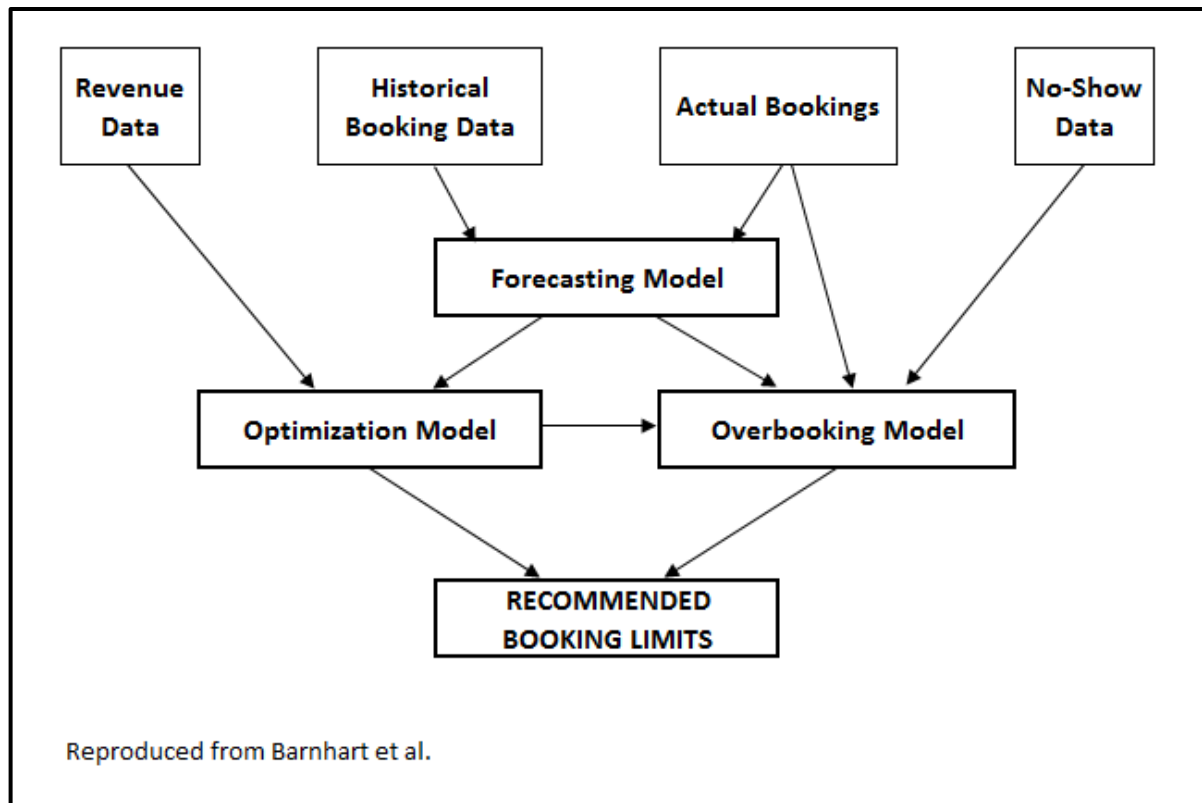
Figure 2.1: Third Generation Revenue Management Component Model, reproduced from Barnhart et al.[5]

II.1.1. Overbooking

The first measure taken to improve revenue performance was to overbook flights. When airlines realized that there are always some so called no-shows, i.e. passengers who do not show up at departure due to short term cancellations, misconnections or other reasons, they started selling above the capacity they actually offered. This avoids a fully booked flight leaving with empty seats. Of course, this creates the risk of possible denied boardings if more passengers show up than expected eventually exceeding the total physical capacity of the operating aircraft. This causes costs and customer dissatisfaction. Consequently, overbooking profiles were developed with sufficient data and appropriate tools to minimize the

risk of denied boardings. The first overbooking models were developed in the late 1960s and early 1970s by Simon[7, 8], Falkson[9], Biermann and Thomas[10], Rothstein[11] and Vickrey[12] and since then further research was done continuously till today. In this thesis the overbooking as RM tool will not be discussed any further.

II.1.2. Forecasting

Another crucial tool of revenue management is forecasting. As mentioned in the earlier Chapter I.1.2 if airlines are offering different fares to the customer there is always the problem of uncertainty about how many seats should be distributed to early booking passengers, typically with lower willingness to pay (WTP) and how many seats should be saved for late booking passengers, usually business travelers with a higher WTP. An accurate forecasting of overall demand of a market but also on a more disaggregated level, i.e. forecast of a certain day of week, of a certain flight and of each fare class, is inevitable to solve this problem and has direct influence on the overall optimization process of RMS.

There are several methods developed and used to forecast passengers' behavior. First research on this topic concentrated on aggregated demand forecast on a macro level. The overall forecast, for example between two regions during a certain time period was projected with Poisson and regression models using historical

[7] Simon, J. 1968. An Almost Practical Solution to Airline Overbooking. *Journal of Transport Economy and Policy.* Volume 2, p. 201-202.
[8] Simon, J. 1972. Airline Overbooking: The State of the Art – A Reply. *Journal of Transport Economy and Policy.* Volume 6, pp. 254-256.
[9] Falkson, L. M. 1969. Airline Overbooking: Some Comments. *Journal of Transport Economy and Policy.* Volume 3, pp. 352-354.
[10] Biermann, H. Jr. and J. Thomas. 1975. Airline Overbooking Strategies and Bumping Procedures. *Public Policies.* Volume 21, pp. 601-606.
[11] Rothstein, M. 1971a. An Airline Overbooking Model. *Transportation Science.* Volume 5, pp.180-192.
[12] Vickrey, W. 1972. Airline Overbooking: Some Further Solutions. *Journal of Transport Economy and Policy.* Volume 6, pp. 257-270.

booking data only. Early regression techniques and experiments with airline data to aggregate airline forecasting are described by Taneja[13] and in the Master thesis of Sa[14].

Later, disaggregated and, moreover, short term booking information was collected and used additionally. The use of this information for demand forecasting models has been discussed by Harris and Marucci[15] at Alitalia, L'Heureux[16] at Canadian Airlines International, Adams and Micheal[17] at Quantas and Smith, Leimkuhler and Darrow[18] at American Airlines. Lee's[19] doctoral dissertation examines several issues of disaggregated airline demand using Poisson models.

Current practice is to use collected information of historical booking data as well as current booking developments as a basis in order to forecast accurately at a disaggregated micro level, i.e. forecast of each fare class on each individual flight. Forecast models can apply either for individual flight legs or for whole Origin-and-Destination (OD) itineraries. The methods, combining historical and future forecasting, most commonly used by airlines RM are pick-up forecasting, time-series models, moving average and exponential smoothing. While Zeni[20] examines the moving average method, the multiplicative pick-up model and the exponential smoothing, Wickham[21] compares pick-up models to linear regression methods and

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[13] Taneja, N.K. 1978. *Airline Traffic Forecasting: A Regression Analysis Approach.* Chapter 1. Lexington Books.

[14] Sa, J. 1987. Reservation Forecasting in Airline Yield Management. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

[15] Harris, P. and G. Marucci. 1983. A Short Term Forecasting Model. *23rd AGIFORS Symposium Proceedings*, Memphis, TN.

[16] L'Heureux, E. 1986. A New Twist in Forecasting Short-Term Passenger Pickup. *26th AGIFORS Symposium Proceedings*, Bowness-On-Windermere, England. pp. 248-261.

[17] Adams, W. and V. Michael. 1987. Short-Term Forecasting of Passenger Demand and Some Application in Quantas. *27th AGIFORS Symposium Proc.,* Sydney, Australia.

[18] Smith B.C., J.F. Leimkuhler and R.M. Darrow. 1992. Yield Management at American Airlines. *Interfaces*. Volume 22, pp. 8-31.

[19] Lee, A.O. 1990. Airline Reservation Forecasting: Probabilistic and Statistical Models of Booking Process, Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MA.

[20] Zeni, R.H. 2001. Improved Forecast Accuracy in Revenue Management by Unconstraining Demand Estimates from Censored Data. Ph.D. Thesis, Rutgers, the State University of New Jersey, Newark, NJ.

[21] Wickham, R.R. 1995. Evaluation of Forecasting Techniques for Short-Term Demand of Air Transportation. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

to simple time series. In his master's thesis Wickham discovered that pick-up forecasting consistently outperforms other methods discussed in his theses leading to the highest revenue outcome. The Pick-up method divides the timeline prior to the flight's departure in certain well specified periods. Then it compares historical booking data within these timeframes with current bookings, thus, forecasting the "picked-up" number of the incremental bookings for each single period. Deeper analysis of classical pick-up forecasting and different time-series models can be found in Zickus[22], Skwarek[23], Usman[24] and Gorin[25].

Due to the very dynamic nature of passenger's booking behavior that changes over time historical booking data may deviate from future booking patterns, hence, disaggregated forecasting on a passenger level turns out to be extremely difficult and complex which results in a permanent research for even more accurate forecasting models. Latest development in this field that should be highlighted here is the hybrid forecast model which combines two different forecasting methods as a reaction of the new environment airlines have entered. This model will be explained explicitly and in detail later in Chapter II.2.

II.1.3. Seat Allocation Optimization

Once having an accurate forecast this information needs to be processed by the seat allocation optimizer or inventory control. There are different approaches of how

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[22] Zickus, J.S. 1998. Forecasting for Airline Network Revenue Management: Revenue and Competitive Impacts. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[23] Skwarek, D.K. 1996. Competitive Impacts of Yield Management Systems Components: Forecasting and Sell-up Models. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[24] Usman, A.S. 2003. Demand Forecasting accuracy in Airline Revenue Management: Analysis of Practical Issues with Forecast Error Reduction. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[25] Gorin, T.O. 2000. Airline Revenue Management: Sell-up and Forecasting Algorithms. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

to achieve the optimal seat allocation in order to maximize revenue and models have evolved during the past four decades. Before inventory control it was a simple first-come-first-served system. In the following subchapters I will briefly discuss the most common and important methods of seat allocation distinguishing between single leg based control and origin-destination (OD) control.

II.1.3.a Leg Based Control

In 1972, Littlewood[26] was the first to present a solution for the question whether a seat should be sold or rather protected in an environment for a single leg flight with two different fare classes, by taking the displacement cost into consideration. In airline revenue management, the displacement or opportunity cost of a booking includes all future revenues that may be lost if the booking is accepted. Thus, Littlewood created a "nesting" rule that sets certain booking limits for each fare class restricting the seats that can be sold at the discounted fare level according to the expected revenue forecast of sellable seats at the higher full fare class. With this method he "linked" the revenues of all fare classes with each other instead of seeing the forecasts of each fare class independently. Littlewoods Rule says that given the average full fare Y and the average discounted fare B, where $Y > B$, full fare demand D and s seats remaining, the demand for the discounted fare should be satisfied as long as

$$B \geq Y\ P(D > s),$$

where $P(D > s)$ is the probability that the demand is greater than the remaining seats.

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[26] Littlewood, K. 1972. Forecasting and Control of Passenger Bookings. *12th AGIFORS Symposium Proceedings*, Nathanya, Isreal, pp. 95-117.

Based on Littlewood's work Belobaba[27] extended this rule to be applicable in multiple fare classes. In his Ph.D. thesis 1987, he created the Expected Marginal Seat Revenue (EMSR) heuristic which he even refined in 1992 to the more robust EMSRb probabilistic decision model[28]. EMSR is referring to the average fare of the seat being considered multiplied by the probability that demand will materialize for that marginal seat. Similar to Littlewood's rule the EMSRb assumes stochastic and independent demand for each fare class and, furthermore, is a top down approach, i.e. a class protection is set for the highest fare class first. Thus, a seat for this higher fare is protected as long as the expected marginal value of saving it exceeds the expected revenue from the fare class below; and so on until total inventory has been allocated to each fare class (Figure 2.2 that is reproduced from Barnet et al.).

total available seats

BL: Y — protected for Class Y from B, M and Q

BL: B — protected for Class Y and B from M and Q

BL: M — protected for Class Y, B, M from Q

BL: Q — protected for Class Y, B and M from Q

Reproduced from Barnhart et al.
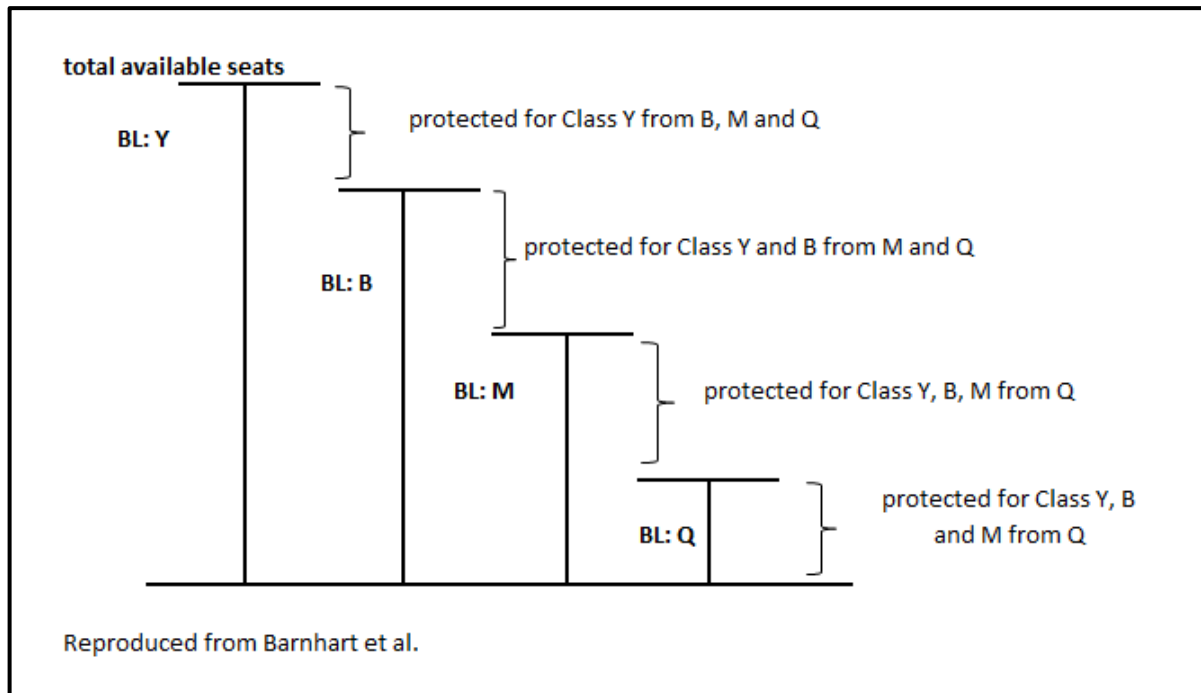
Figure 2.2: Nested Booking Limits (BL) and Class Protection Levels, reproduced from Barnhart et al.[5]

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[27] Belobaba, P.P. 1987. Air Travel Demand and Airline Seat Inventory Management- Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[28] Belobaba, P.P. 1992. The Revenue Enhancement Potential of Airline Revenue Management Systems. *ASTAIR Porc. Adv.Software Tech. Airport Transport*, London, UK.

The EMSRb model optimizes the revenue of a single leg by setting booking limits per fare class from the highest fare class top down. But since it is a leg-based algorithm that optimizes each leg independently might not maximize revenue for transfer passengers who travel more than one leg on their trip. Although if a transfer passenger contributes less on one flight leg than a local passenger the transfer might bring more revenue in total for the airline, meaning EMSRb does not maximize overall network revenue. It is obvious that especially hub-and-spoke network carrier need to optimize the overall revenue, i.e. all traffic types have to be taken into consideration, local but also transfer. This enhancement will be discussed in the following subchapter.

Although other authors such as Curry[29], Wollmer[30], Robinson[31], Brunelle and McGill[32] have developed optimal seat allocation algorithms for multiple fare classes independently as well, Belobaba's EMSRb model has become accepted and incorporated in many airlines' revenue management systems worldwide. More detailed information about the EMSRb model provides Belobaba and Weatherford[33], Williamson[34] and Lee[35].

[29] Curry, R.E. 1990. Optimal Airline Seat Allocation with Fare Classes Nested by Origin and Destination. *Transport Science.* Volume 24, Issue 3, pp. 193-204.
[30] Wollmer, R.D. 1992. An Airline Seat Management Model for a Single Leg Route when Lower Fare Classes Book First. *Operations Research*. Volume 40, Issue 1, pp. 26-37.
[31] Robinson, L.W. 1995. Optimal and Approximate Control Policies for Airline Booking with Sequential Nonmonotinic Fare Classes. *Operations Research*. Volume 43, Issue 2, pp. 252-263.
[32] Brunelle, S.L. and J.I. McGill, 1988. Airline Seat Allocation with Multiple Nested Fare Classes. *Fall ORSA/TIMS Conference*, Denver, CO.
[33] Belobaba, P.P., L.R. Weatherford. 1996. Comparing Decision Rules that Incorporate Customer Diversion in Perishable Asset Revenue Management Situations, *Decision Sciences*, Volume 27, Issue 2, pp. 343-363.
[34] Williamson, E.L. 1992. Airline Network Seat Inventory Control: Methodologies and Revenue Impacts. Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[35] Lee, A.Y. 1998. Investigation of Competitive Impacts of Origin-Destination Control using PODS. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

II.1.3.b Origin-Destination Control

Airlines with leg based inventory control as RM technique, as discussed in the previous chapter, registered significant revenue improvements compared to simple first-come-first-serve systems. Since the 1980s the number of connecting passengers, travelling more than just one leg, dramatically increased which went along with an expansion of hub-and-spoke networks. However, in a hub-and-spoke network with multiple legs a leg based inventory control might lead to sub-optimal results, especially in bottleneck situations, as the system forecasts and optimizes each leg while the passenger's booking behavior is per path or OD (Origin-Destination) that may consist of more than just one leg. So OD based optimization was developed in order to meet the growing hub-and-spoke network needs accordingly by allocating the seats rather on paths than on individual legs. An example of such a situation leading to suboptimal results is shown in Table 2.1; assuming a two leg network environment and two fare classes available: Y and B. The price for the local passenger shall be 800 in Y class and 500 in B class while the fares for the transfer passenger shall be 1500 and 1000 in Y, respectively B class. The first leg faces high demand offering higher class Y only while on the second leg with low demand still both classes, B and Y are available.

pax type	fare class	price	LEG 1 high demand: Y class open only	LEG 2 low demand: Y and B class open
local passenger (using leg 1 only)	Y	800	accepted	n/a
	B	500	rejected	n/a
transfer passenger (using both legs)	Y	1500	accepted	accepted
	B	1000	rejected	accepted

Table 2.1: bottle neck situation with leg based optimization

Due to different journey destinations the transfer passenger might contribute more revenue in total in a lower class than a local passenger in a higher class as assumed above. In order to get a specific class accepted this class must be available on the whole itinerary; otherwise this booking request will be rejected. In a leg based optimization the system would reject a transfer passenger in B class on leg 1 who is willing to pay 1000 in total for both legs but favoring a local Y class passenger paying 800 instead. A transfer passenger might contribute less revenue to a single leg than a local and is thus rejected. But in total the transfer passenger has a higher revenue contribution to the network. An OD algorithm would recognize this difference as it takes the whole journey of a passenger into consideration instead of individual legs.

The first method for OD control was developed by Smith and Penn[36] at American Airlines in 1988. They did not compare fare classes anymore but Origin-Destination-Fares (ODF) of local and transfer passengers. Smith and Penn created RM internal "virtual buckets"; the ODFs of each passenger were clustered into single leg booking classes and allocated according to their values into the "right" virtual bucket. This process of "virtual nesting" enables a better comparison of passengers' values contributing to the total network. Then, booking limits are set in these virtual buckets, thus achieving a better network control.

Unlike the leg based control, this method always favors the highest fare which might result in favoring transfer over local passengers, even if two locals would bring more total revenue together. A simplified example of such a situation can be found in Table 2.2 where high demand is assumed on both legs but only one seat is left to sell on each leg.

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[36] Smith, S.L., C.W. Penn. 1988. Analysis of Alternative Origin-Destination Control Strategies, *28th AGIFORS Symposium Proceedings*, New Seabury, MA, pp. 123-144.

pax type	price	LEG 1 high demand: one seat left	LEG 2 high demand: one seat left
local passenger A (using leg 1 only)	500	rejected	
local passenger B (using leg 2 only)	700		rejected
transfer passenger (using both legs)	1000	accepted	

Table 2.2: bottleneck situation with virtual bucket OD based control

Subsequently, Smith and Penn[34] refined their process and developed Displacement Adjusted Virtual Nesting (DAVN) that corrects the ODF by taking the costs of displacing another local passenger into consideration. Shadow prices that can be interpreted as displacement costs are generated for each single leg using linear programming. Those shadow prices and the actual fare are then used to calculate a "pseudo fare" which represents the ODF corrected by the displacement costs or, in other words, the network revenue value. As a consequence, connecting passengers are not necessarily favored over local passengers anymore. More in-depth information on DAVN approach and OD control provide Williamson[37], Vinoid[38], Lee[33] and Wei[39].

Another widespread method of OD control is the Bid Price Model (BP) that was developed by Simpson[40], Williamson[41] but also discussed by Smith and Penn[34].

[37] Williamson, E. L. 1988. Comparison of optimization techniques for origin-destination seat inventory control. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA

[38] Vinoid, B. 1995. Origin and Destination Yield Management. *The Handbook of Airline Economics*, D. Jenkins (ed). The Aviation Weekly Group of the McGraw-Hill Companies, New York, NY, pp 459-468.

[39] Wei, Y. J. 1997. Airline O-D Control using Network Displacement Concepts. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA

[40] Simpson, R. W. 1989. Using Network Flow Techniques to find Shadow Prices for Market and Seat Inventory Control, Memorandum M89-1, Massachusetts Institute of Technology, Cambridge, MA

This RM method is using linear programming and the expected demand (instead of random forecast) to calculate a bid price for each individual leg, thus incorporating the displacement cost. A booking is accepted when the OD fare of the requested class is greater than the sum of all bid prices on the passenger's itinerary. The bid price replaces multiple booking limits and pseudo fares that need complex calculation efforts for each offered ODF and is a much simpler approach and easier to implement then virtual buckets. This is why, the bid price model method has achieved best acceptance in most network carrier's RM systems.

More information about the calculation of different bid price algorithms provides Belobaba[42] who developed the Network Bid Price and the Heuristic Bid Price method and Bratu[43] for the Probabilistic Bid Price method.

All RM methods were successful tools to maximize revenue until the low cost carrier emerged worldwide with a new business model that harmed network carrier and their traditional RM methods. The low cost carrier business model and the subsequent development will be explained in detail in the following chapters II.2 and III.1.

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[41] Williamson, E. L. 1992. Airline Network Seat Inventory Control: Methodologies and Revenue Impacts. PhD Thesis, Massachusetts Institute of Technology, Cambridge, MA

[42] Belobaba, P.P. 1998. The evolution of airline yield management: fare class to origin-destination seat inventory control. *The Handbook of Airline Economics*, D. Jenkins (ed). The Aviation Weekly Group of the McGraw-Hill Companies, New York, NY, pp 285-302.

[43] Bratu, S. J-C. 1998. Network value concept in airline revenue management. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA

II.2. Low Cost Carrier Business Model

According to Swelbar[44], typical target markets for low cost carrier (LCC) are "under-served and over-priced" shorthaul markets where no prompt reaction from another competitor is expected. The LCC offer parallel service on high demand routes at lower fares and often lower service levels, i.e. no food service on board or only against a fee. With this strategy a lot of new carrier all over the world emerged and quickly gained huge market share from traditional network carrier (NWC), beginning in the 1990s in the US and followed by Europe, Asia and Australia. Southwest, Ryanair and Easy Jet, Tiger, Virgin Blue and Jet Blue are some names of the world wide operating LCC today. The reason why LCC's concept has been succeeded is indeed the name giving lower cost factor. They operate at a lower cost level which allows them the possibility of offering lower fares to the customer.

One main reason why LCC bear lower cost than NWC is their fleet. Since LCC started operations a few years ago, to serve their shorthaul network, they use a new and harmonized fleet. Having aircrafts from one aircraft family only qualifies all employees to work on each airplane. This increases flexibility in terms of workforce scheduling and reduces cost of crew training. In contrast, NWC usually have a fleet, consisting of many different aircrafts types, not only due to their longhaul and international flight operations but also due to historical growths. Hence, a crew or the technicians for a longhaul airplane needs to be trained differently than on a shorthaul plane and both crews cannot serve on a different type of aircraft. That increases the cost of work. Furthermore, the average age of a NWC's fleet is most likely higher than LCC's fleet which results in clearly lower cost of maintenance for a young and harmonized fleet.

Additionally, LCC mainly transport point-to-point passengers on shorthaul routes only, using comparable large aircrafts. That decreases the average cost per unit.

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[44] Swelbar, W.S. 2002. The Role of Low-Cost-Carrier. *ECLAT Consulting*, Washington, D.C.

On shorthaul routes there usually is enough demand to fill aircrafts with point-to-point traffic. That is why LCC do not offer any longhaul flights where more transfer passengers are needed in order to satisfy demand. Since LCC usually do not have a hub-and-spoke network they might not be able to fill those longhaul flights, in contrast to NWC, which operate even larger aircrafts on longhaul flights with a high share of connecting passengers. This means more passengers to board and deboard, more time to clean the airplane and more waiting time due to delayed connecting incoming flights, hence, more time on ground for NWC's aircrafts. Turnarounds for hub-and-spoke carrier simply need more time than for carrier serving point-to-point passengers only. Consequently, LCC's aircraft utilization is usually higher which further reduces the overall cost.

Another reason of LCC's reduced cost can be found in their distribution and passenger processing. The distribution channels of LCC are often limited to their own reservation system only, i.e. passengers can book the airline's own webpage or own call center only, and moreover, LCC make increased use of electronic ticketing, i.e. no printed ticket is occurring and, hence, no ticket printer needed anymore. Both minimize cost over NWC's methods; beside their own call center and web page NCW also participate in different expensive global reservation systems which, however, make them available and bookable for a majority of travel agents too.

Finally, the service offered to the customer usually differs between the two airline business models. NWC often claim to be an all-in carrier, offering free drinks and food on board, a lounge service as well as a lot of pre-flight services free of charge, e.g. seat reservation. LCC usually charge extra for each additional service requested and they do not offer any business or first class service at all. However, there is clear convergence of both different approaches as more and more NWC start charging an additional fee for certain services copying their competitor's behavior while some LCC tend to relax their fee policy, e.g. granting free non-alcoholic drinks on board.

Due to these cost advantages LCC are able to offer lower prices in the market than NWC. But the most crucial difference between NWC and LCC is not the price level itself but the lack of restrictions within LCC's fare structure. LCC do not segment passenger demand according their WTP like NWC traditionally do in order to maximize their revenue; the sole differential between the pricing levels simply depends on how close the time of booking is to the day of departure. LCC usually offer one-way pricing, thus, not distinguishing the demand by its point-of-origin and, furthermore, repealing the minimum-stay or Saturday/Sunday rule that is used by NWC to segregate demand. This lack of restrictions in combination with lower fares triggers the spiral-down effect that heralded the ruin of many airlines. The reasons and consequences of the spiral-down effect will be exactly described in the subsequent Chapter III.1.

With these advantages over NWC, LCC usually avoid direct competition with other LCC but rather seek to compete against NWC where they exploit their advantage, thus, stealing market share. This strategy provides sustainable profitability for the LCC – at least in the short run. However, it can be observed that over time both, LCC and NWC adept parts from their competition's business model in their own. A good analysis of the LCC business model compared to the NWC's as well as brief expectations of its development in near future provides Dunleavy and Westermann[45]. Since the raise of LCC, NWC realized that they needed to optimize their cost to a more competitive level copying some of LCC's strategies. In contrast, LCC realized that the more they grow the more they become a network carrier – with all the benefits and drawbacks. Moreover, as NWC will respond cost wise or LCC will compete directly against each other eventually, it is obvious that the today's LCC business model needs to be adjusted as well in the long run, focusing also on a better demand differentiation with a more sophisticated RM – related with higher cost.

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[45] Dunleavy, H. and D. Westermann. 2005. Future of Airline Revenue Management. *Jounal of Revenue and Pricing and Revenue Management.* Volume 3, Number 4, pp. 380-383.

Summarizing the cost advantages of a LCC business model over a NWC model Gorin[46] can be quoted as follows: low fares combined with low-frills service, simplified distribution and passenger processing, higher aircraft utilization with a simplified fleet and higher labor productivity. Deeper information about the business model of LCC provides Weber and Thiel[47].

II.3. Chapter Summary

This chapter started with a brief review of traditional airline revenue management tools showing how overbooking, forecasting and seat allocation are used to maximize revenue. Since there are always passengers who do not show up at departure the RM tool of overbooking is used to avoid having fully booked flights departing with empty seats. An accurate forecasting separates passenger demand and is a precondition for each RM system, also for the seat allocation optimization that maximizes revenue by protecting seats for passengers with higher willingness to pay. Later, an insight of the low cost business model followed presenting the most important differences to traditional legacy network carrier and the reasons for their lower cost that enables LCC offering lower fares in the market. In the following section the consequences of the rise of low cost carrier will be discussed and how legacy carrier reacted. Next, the hybrid forecaster will be explained as a revenue management tool of this new environment.

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[46] Gorin, T.O. 2004. Assessing low-fare entry in airline markets: impacts of revenue management and network flows. PhD Thesis, Massachusetts Institute of Technology, Cambridge, MA
[47] Weber, K. and R. Thiel. 2004. Methodological Issues in Low-Cost Carriers Revenue Management. Presentation at *AGIFORS Symposium Proceedings*, Auckland, New Zealand.

III.   CHANGES OF RM METHODS

The previous chapter presented the business model of LCC and provided reasons why they can offer tickets at a lower price than traditional network carrier. Their fast gain on market share at the cost of the NWC made the latter one realize that they need to react. But it was not as simple as just reducing prices to the LCC's lower level after their emergence. This chapter describes the problems and the consequences NWC still face when matching fares and, more crucial, all fare conditions of their low cost competition. The second part of this chapter describes new RM techniques that have been developed as a consequence of the new environment focusing on the hybrid forecast and optimization model.

III.1. Fare Conditions and the Spiral-Down Effect

As described in previous sections NWC try to distinguish between leisure passengers with a lower willingness to pay who usually book very early prior departure and business travelers, usually late bookers with less price sensitivity. Though, a rational person will always choose the cheapest available fare independently of her/his WTP as long as there is no incentive or restriction that keeps them in classes corresponding to her/his WTP. So how do airlines "force" business passengers purchasing higher fares? This can be achieved by conditions or so called "fare rules" that apply for certain classes. E.g. lower fares usually can neither be rebooked nor refunded while higher fares offer more flexibility to the passenger. This flexibility condition is often more important to business travelers having meetings cancelled or rescheduled on short notice than to leisure travelers

who fix their holiday including the flight much earlier and have no necessity to change it afterwards. Lower fares usually have an "advanced purchase" conditions (AP), i.e. they can be booked until a specific number of days prior departure only. Closer to departure than the days set in the AP rule of the fare class the fare is not available anymore so that passengers booking on short notice need to buy-up to a higher fare with a less restrictive or even without an AP rule. In general, it can be stated that the closer to departure the booking is made, the higher the probability for the lower class to be closed. Furthermore, lower fares often have so called "Minimum Stay" (MN) or "Saturday/Sunday" rules. These fares only apply if the passenger stays at least a certain number of days before returning home or, alternatively, the night from Sat to Sun over the weekend. All those conditions might restrict (business) travelers with higher WTP of purchasing low fares because they usually do not stay longer than one night or over the weekend for business reasons. Typically, they book a daytrip during the week. An example of possible conditions per fare class can be seen in Table3.1.

example of a more restricted fare structure					
fare class	price	AP	MN	Sat/Sun	Rebooking	Refund
Y	1000	none	none	none	Free of Charge	Free of Charge
B	700	7	2	none	against a fee of $ 100	against a fee of $ 100
M	500	14	3	yes	against a fee of $ 100	against a fee of $ 100
Q	300	21	5	yes	not possible	not possible

Table 3.1: Example of a More Restricted Fare Structure

The price per fare is as follows: Y > B > M > Q; contrarily is the degree of restriction: Y class represents the full fare that has no restrictions at all and offers full flexibility while Q class, as the most discounted one, has several restriction. MN and Sat/Sun rule are usually linked with an "or"-function, so a passenger needs to stay at least five days or one night from Saturday to Sunday before returning in order to be able

to purchase Q class fare. In addition, she/he needs to book at least 21 days before departure and this fare is neither re-bookable nor refundable. All these conditions are typically not favored by business travelers and keep full-fare passengers from buying lower classes, thus, reflecting their higher WTP. All airline revenue management systems which have been developed in the 20 years between 1980 and 2000 were designed for restricted fare structures like the example in Table 3.1 assuming segmented independent fare class demand; forecast models using these historical booking data were adequate as long as passenger segmentation was possible with fare class restrictions.

When low cost carrier entered the markets they usually introduced not only lower fares because of their lower cost structure but offered also a fare structure with more relaxed fare condition or even removed them completely. Due to the one way fare pricing concept of many low cost carrier the minimum stay rule became obsolete anyway. As a first reaction to regain market share legacy carrier often matched their low cost competition – pricing and condition wise – changing their traditional fare concept (compare Table 3.1) to a so called semi-restrictive or simplified fare structure. An example of a semi-restricted fare structure can be seen in Table 3.2. Hence, the most effective segmentation restrictions have been relaxed or even removed and passengers with high WTP can purchase lower fares. In extreme cases or highly competitive markets fare conditions were removed completely, i.e. the only separation left between fare classes is a different price level as presented in Table 3.3.

example of a less restricted fare structure						
fare class	price	AP	MN	Sat/Sun	Rebooking	Refund
Y	700	none	none	none	Free of Charge	Free of Charge
B	450	none	none	none	Free of Charge	Free of Charge
M	250	7	none	none	against a fee of $ 100	against a fee of $ 100
Q	150	14	none	none	against a fee of $ 100	against a fee of $ 100

Table 3.2: Example of a Less Restricted Fare Structure

example of an unrestricted fare structure						
fare class	price	AP	MN	Sat/Sun	Rebooking	Refund
Y	700	none	none	none	Free of Charge	Free of Charge
B	450	none	none	none	Free of Charge	Free of Charge
M	250	none	none	none	Free of Charge	Free of Charge
Q	150	none	none	none	Free of Charge	Free of Charge

Table 3.3: Example of an Unrestricted Fare Structure

This had dramatic consequences for legacy carrier's revenue and RMS known as the "spiral down" effect (see Figure 3.1). With fewer restrictions on lower fares passengers with higher WTP will "buy-down", e.g. from Y class to B, M or Q class. As a consequence the revenue management system that retrieves its information also from historical as well as future bookings receives the input that less bookings in higher classes occur but more in lower classes instead which leads the system to forecast and protect less seats for high yield passengers and grant more availability in lower classes in future, i.e. keeping B, M, Q classes open. This will encourage even more passengers to buy-down which leads this cycle to repeat resulting in severe revenue dilution.
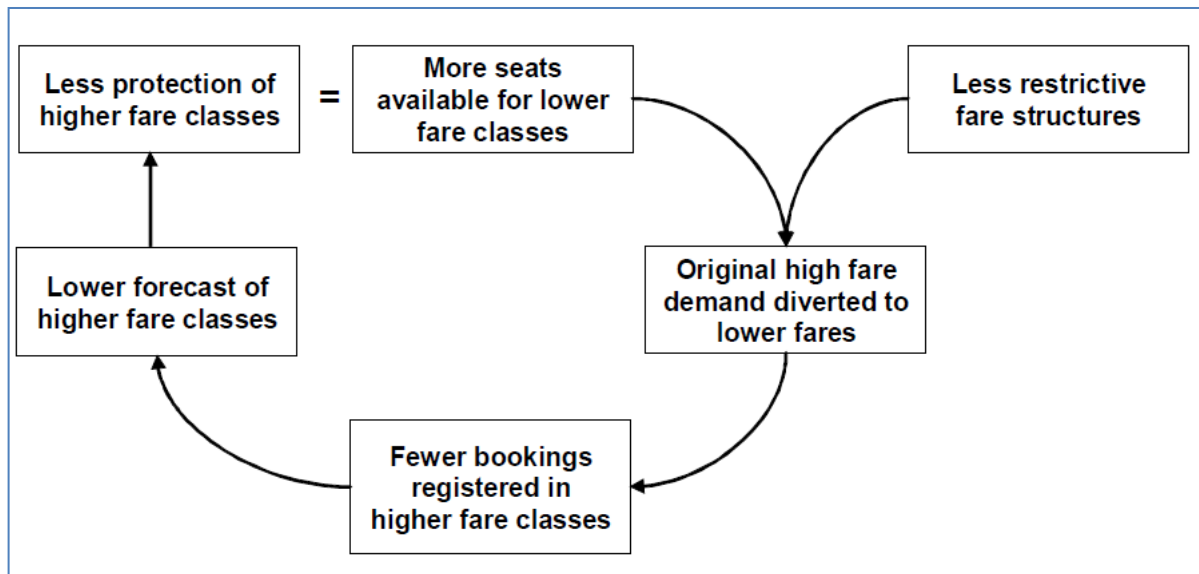
Figure 3.1: The Spiral Down Effect, reproduced from Cléaz-Savoyen[53]

Summarizing, the new adjustments to less restricted fare structures traditional revenue management systems suddenly were not able to maximize revenue anymore; forecasting models became invalid not being able to reflect the true high fare demand anymore.

Cooper et al.[48] developed a mathematical model describing the spiral down effect while Cusano[49] has analyzed the consequences of the spiral down effect in his master thesis. The need of adjusted RM methods and new ways to maximize revenue was obvious.

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[48] Cooper, W. L., T. Homem-de-Mello, A. J. Kleywegt. 2004. Models of the Spiral-down Effect in Revenue Management. Working Paper, Department of Mechanical Engineering, University of Minnesota, Mineapolis, MN.
[49] Cusano, A. J. 2003. Airlines Revenue Management under Alternative Fare Structures. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

III.2. RM Tools of the New Environment

Before the rapid rise of LCC, NWC offered more restrictive fare structures than today, where they were still able to separate demand into business and leisure travelers, thus, forcing passengers to pay prices close to their WTP, by having conditions to separate the different price levels. Then, NWC have adjusted their fare structure to a less restrictive one in order to gain back market share. Consequently, traditional RMS used by NWC suddenly failed segregating the demand in high and low value customers which led to severe revenue dilution through a spiral down effect. In this section a detailed explanation about Hybrid Forecast (HF) will follow as a new approach of classifying the demand within fully undifferentiated fare structure environments by merging two different forecast methods. Later in this section a brief insights about Fare Adjustment will be presented too which is another approach to counter-steer against yield declines of NWC. While HF is used for the simulation in this thesis FA is not. Both techniques are supposed to help recapturing some of the lost revenue due to the removal of the important fare conditions.

III.2.1. Hybrid Forecasting

Although facing completely unrestricted fare structures the two customer types and their different booking behavior remain. Leisure travelers keep booking earlier than business customers who still have a higher WTP. The latter just take advantage of unrestricted fares and "buy-down" from a higher class they would have been willing to pay to a lower class enjoying a big consumer surplus. While traditional RM tools cannot handle this change, HF is one method of the new RM generation that is supposed to have a solution for the buy-down spiral. HF aims to reflect the

passengers' willingness to pay and, furthermore, the potential sell-up not taking the segregation through fare restrictions into consideration. Instead of considering total demand as a whole, it classifies passenger demand in two different categories: yieldable (or product-orientated) and priceable (price-orientated). Product-oriented demand purchases a higher fare with desired product characteristics while a price-oriented passenger buys the lowest available fare only. The segregation of yieldable and priceable demand was firstly proposed by Boyd and Kallesen[50].

Facing two different demands means creating two separate forecasts, thus, HF also uses a different forecast methods for each: yieldable and priceable demand. In order to forecast yieldable demand traditional RM foresting methods like pick-up forecasting (see Chapter II.1.2) are used. Those forecasting techniques remain still valid for the product-orientated or yieldable customer presuming independence among each fare class. So no new techniques need to be adopted.

In contrast, priceable demand is more tricky and modeled by a technique called Q-forecasting that assumes fully unrestricted and undifferentiated fares so that each passenger always buys the lowest fare. Instead of forecasting each fare class separately, Q forecasting forecasts the demand at the lowest fare only (traditionally called Q class in former times – hence the name), and then uses estimates of passengers' WTP to force sell-ups by closing lower fares classes. Those estimates are done taking historical booking data. Q-Forecasting was developed by Hopperstad and Belobaba[51, 52] and further discussed by Cléaz-Savoyen[53] in his Master's Thesis. A basic overview of the Q-forecasting process can be found in Figure 3.2.

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[50] Boyd, E. A., R. Kallesen. 2004. The Science of Revenue Management when Passengers Purchase the Lowest Available Fare. *Journal of Revenue and Pricing Management*. Volume 3, Issue 2, pp. 171-177.

[51] Belobaba, P., C. Hopperstad 2004. Algorithms for Revenue Management in Unrestricted Fare Markets. *INFORMS Section of Revenue Management*, Massachusetts Institute of Technology, Cambridge, MA.

[52] Belobaba, P., C. Hopperstad. 2004. "Q investigations – Algorithms for Unrestricted Fare Classes". *PODS Consortium Meeting*. Amsterdam.

[53] Cléaz-Savoyen, R. L. 2005. Airline Reservation Management Methods for Less Restricted Fare Structures. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
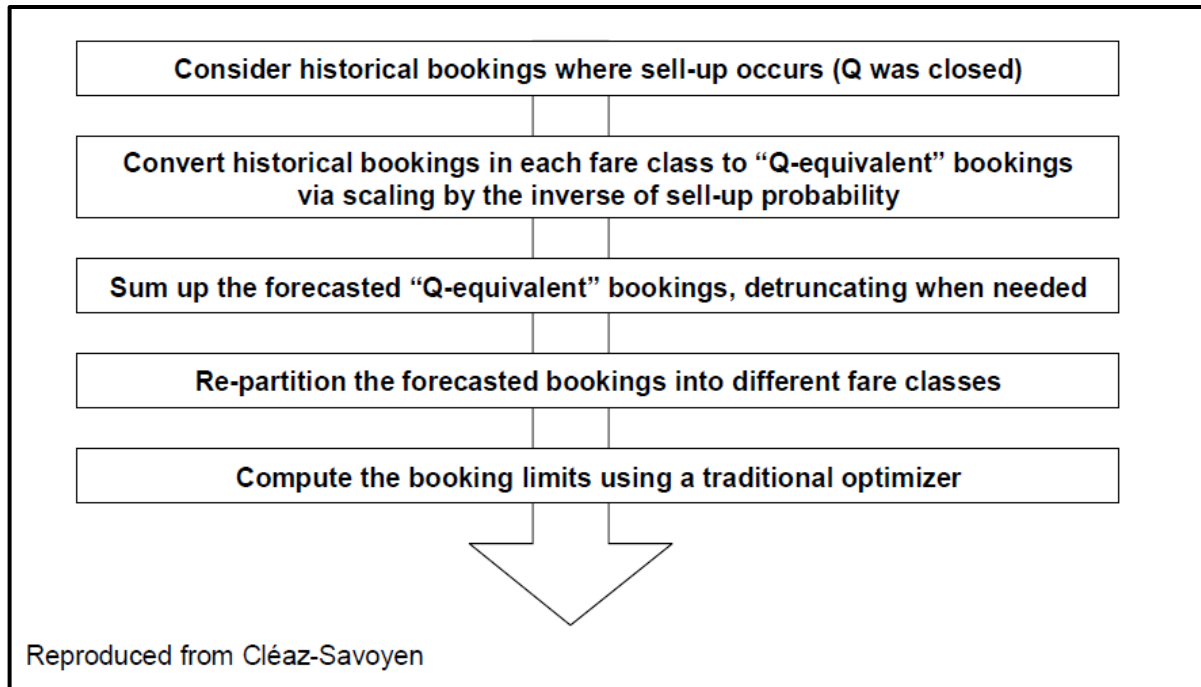
Figure 3.2: Q-Forecasting Process, reproduced from Cléaz-Savoyen[53]

Q-forecasting starts with the conversion of historical bookings to equivalent Q-bookings. I.e. upsell when lowest class (formerly Q class) is closed, which is calculated by the sum of inverse cumulative bookings divided by its sell-up probability. However, this conversion requires estimates of sell-ups from the lowest class. Those sell-up rates equal WTP curves and can be estimated by collecting data from historical bookings by fare class. Especially bookings in higher classes given lower classes closed contain valuable information about WTP and sell-up behavior. With historical bookings per fare class the inverse cumulative bookings are calculated, thus, estimating the sell-up probability for each fare class with following formula:

$$P(Sell-up\ from\ Q\ to\ x) = \frac{inverse\ cumulative\ bookings}{\sum(x)\ (total\ inverse\ cumulative\ bookings)}$$

Fare Class x	Price	Ratio to lowest class	Historical Bookings in class x	Inverse Cumulative Bookings	Sell-up Probability from Q to class x
Y	500	5,00	5	5	10%
B	300	3,00	8	13	25%
M	200	2,00	17	30	58%
Q	100	1,00	22	52	100%

Table 3.4: Example of Inverse Cumulative Estimator of Sell up

Table 3.4 provides an example of calculating the Sell-up estimator. The sell up estimations are usually done for several time periods before departure, so called data collection points (DCP). Each DCP represents a time frame between 360 days prior departure and the actual day of departure in which all booking and cancellation information is collected and forecasted for future flights. DCPs usually grow smaller as they approach closer to the days of departure because more bookings are made closer to departure. An example of a DCP list can be seen in Table 3.5.

DCP #	1	2	3	4	5	6	7	8	9
days prior departure	360	234	174	122	90	69	49	38	28

DCP #	10	11	12	13	14	15	16	17	18
days prior departure	22	15	10	8	6	3	1	0	-1

Table 3.5: Example of a DCP Table

With the sell-up probabilities the WTP curve and the FRAT5 for each DCP is estimated. FRAT5 is the Fare Ratio at with 50% of passengers will sell up from the lowest fare class; i.e. FRAT5 is the median for passenger's WTP. Continuing with the example before, this results in a FRAT5 of approximately 2,1; so 50% of all passengers are likely to pay a factor of 2,1 of the lowest class. The curve to that example is presented in Figure 3.3 with the sell-up probabilities on the X-axis and

the fare ratio on the Y-Axis. Higher FRAT5 curves indicate higher WTP or more sell up from lower to higher fare classes.

Next, the FRAT5s of all DCPs are calculated and plotted on a time scale as presented in Figure 3.4. The FRAT5 curve per DCP reflects the customer type mix (leisure versus business passenger) as the curve increases closer to departure representing the WTP the late booking business traveler with higher WTP. Now, the sell-up probability can be estimated for the point of time prior departure. More detailed discussion about inverse cumulative and sell up estimations are provided Hopperstad[54], Gou[55] and Bohudinsky[56].
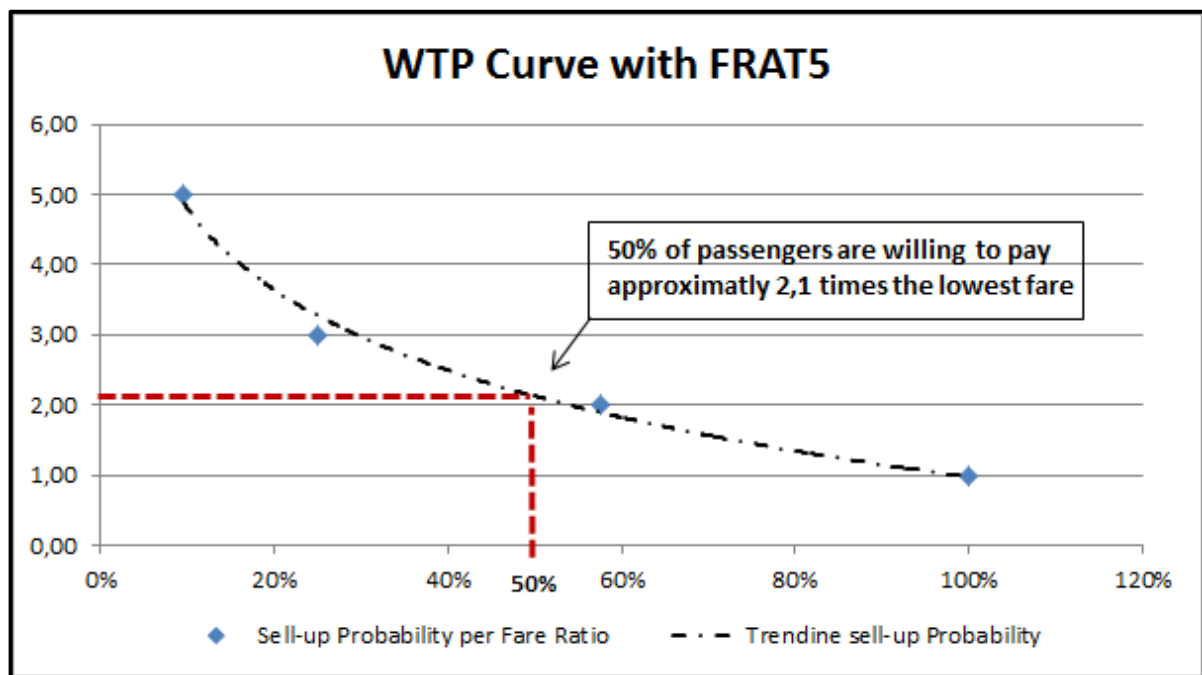
Figure 3.3: Example of FRAT5 WTP Curve within a DCP

[54] Hopperstad, C. 2007. Methods for Estimating Sell-up: Part II. *AGIFORS Joint Revenue Management and Cargo Study Group Meeting.*
[55] Gou, J. C. 2008. Estimating Sell-Up Potential in Airline Revenue Management Systems. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
[56] Bohutinsky, C. H. 1990. The Sell Up Potential of Airline Demand. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.
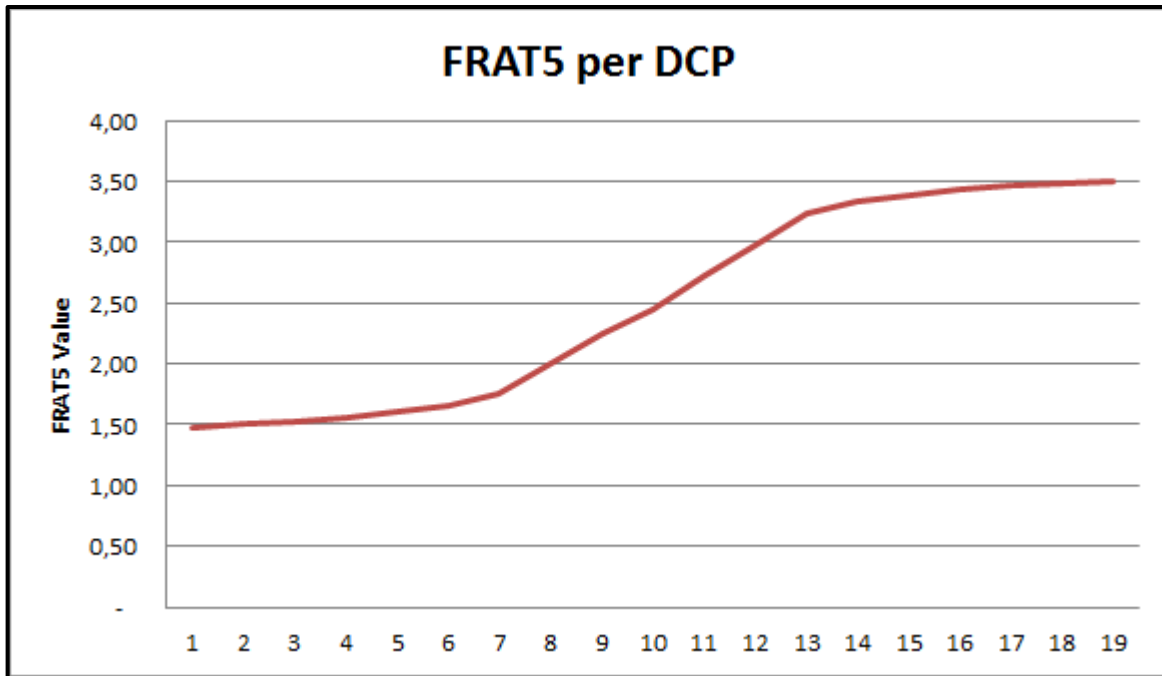
Figure 3.4: Example of FRAT5 Estimates over all DCPs

Once having the sell-up estimation per fare class and DCP the Q- equivalents can be calculated with the formula mentioned already above:

$$Total\ Q\ equivalent\ bookings\ =\ \sum(x)\frac{historical\ bookings\ in\ class\ x}{probability\ of\ sell\ up\ from\ Q\ to\ x}$$

Continuing the calculation of the example from above Table 3.6 shows the total Q-equivalent bookings amount to 133. Finally, the Q-equivalents and sell-up rates are both used to generate demand forecast for higher fares classes as follows:

$$Forecasted\ demand\ for\ class\ x$$
$$=\ Total\ Q\ equivalent\ bookings$$
$$*\ [P(sell\ up\ from\ Q\ to\ x)\ -\ P(sell\ up\ from\ Q\ to\ (x-1))]$$

Table 3.7 provides the final calculation of the continuing example showing a final demand forecast of 13 passengers in highest booing class Y and suggests 56

passengers in lowest Q class. B class and M class have a demand of 20, respectively 44 passengers.

Fare Class x	Historical Bookings	Sell-up Probability	Q-equivalent Bookings for x
Y	5	10%	5/0,10 = 50
B	8	25%	8/0,25 = 32
M	17	58%	17/0,58 = 29
Q	22	100%	22/1,00 = 22
			Total Q-equivalent Bookings = 133

Table 3.6: Example of Calculating Q-equivalent Bookings

Fare Class x	Historical Bookings	Sell-up Probability	Repartitioned Demand for Booking Class x
Y	5	10%	133 * (0,10-0,00) = 13
B	8	25%	133 * (0,25-0,10) = 20
M	17	58%	133 * (0,58-0,25) = 44
Q	22	100%	133 * (1,00-0,58) = 56

Table 3.7: Example of Calculating Repartitioning Demand to each Fare Class

Taken the demand provided by Q-forecasting for the price-oriented customer and the demand from pick-up forecasting for yieldable demand together, these two different forecast models provide the total "hybrid" demand for each fare class for each itinerary sent to the seat allocation optimizer. A summary of the HF model is presented in Figure 3.5.

In his master's thesis Cléaz-Savoyen[53] proofs that Q-forecasting in unrestricted fare environments is effective in reducing the revenue loss that airlines suffer due to the removal of fare restrictions.
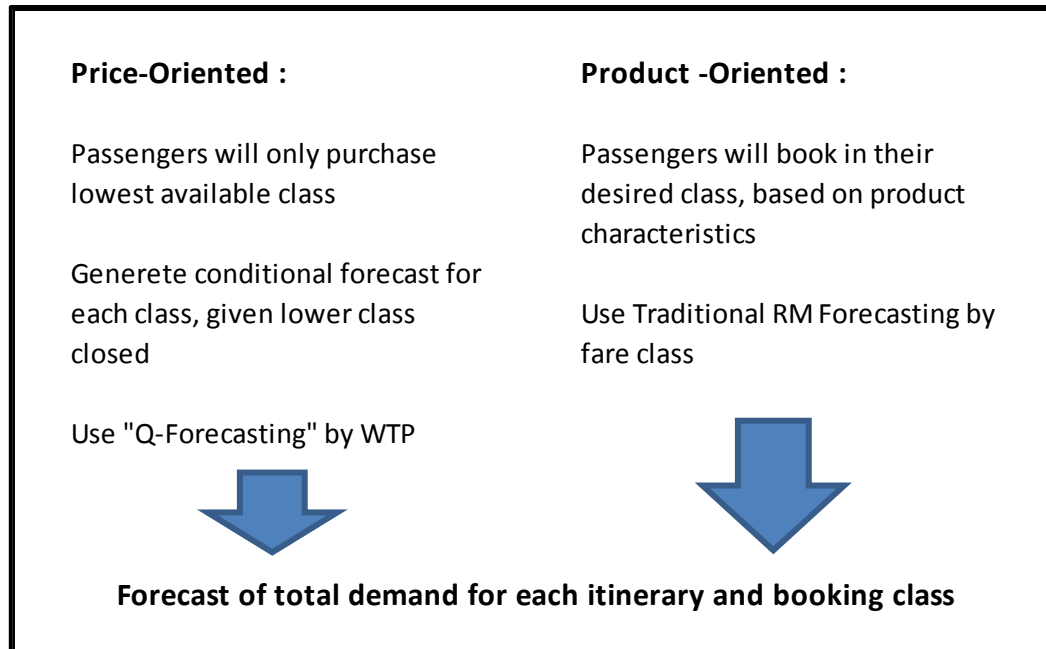
Figure 3.5: Hybrid Forecast Model

III.2.2. Fare Adjustment

Another RM method of the new generation is Fare Adjustment (FA) which was developed by Fiig and Isler[57] at Swiss air and Scandinavian Airlines. This technique is also supposed to be an answer to the buy-down behavior and heavy yield decline. FA applies in market environments where NWC face both, less restricted fare structures in presence of low cost competition and more restricted fare structured in less competitive markets. Usually, booking classes of both fare structures are allocated in the same virtual bucket when using DAVN optimization. FA adds the Marginal Revenue Transformation into the DAVN process and

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[57] Fiig, T., K. Isler. 2004. "SAS O&D low cost project." *PODS Consortium Meeting*, Minneapolis, MN.

"adjusts" the original OD fares in less restricted fare structures. Figure 3.6 offers an overview of this process. However, FA does not apply in the scenario of this thesis.
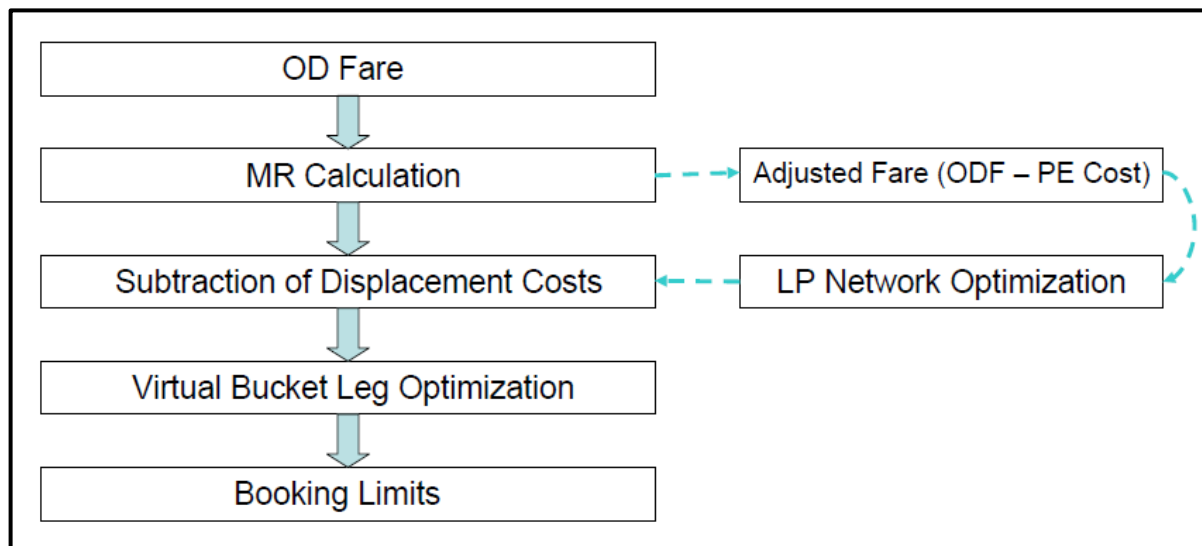
Figure 3.6: Integration of Marginal Revenue into DAVN process, reproduced from Keyser[58]

In less restricted structures there is a risk that passengers buy-down; so the OD fares are re-calculated by deducting the cost of price-elasticity (PE) from the original fare, thus, giving them a new (lower) value. However, differentiated fares in more restricted structures are not affected as there is no such risk of buy-down due to the demand segregation through restrictions. This decoupling process of more restricted and less restricted fare structures allows the airline to control both independently, thus, allocating them into different virtual buckets. Therefore, this technique increases the effectiveness of DAVN optimization in terms of revenue maximization. Figure 3.7 provides an overview of the adapted process. As the original pseudo fare of the less restricted structure would have been allocated into the same virtual bucket V4, like pseudo fares from the more restricted structure without FA, and hence having availability. With FA, however, it is distributed into (closed) virtual bucket V5 after the adjustment of the PE costs, with no availability.

Cléaz-Savoyen[53] and Kayser[58] provide more detailed information about FA in combination with HF in their masters' thesis.
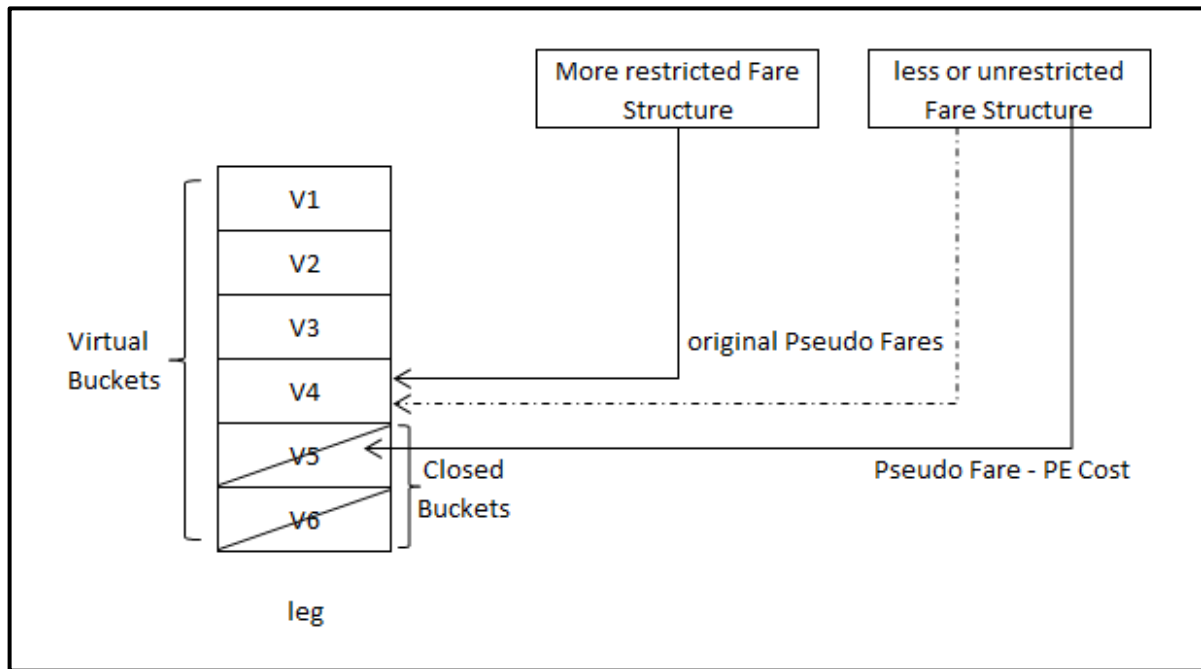
Figure 3.7: Example of Decoupling Multiple Fare Structures, reproduced from Keyser[58]

III.3. Chapter Summary

This Chapter started explaining the spiral-down effect; the reasons that caused this phenomenon as well as the consequences it had on traditional RMS.

Next, hybrid forecast was discussed and how this technique forecasts two different demand types: yieldable and priceable demand. While forecasting yieldable

[58] Kayser, M.R. 2008. RM for Multiple Fare Structure Environments. Master's Thesis, Massachusetts Institute of Technology, Cambridge, MA.

demand is still possible with traditional RM methods, priceable demand needs a new approach, Q-forecasting, to be forecasted. Q-forecasting seeks to forecast the maximum demand potential at the lowest fare and converts it into partitioned forecasts for each fare class. However, this requires an estimation of passenger's WTP and sell-up probability by time of departure. HF presumes a less or unrestricted fare structure environment and is supposed to handle the forecast problems that rose with the spiral-down effect much better than traditional RM tools.

At last, Fare Adjustment was briefly presented as another technique recently developed to meet the new market conditions. FA presumes an environment in which both, less and more restrictive fare structures exist. FA transforms the DAVN optimization process by adjusting fares from a less restricted fare structure allowing RMS to allocate them differently than fares from the more restrictive structure. Thus, FA improves revenue maximization results of the DAVN process in competitive markets.

IV. SIMULATION ENVIRONMENT – AN APPROACH TO REMATE

To test RM methods in an environment where competitive behavior of airlines as well as the dynamic behavior of passenger choices is considered, a simulation is a valuable tool for experimentation and validation. For the purpose of this thesis it was decided to simulate this environment with REMATE, which will be introduced and explained in the following chapter. REMATE is a simulation system that models airline revenue management as a combination of flexible customer behavior, realistic algorithmic systems of forecast and optimization methods and competitor interaction. It also is used to test and validate the impact of Hybrid Forecasting and Optimization for this thesis.

The simulation system REMATE was developed by Deutsche Lufthansa AG together with the University of Berlin and means **Re**venue **Ma**nagement **T**raining for **Ex**perts. Its main goal is to set up realistic scenarios in order to train Lufthansa employees and to improve overall RM know-how, understanding complex interactions of RMS and giving decision support in RM situations during daily work. It hence can be used to validate expected economic benefits of changes in methods, like switching to another RM method or to validate benefits of strategic changes like the introduction of new unrestricted fares.

REMATE is a simulation of an interaction of two groups – passengers and airlines – in a user-defined environment (transportation network). More concrete, it links passenger's choices to the output of airline's RMS in order to analyze the effectiveness of different RM techniques. The different passenger groups have their own characteristics, including a particular choice set with the preference of airline, Origin-Destination-Itinerary (ODI), and maximum price, respectively booking class. Then, this decision meets the airlines offer, based on the RMS output but also on

the schedule and other factors. If it fits passenger's expectation a booking is done, otherwise rejected. An overview of REMATE's architecture is presented in Figure 4.1.
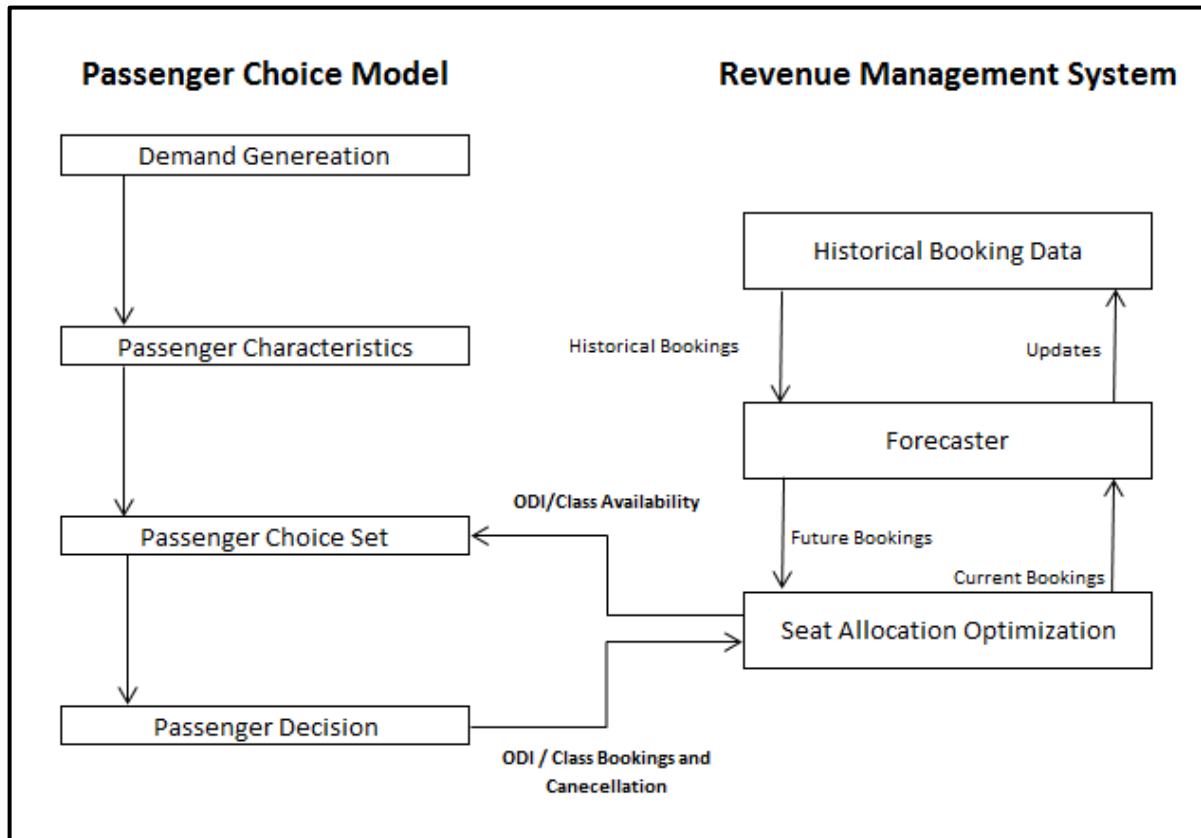
Figure 4.1: Basic REMATE Structure

Various prerequisites are needed for this simulation: a number of basic blocks including customer types and their preferences representing the demand side (passengers) and data sets describing supply plus RM methods (airlines) that have to be defined before running and analyzing the simulation. A detailed description of these prerequisite utilities for the scenario follows in the next section. The demand set up includes the definition of the customer type models and the buying and booking behavior in terms of distribution curves. For the supply network and destinations, the participating airlines, aircrafts and the possible aircraft

configurations have to be defined. Additionally the flight schedule, the booking classes and the prices need to be set up. Afterwards, the Revenue Management Method needs to be specified, i.e. which method of forecasting and allocation optimization shall be used in the scenario. Historical booking data of each scenario is created by doing 500 simulation runs before the actual simulation starts running. The following sections are mainly based on REMATE's user manual[59]. For the scenario presented in this thesis, the values chosen for the attributes of demand and supply of this scenario are assumptions taken by the author's close monitoring and experience of several years in the airline industry and verified by a few more persons all working for an airline in revenue management department having as well several years of experience. Furthermore, those values were tested to be plausible to reflect realistic parameters and then calibrated to the specific scenarios in this thesis.

IV.1. Supply Setup

Supply, in terms of airline revenue management, is understood as capacity offered, more concrete, how many seats in which aircrafts on which routes. The necessary basic step of the simulation is to set up a network with origins and destinations, airlines, flight schedules and aircraft types that also need to be chosen. This subchapter describes the setup of the supply side.

In this scenario two airlines are competing in the same hub. Carrier 1 is a traditional network carrier (NWC) called "AA", which offers also connecting transfers via its hub next to point-to-point transportation. Carrier 2, on the other hand, is a low cost carrier (LCC), called "LC" offering point-to-point transportation only. LCC uses solely

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[59] REMATE 6.0 User Manual for Administrators, Version 21.03.2011

Boeing 737 (B737) aircraft types with 140 seats per aircraft while the NWC uses Airbus 320 (A320) and 319 (A319) offering 140, respectively 120 seats. As many low cost carrier offer no Business Class at all, it was for the purpose of the scenario assumed that both, LCC and NWC offer economy class only.

The **Network** for this scenario includes one hub in Vienna (**VIE**) and three more destinations: Brussels (**BRU**), Berlin (**BER**) and Moscow (**MOW**) which can be seen in Figure 4.2.
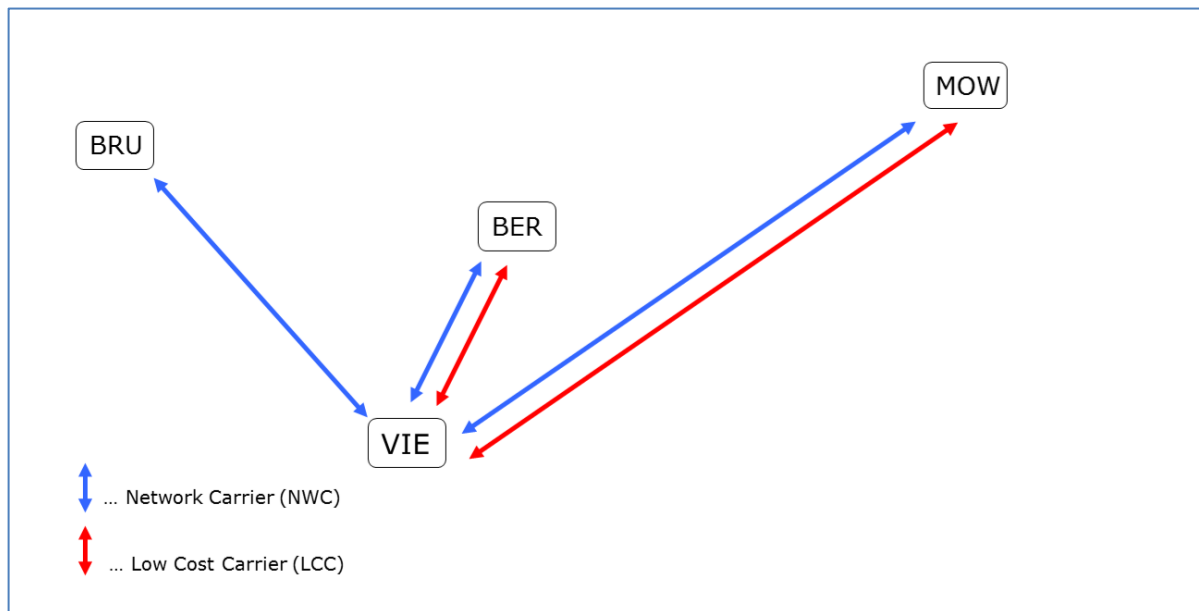
Figure 4.2: Airline's Simulation Network

The network shows three routes with different competitive levels. The route between MOW and VIE is dominated by the NWC flying three times a day while the LCC offering two daily flights only. The route from BER to VIE is dominated by the LCC operating four times a day versus NWC with three daily frequencies. BRU-VIE route is flown solely by the NWC three times a day. The exact schedule for all flights of both competitors including arrivals, departures and travel time is shown in Tables

4.1 and 4.2. For simplification it is assumed that this schedule is valid every day and the simulation is on a one-day-basis only. Summarizing, NWC offers 18 flights (12 ODs, i.e. 12 possible journeys including all transfer connections within the defined time frame) with 2400 seats per day in total while LCC has 12 flights (4 ODs) and 1680 seats to sell each day. In total there is a supply of 4080 seats to sell on one day.

NETWORK CARRIER AA					
Origin	Destination	Departure	Arrival	Traveltime (min)	A/C type
VIE	BER	07:15	08:30	75	A320
VIE	BER	17:50	19:05	75	A320
VIE	BER	20:10	21:25	75	A320
BER	VIE	07:20	08:40	80	A320
BER	VIE	15:10	16:30	80	A320
BER	VIE	20:00	21:15	75	A320
VIE	MOW	10:05	14:55	170	A320
VIE	MOW	12:45	17:30	165	A320
VIE	MOW	20:35	01:15	160	A320
MOW	VIE	05:45	06:30	165	A320
MOW	VIE	15:45	16:40	175	A320
MOW	VIE	18:20	19:20	180	A320
VIE	BRU	07:10	08:55	105	A319
VIE	BRU	15:10	16:55	105	A319
VIE	BRU	17:25	19:10	105	A319
BRU	VIE	10:10	12:00	110	A319
BRU	VIE	17:45	19:35	110	A319
BRU	VIE	20:00	21:45	105	A319
transfer /connecting flights via VIE Carrier AA					
BER	MOW	07:20	14:55	335	A320/A320
MOW	BER	05:45	08:30	285	A320/A320
MOW	BER	15:45	19:05	320	A320/A320
MOW	BER	18:20	21:45	305	A320/A320
BER	BRU	15:10	19:10	240	A320/A319
BRU	BER	17:45	21:25	220	A319/A320
BRU	MOW	10:10	17:30	320	A319/A320
BRU	MOW	17:45	01:15	330	A319/A320
MOW	BRU	05:45	08:55	310	A320/A319
MOW	BRU	15:45	19:10	325	A320/A319

Table 4.1: NWC AA's Schedule

LOW COST CARRIER LC					
Origin	Destination	Departure	Arrival	Traveltime (min)	A/C type
VIE	BER	06:25	07:40	75	B737
VIE	BER	08:45	09:55	70	B737
VIE	BER	14:55	16:10	75	B737
VIE	BER	19:25	20:40	75	B737
BER	VIE	06:40	07:55	75	B737
BER	VIE	08:50	10:05	75	B737
BER	VIE	17:20	18:35	75	B737
BER	VIE	21:20	22:35	75	B737
VIE	MOW	11:10	15:45	155	B737
VIE	MOW	18:10	22:45	155	B737
MOW	VIE	06:05	06:50	165	B737
MOW	VIE	16:30	17:10	160	B737

Table 4.2: LCC's Schedule

As mentioned before, due to simplification the scenario date range includes one flight day only, i.e. 24 hours from 06.February 2012, 00:00 to 06.February 23:59. The **Maximum** and **Minimum Connecting Time** decides which two legs are considered to be a transfer OD and which are not accepted as a transfer connection anymore. In this scenario the minimum connection time is 30 minutes while the maximum time for a combination with another flight allowed is three hours. Thus, the time period of the arrival of one flight and the departure of another potential connection flight must be between 30 and 180 minutes. The **Maximum Travel Distance** specifies the factor between origin and destination in relation to the total distance flown; it prevents passenger flying irrational itineraries. A factor of 2 for example allows a passenger to travel a maximum of 200 Kilometer via a transfer hub if the distance between his origin and destination is 100 Kilometer. Since this a small network with only a few destinations this attribute is not relevant.

Both airlines have four pricing levels in four booking classes in order to generate an upsell. NWC's nesting order of booking classes is Y, B, M and Q, whereas Y refers to highest and Q to the lowest booking class. The LCC's booking class structure is E, K, L, T, whereas E is the highest and T the lowest class. The availability of all

booking classes is according forecast and booking behavior since there are no restrictions anymore that separate leisure from business class passengers (see section III.1.). Hence, an upsell from a lower to a higher class according customers' WTP cannot be obtained with restrictions but is possible only if the lower class is closed. Therefore an accurate forecast and optimization is needed. The price structure on a specific OD is exactly identical in both directions, e.g. pricing points for the itinerary VIE-BER-VIE equals BER-VIE-BER. It which is common practice for LCC to have the same pricing structure in both directions; this method was adapted for this scenario as well. The simulation will be made when the NWC has already reacted on LCC's market entry by removing all restrictions in all booking classes. Moreover, NWC's prices are matched according LCC'S pricing structure on all routes where both airlines operate wing-to-wing, i.e. on VIE-BER v.v. and on VIE-MOW v.v. route. Precise information about the all booking classes and pricing points can be found in Table 4.3.

ONDs	prices per booking class				
	Q	M	B	Y	Carrier
VIE-BER v.v.	89	138	208	306	AA / LC
VIE-BRU v.v.	99	155	225	344	AA
VIE-MOW v.v.	179	256	354	543	AA / LC
BRU-BER v.v.	179	256	354	543	AA
BER-MOW v.v	219	296	394	583	AA
BRU-MOW v.v.	239	323	421	631	AA

Table 4.3: Carrier's Pricing Structure (matched)

All values needed for the supply setup, i.e. time schedule and the price matrix of both airlines, are derived from actual airlines and calibrated to the specific scenarios in this thesis. Furthermore, the distances between the cities used in this network equal the actual geographical distances.

IV.2. Demand Setup

Setting up the demand side means to create a volume of theoretical passengers and to simulate passenger behavior in the most realistic way. The decision if a passenger finally books a certain flight or turns the offer down or even cancels it again after the booking has been made is influenced by numerous external factors that have to be defined. Answers to the questions "When is the passenger's preferred departure time?" and "How much is he or she willing to deviate from that preferred time?", "What is the minimum and the maximum a passenger is willing to pay for a flight?" are just some of the characteristics that can influence this choice and those have to be defined. As mentioned before there is also not only one type of passenger, but the leisure, early booking, and also the business, late booking, passenger. It is obvious these two types have a lot of different booking characteristics so that is why there are two different types defined in this scenario. This section explains the demand set up for this simulation foremost giving insight about the mathematical distributions and formulas that simulate the passenger behavior in following sub chapters. The two passenger types and their attributes are explained in detail subsequently while the final demand generation is presented afterwards.

IV.2.1. Distributions

Each passenger has his own preferences when booking a flight that are described in distribution functions in this simulation. Those distributions define the passenger preferences. The distribution utility offers four different distribution functions that have to be defined: the departure time distribution, request date distribution,

cancellation distribution and day-of-week distribution. Again, for each customer type a different distribution pattern shall apply according to realistic customer behavior.

Departure Time Distribution describes the time of day at which the passenger prefers to depart. The time of day is separated into 24 data point where each can reach a value between 0 and 1. The expected probability that any of the hours is going to be the preferred departure time of a customer is equal to the weight assigned to this hour divided by the sum of all weights. Within those hours, the preferred departure time in minutes is drawn from a uniform distribution.

The **Request Date Distribution** describes at which point of time prior to departure a passenger is likely to make his booking. A flight can be booked earliest one year prior to departure and on departure day at the latest. This period is separated into certain intervals that grow smaller as departure approaches. The weights attributes of each interval are cumulative and the probabilities sum up to 1, so every customer will end up having requested a booking at one of the days before departure from 360 to 0. The fact that each passenger requests a booking does not necessarily mean that he accepts this offer. The passenger might reject it because of the the price or the travel time that is not according his desire. Within the intervals, the request date in days is drawn from a uniform distribution.

Cancellation Distribution – Similar to the request date distribution, the time of cancellation is divided into the same intervals and the weights of each interval is cumulative too. However, a passenger can only cancel after a successful booking has been made. So the probability pattern that is entered refers to a customer who has booked one year prior departure only. For every booking done later the cancelation distribution is derived from this original pattern.

Day of Week Distribution – This distribution allows a customer's preference concerning the week day of departure. Since this scenario simulates only one departure day, this distribution is irrelevant and the Day of week Distribution will be uniform for each week day.

IV.2.2. Customer Types

As a basis for the demand side of the simulation customer types have to be created which should reflect the demand side through realistic passenger behavior. Two types are created: a low value and a high value passenger type. In the next paragraphs the various attributes that define each customer type are described in detail before presenting the values of all attributes for each type.

The **Error Term** of a certain customer type is used to cause volatility in demand generated from this type and is drawn from a normal distribution with an expected value of 1. The error term is the value of the standard deviation. Hence, a larger deviation creates higher volatility for every simulation run. The **Willingness to Pay Factor** reflects the highest price a customer is willing to pay for his ticket and depends on the distance travelled. In REMATE simulation tool a value between 1 and 15 is considered to be a high price sensitive customer type while a value between 15 and 30 reflects low price sensitivity. The **Willingness to Pay Error Factor** causes more volatility and allows a wider range of maximum prices accepted in the demand generated from this customer type and is drawn from a normal distribution with the expected value of 1. The value of the WTP error factor represents the standard deviation. Hence, the passenger's maximum price he is willing to pay is described through following function:

$$WTP(maximum\ price) = (WTP\ factor \ast WTP\ error) \ast \sqrt{travel\ distance,}$$

$$where\ WTP\ error = Norm\ (1,\ WTP\ error\ factor)$$

As a simplified example two different passenger types shall travel from Vienna to Berlin where the distance between these two cities amounts to approximately 550 kilometer. First passenger type has a WTP factor of 5 with a WTP error factor set that the maximum deviation shall be 40% (i.e. 40% of 5 = 2) while the second customer type has a WTP factor of 20 with a WTP error factor set that the error term equals a maximum 15% (i.e. 15% of 20 = 3). The two functions are as follows:

$$WTP(maximum\ price)\ of\ first\ customer\ type\ =\ 5 \pm 2 * \sqrt{550}$$

$$WTP(maximum\ price)\ of\ second\ customer\ type\ =\ 20 \pm 3 * \sqrt{550}$$

The exact amount is calculated for each single passenger in each run within this simulation. The range for these outputs can vary according to the attribute values set. In this example the first passenger type accepts a range of maximum prices between 70 and 164 while the second type is willing to accept a price in a range from 399 to 539. All these values result in the maximum WTP, leading the passenger's acceptance of the offer if the price is below the calculated value. This holds true unless the booking is cancelled afterwards again. This attribute is defined via the **Cancellation Probability** of a passenger type. It sets the probability that a customer type will cancel after having made a successful booking.

The above mentioned WTP value can additionally be affected by other attributes as well. In order to compensate negative aspects of passengers' expectation, such as not preferred departures times or certain restrictions, cost can be added up that decreases the customer's willingness to pay and thus influence his choice of booking. Each of those restrictions represents the conditions within a certain booking class a customer may accept or not. Low Cost Carrier usually do not offer any restrictions such as "nonrefundable" tickets or tickets requiring a "minimum stay"; not even in their lowest booking class. Within the proposed scenario, an environment with low cost competition is presented where the network carrier has already matched all conditions of its competitor. Meaning the booking classes will have no restrictions offered but "Eco" for each carrier's booking class. Eco describes if a booking class belongs to economy or business class, but as mentioned earlier, no business class is offered in the simulation anyway. The customer may then accept the next higher class or reject the offer, i.e. no booking is made, depending on the defined customer type. In this scenario all booking classes are offered in economy class only and no business class is offered. The **Restriction Factor** and the **Restriction Value** are used to define which customer type accepts which restriction, respectively which cost arise if a restriction does not meet

passenger's expectation by following function depending on the distance of the route travelled:

$$restriction\ value\ =\ restriction\ factor\ *\ \sqrt{travel\ distance}$$

As in this scenario the NWC matched the LCC's conditions, this utility function is redundant for this thesis and hence the values are set to zero. The **Departure Cost Factor** and the **Maximum Accepted Departure Deviation** determines the cost associated with the deviation from a preferred departure time, respectively the maximum deviation a customer type is willing to accept. The same concept applies to the **Transfer Cost Factor** and the **Maximum Number of Transfers**. The scenario, however, displays itineraries that include mainly point-to-point traffic or a maximum number of one transfer in this scenario and hence this restriction is not relevant either. The **Maximum Travel Time Factor** describes the factor by which the acceptable total travel time may be greater than the minimum connecting time for a certain OD. It is calculated by the following function:

$$maximum\ travel\ time$$
$$=\ min\ connecting\ time\ +\ max\ travel\ time\ factor$$
$$*\ \sqrt{travel\ distance}$$

If customers of a certain type prefer or detest a specific brand it can be also associated with a positive or negative **Brand Cost Factor**. This applies for a certain percentage of the customer type which is set in the **Operating Carrier Preference**.

Thus, two customer types are defined in this scenario, each one with different attribute values in accordance with realistic passenger behavior. The customer type **Low Value Passenger** refers to leisure travelers that are usually very price sensitive and show long term booking behavior. In order to reflect this adequately the willingness-to-pay-factor is set at a low level of 6,0 with a WTP Error of 0,4 while the cost factor for departure time deviation is almost zero, i.e. 0,25 cost units per minute deviated to the preferred time and the cost for a possible transfer is 20. For a lower price a longer travel time and a bad departure time is accepted. Once the

leisure passenger fixed the journey the cancellation probability is rather low, thus, a factor of 5% is chosen here. In general, leisure passengers are not loyal to a certain brand meaning the brand cost factor is zero. In order to meet the requirements of the low-value-customer type the distribution curves for request date and cancellation are set on a long term basis. Departure times are usually equally distributed during the day time as they are not that important as for business travelers. For that reason the departure cost factor is set at a low level of 0,25 per minute and the maximum-accepted-departure-deviation is high at 240 minutes. All values and distribution curves comparing leisure with business travelers will be summarized in Figures 4.3 to 4.6.

On the other hand, the customer type **High Value Passenger** describes the business client that books on short notice. This type displays a much higher willingness to pay, compared to leisure customers but also a clear expectation of the time to depart and the travel time. These attributes are reflected in the higher willingness-to-pay-factor of 18,0 with a WTP error of 0,3 and the higher departure-cost-factor of 2,0 per minute. Since the WTP variation is expected to be higher among the low value customer group (i.e. a standard deviation value of 0,4), the WTP error factor of the high value passenger group is set lower with a value of 0,3. The departure-time-distribution curve has its peaks in the morning and early evening and the short term request- and cancellation-date-distribution are as characteristic for business travelers as the higher cancellation probability of 20%. For business passengers the maximum accepted departure deviation and the maximum travel time factor need to be set lower as well (i.e. at 90 minutes) due to the expectations of business travelers of reaching the final destinations within tight time frames. Business clients tend to be loyal to a certain brand expecting standards that low cost carrier do not offer, participating in certain loyalty programs NWC usually offer. Especially business passengers who fly more frequently than leisure travelers benefit from those loyalty programs. Hence, there is a small negative cost of -25 associated with the network carrier AA. Five percent of high value passengers prefer AA as carrier over another one.

Additionally it is noted that the day-of-week distribution is not relevant and uniform for all three customer types, as the scenario includes only one operational day. Same applies for the maximum-transfer-limit which is set at a value of 1. The error term of each customer type and each willingness-to-pay-factor, equals to the standard deviation, is set at a value of 0,1 for both types in order to grant some volatility. The maximum travel time factor is set at a value of 4,0 for both customer types. Table 4.4 presents an overview of all customer type's values.

Attributes	low value CT	high value CT
Error Term	0,1	0,1
Willingness to Pay Factor	6,0	18,0
WTP Error	0,4	0,3
Cancellation Probability	0,05	0,2
Depature Cost Factor	0,25	2,0
Max Accepted Depature Dev	240	90
Transfer Cost Factor	20	80
Max Transfer	1	1
Max Travel Time Factor	4,0	4,0
Brand	-	AA
Brand Cost Factor	-	-25
Operating Carrier Preferrence Factor (ocp)	-	0,05

Table 4.4: Customer Type Attribute's Values

As mentioned before, all those values are verified and calibrated to this specific scenario. The functions below show how each attribute affects the passenger's WTP and thus, the final booking decision:

$$WTP \equiv f\ (WTPF, WTPE, TD, C, error\ term)$$

$$WTP = \ WTPF * Norm(1, WTPE) * \sqrt{TD} - C$$
$$C = departure\ cost\ + transfer\ cost + brand\ cost$$

$$departure\ cost$$
$$= departure\ cost\ factor(CT)$$
$$* minutes\ (deviation\ from\ prefered\ depature\ time)$$

$$transfer\ cost = \begin{cases} 0\ if\ transfer\ \leq\ 0 \\ tranfer\ cost\ factor(CT)\ if\ transfer = 1 \end{cases}$$

$$brand\ cost = \begin{cases} 0\ if\ brand = LC \\ brand\ cost\ factor(AA) * ocp(AA)\ if\ brand = AA \end{cases}$$

where

WTPF = willingness to pay factor

WTPE = willingness to pay error factor

C = total cost factor

CT = customer type (attribute from high value or respectively low value CT)

TD = travel distance

ocp = operating carrier preference factor

The functions show that the passenger's WTP is positively influenced by the WTP factor (WTP error factor causes more volatility and allows a wider range of maximum prices accepted), the travel distance and eventually by the brand cost factor (that are usually negative costs). Each condition that does meet the exact expectations of a passenger is associated with "costs" that are deducted from the

total passenger's WTP. Those cost conditions are for example if a passenger needs to transfer instead of flying directly or if the actual departure time of the flight deviates from his expectations. With each minute of deviation from the passenger's preferred departure time the departure cost increases. The preferred departure pattern of each customer type is presented in the subsequent paragraphs. Hence, those costs affect the passenger's WTP in negative way. Nevertheless, a booking is accepted by if following four conditions hold:

$$WTP \geq Price$$

$$max\ accepted\ departure\ dev \leq \begin{cases} 240\ minutes\ for\ low\ value\ CT \\ 90\ minutes\ for\ high\ value\ CT \end{cases}$$

$$max\ transfer \leq 1$$

$$max\ travel\ time\ factor \leq 4$$

Of course, the passenger's WPT has to exceed the price offered by the airline but also some other travel attributes must not be exceeded, as the maximal time of travel, the maximal number of transfers and the limits of deviation from the desired departure time, so that a booking is finally accepted by the passenger.

The following tables show all distribution curves that are described in Chapter IV.2.1 for both passenger types. Starting with the preferred departure time in Figure 4.3 it can be seen that the high value customer type on the right has peaks between 6 and 8 a.m. and 4 and 7 p.m. while during the rest of the day time it is very low and during night time mostly zero. The low values passenger's curve on the other hand is much smother during the day time; only from midnight to 6 a.m. the demand to depart it is very low.

Figure 4.3: Preferred Departure Time Distribution of both Customer Types: Low Value Passenger (left) and High Value Passenger (right)

The comparison of distribution curves displayed in Figures 4.4 and 4.5 shows the request date and the cancellations of both customer models. As one can see the time of booking for the low value travelers, the left graph, is rather early, starting even 360 days before departure. The same behavior, however, also applies for a potential cancellation in case there is one. Most of the cancellations are done more in advance and only very few leisure passengers cancel on short notice. The high value type will request the booking later, with a good chance of booking even on the day of departure itself. Same applies for the possible cancellation that takes place on very short notice, sometimes even at the day of departure.
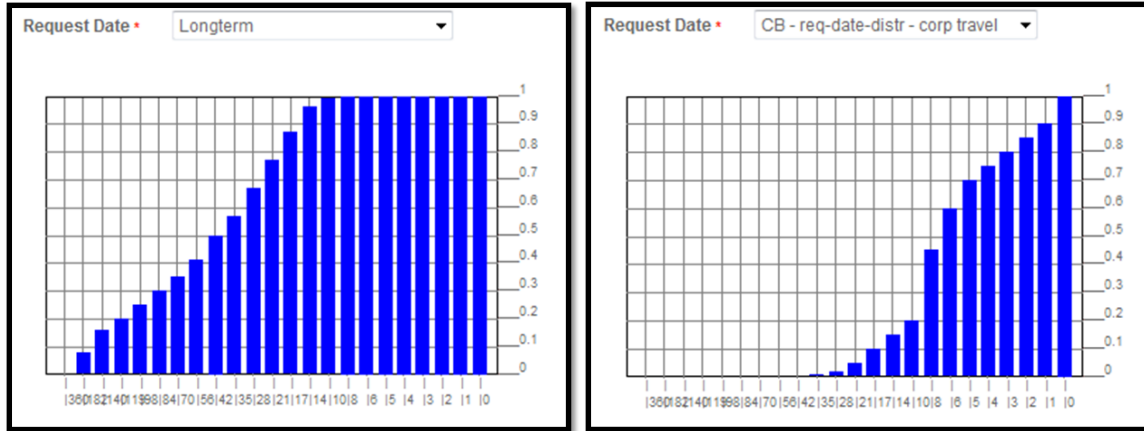
Figure 4.4: Request Date Distribution prior Departure of both Customer Types: Low Value Passenger (left) and High Value Passenger (right)
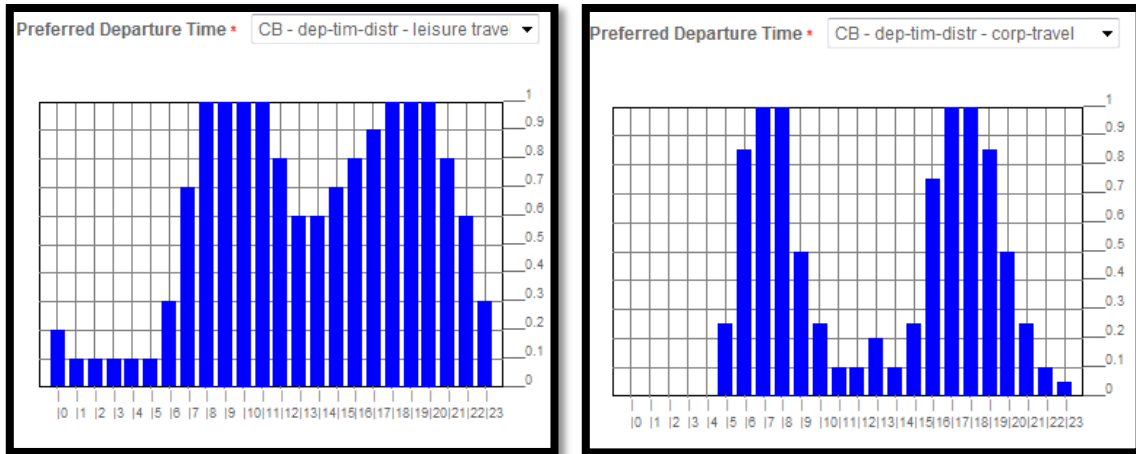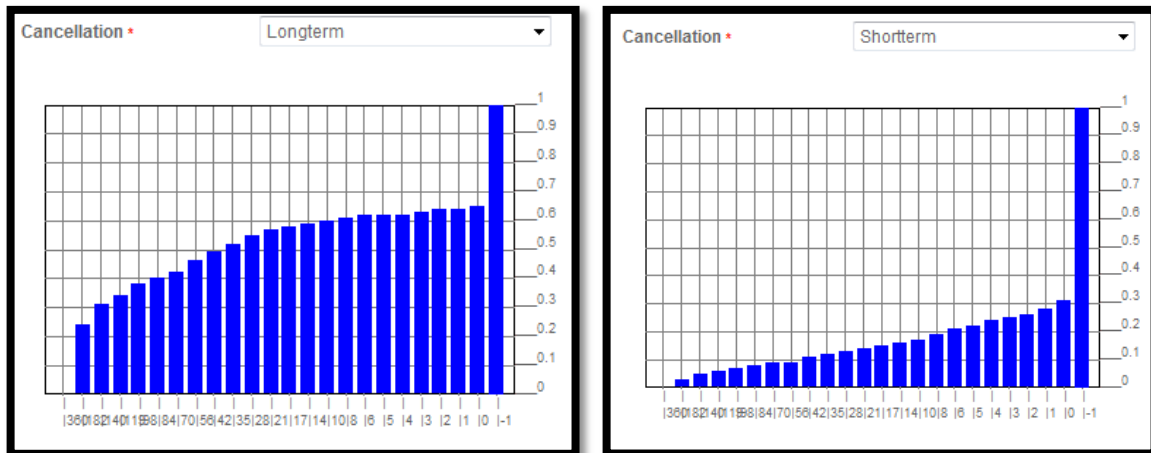

Figure 4.5: Cancellation Date Distribution of both Customer Types: Low Value Passenger (left) and High Value Passenger (right)

The last distribution curve, displayed in Figure 4.6, represents the preferred day of departure. As this simulation only runs through a single day it is exactly the same for both customer models and irrelevant. While low value types usually start the

journey on Fridays or weekends the high value passenger hardly travels on Saturdays or Sundays but almost always departs during the week.
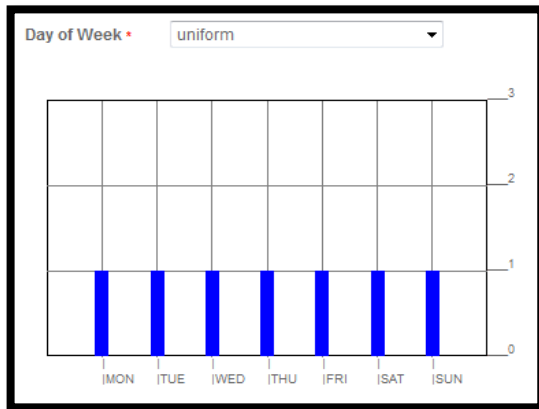
Figure 4.6: Preferred Day of Departure

In this subchapter all attributes for the two customer types low value and high value passengers have been presented. In the following section the final demand creation will be discussed.

IV.2.3. Demand Generation

In order to create the final demand eventually, the number of requests per day is set at a level of approximately 8000. Requests are the search for the respective itinerary and price, indifferent of an occurring booking or not. The amount has been derived from the standard requests an airline receives on its webpage for routes similar to the simulation. This demand is distributed among the different markets to all destinations and further among all customer types. Furthermore, it is assumed that the demand for a certain flight is not only at the point of origin but also at the final destination or even at another place, i.e. rest of the world (RoW). In order to

have statistical confidence the demand is created within 1500 runs in this simulation. For all journeys starting in Vienna 81% are done there while 15% request their booking at the point of destination. In Berlin, Brussels and Moscow the requests at the point of origin are a little lower between 64% and 71% but higher at the point of destination. Four percent are distributed equally to all other markets (rest of the world). The exact demand distribution can be seen in Table 4.5, respectively Figures 4.7 and 4.8.

Origin	Destination	Requests per day	Low Value Customer	High Value Customer	at Point of Origin	at Point of Destinaion	RoW (rest of world)
VIE	BER	958	686	272	81%	15%	4%
VIE	BRU	938	672	266	81%	15%	4%
VIE	MOW	979	701	278	81%	15%	4%
BER	VIE	673	482	191	64%	32%	4%
BER	BRU	528	378	150	64%	32%	4%
BER	MOW	550	394	156	64%	32%	4%
BRU	VIE	659	472	187	70%	26%	4%
BRU	BER	528	378	150	70%	26%	4%
BRU	MOW	538	386	152	70%	26%	4%
MOW	VIE	666	477	189	71%	26%	4%
MOW	BER	533	382	151	71%	26%	4%
MOW	BRU	522	374	148	71%	26%	4%

Table 4.5: Detailed Requests per Day Distribution
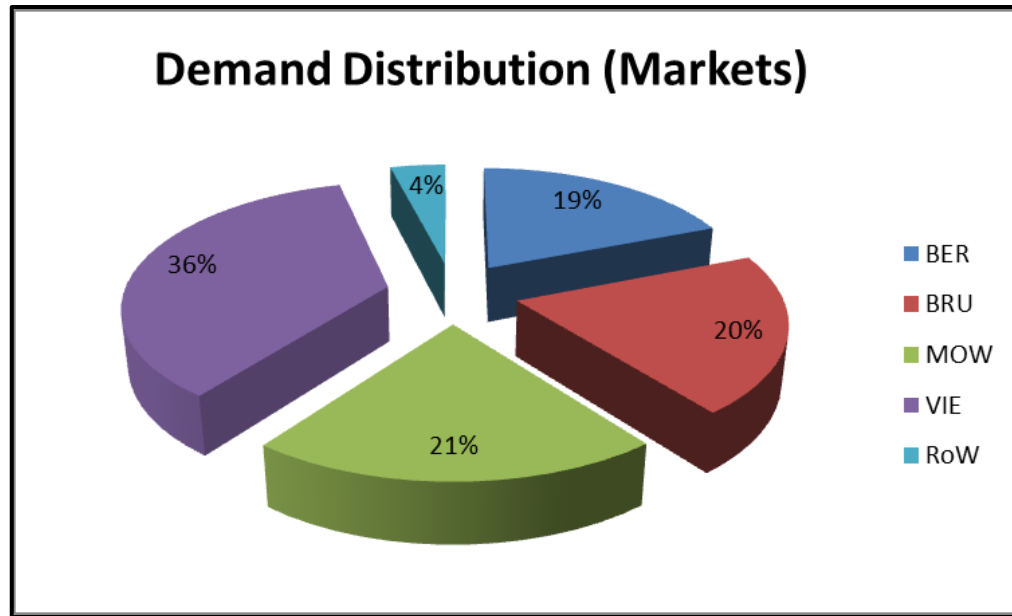
Figure 4.7: Demand Distribution per Market

This leads to the market distribution shown in Figure 4.7. As Vienna is the hub of both carrier the demand from the home market is the highest of all markets, summing up to 36% of all booking requests. All other markets have between 19% and 21% of total demand while four percent are distributed equally among all other markets (rest of the world).

The request distribution between low and high customers is 72% to 28% which represents a realistic ratio between leisure and business demand. This does not necessarily mean, however, the passengers that eventually depart have the same distribution ratio. This is reasoned by the fact that both user groups have different conditions whether they buy or they do not buy the ticket.
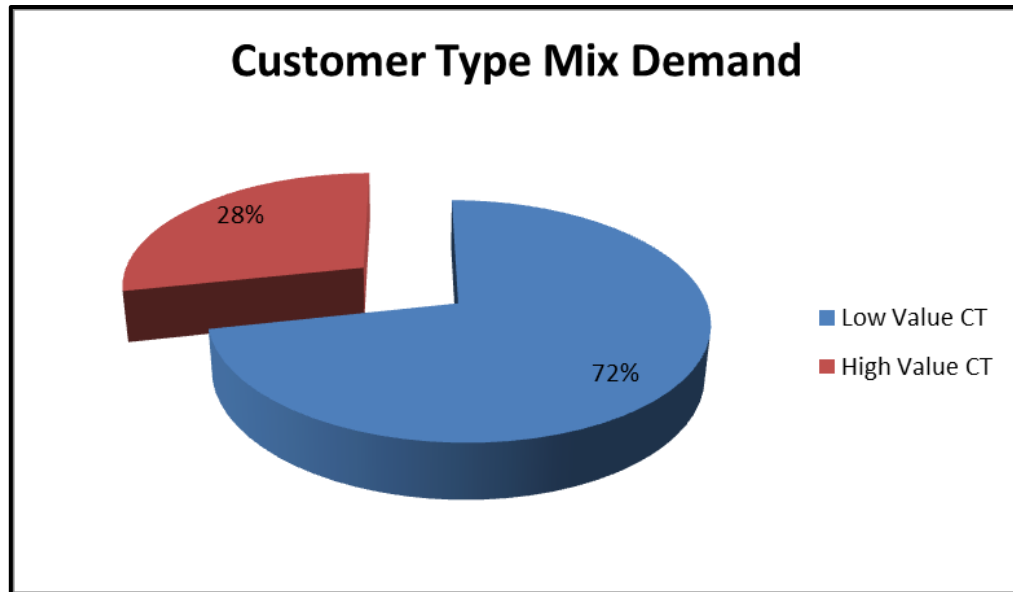
Figure 4.8: Demand per Customer Type

Given the previously set and discussed for both customer types added together, the following results can be obtained to describe the demand preview by a WTP curve, the demand over time of Day and the Demand / Cancellation over DBD (Days Before Departure) as shown in Figures 4.9 to 4.11 below.
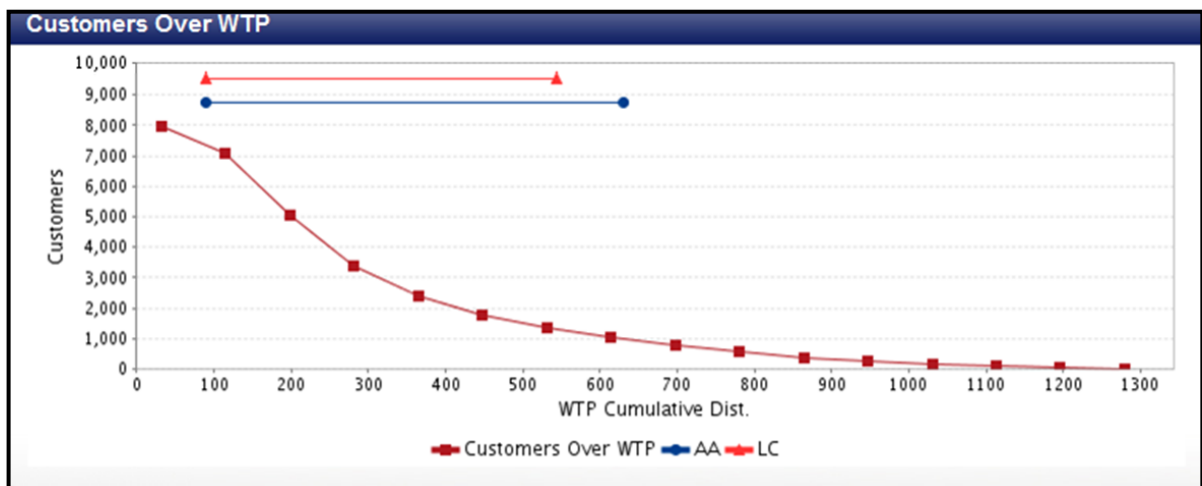
Figure 4.9: Overall WTP Curve

While the X-axis of this customers-over-willingness-to-pay chart represents the monetary value in terms of the price, the Y-axis shows the expected number of customers who have WTP greater than the price offered. The blue and the red straight lines on the top of the chart show the price range both airlines offer in the market. The red line represents the airline LC and starts at a price of 89 ending at 543 in the highest class. The blue line displays airline AA, offering a price range from 89 to 631. The expected number of customers as a function of the price is as follows:

$$E[Y(WTP \geq P) = R * [1 - Norm(WTPF * \sqrt{TD}, WTPE * WTPF * \sqrt{TD}(P))]$$

Where:

Y = number of customers

P = price

WTPF= willingness to pay factor

WTPE = willingness to pay error factor

R = total requests

TD = travel distance

Here, Norm(μ, σ)(x) denotes the value of the cumulative normal distribution with mean mu and standard deviation sigma calculated at x. E[Y] denotes the expected value of the random variable Y.

These values describe all customer types together on all ODs. All approximate 8000 customers requesting a booking would be willing to pay a price of 32, which can be considered the starting point of the WTP curve. Afterwards it displays a sharp

decline towards the x-axis as the passenger volume declines with the price level. Only about 1000 passengers are expected to be willing to pay 600 for a ticket.

Figure 4.10 shows the expected request and cancellation distribution of both passenger types over time; differentiated in low value customer type on the left and the high value passenger type on the right. The X-axis describes the timeline to departure, i.e. days before departure (DBD). On the Y-axis both, the expected cumulative demand per day (primary) and the expected cumulative cancellations per day (secondary), are displayed, both preconfigured to the customer type distributions explained in the previous Chapters IV.2.1 and IV.2.2.
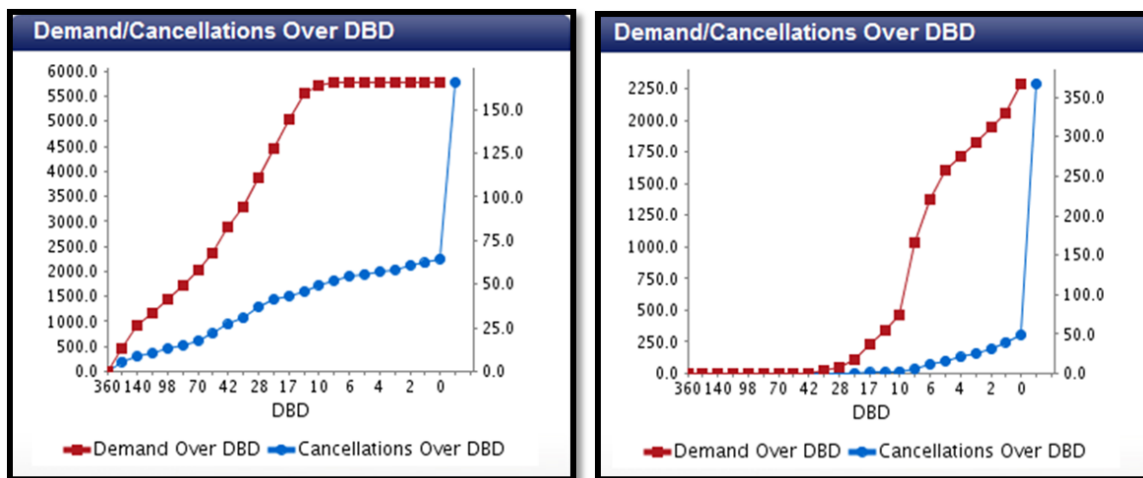
Figure 4.10: Demand and Cancellations over DBD of both Customer Types: Low Value Passenger (left) and High Value Passenger (right)

The demand developments of both customer types put together can be seen in Figure 4.11, as well as the demand-over-time-of-day chart. Again, the X-axis represents the time – in the chart on the right the hours of the days – and the Y-axis the expected number of customers at time t. The demand at the time t is the product of the total requests and the probability that a request occurs at time t related to the distribution described in previous Chapters IV.2.1 and IV.2.2.

Figure 4.11: Total Demand and Cancellations over DBD and Demand over Time of Day (both Customer Types together)

Whereas there is a total expected demand of 8070 passengers, only 4758 are active expected demand, that means customers that actual book and pay for a flight. This was found to be true after 1500 runs of simulating the demand, i.e. 58.96% of all potential customers. On the other hand the results show 3312 expected duds, that is the number of customers that do not end up with a booking eventually. Duds occur if passengers' WTP is too low or based on a not accepted restriction or on the acceptable deviation from their desired departure time of a passenger. A detailed overview of the final demand output, also separated into the two customer types, is shown in Table 4.6.

	TTL Customer Demand	Low Value Passenger	High Value Passenger
WTP Average	302	200	403
Total Demand	8070	5780	2289
Active Demand	4758	3453	1305
Active Demand %	58,96%	59,74%	57,00%
Active Demand as % of CT	100%	72,57%	27,43%
Duds	3312	2327	985
Duds %	41,04%	40,26%	43,00%
Duds as % of CT	100%	70,27%	29,73%
Duds d/t ODI	2121	1144	977
Duds d/t ODI %	26,28%	19,78%	42,65%
Duds d/t class	1192	1184	8
Duds d/t class %	14,77%	20,48%	0,35%
No Shows	104	101	3,18
No Shows %	1,29%	1,75%	13,89%

Table 4.6: Final Demand output

The average overall willingness to pay, based on the 1500 simulation runs and calculated as described in Chapter IV.2.2, amounts to 200 for low value passengers and 403 for high value customers. As the WTP is dependent on the travel distance it does vary from OD to OD. Therefore for each customer set a list of acceptable ODIs and acceptable booking classes is calculated. If the airline offers both, accepted ODI and right booking class at the time of request the customer becomes an active demand. Both customer types have an active expected demand rate closely below 60% of their total demand and show a rate a little above 40% of duds within their customer group. The majority of all duds, however, can be found within the low value passenger type with a rate of 70,27%. The reason therefore can be found at the same stake in both among low value customers: not fitting OD itineraries and the lack of willingness to pay the lowest available class. Not surprisingly the willingness to pay is hardly a reason for the high value passenger to refuse a booking as the percentage amounts only 0,35% of those travelers. Here the lack of a perfect schedule according to their travel plan expectations plays a

more important role: 42,65% of this customer type refuse to book because of this reason. The No-Show rate, i.e. booked passengers that do not turn up at the departure is low, in total at a rate of 1,29%, respectively 104 passengers. Within the high value passenger group, however, it is significantly higher due to the late cancellation behavior and higher cancellation rate of this customer type.

IV.3. Chapter Summery

This chapter delivered insight into the REMATE simulation tool and the two basic requirements that are necessary for the simulation: The supply including a hub-and-spoke network with schedule and price matrices for both airlines as well as the demand generation with its two customer type models. The demand set-up defines the different attributes of the two customer types, especially determining the WTP of each passenger, i.e. which maximum price he or she is willing to accept to make a booking. The price matrices of each carrier, i.e. different price levels for each booking class (Q, M, B, Y for carrier AA, respectively T, L, K, E for carrier LC) on each itinerary, are fixed. However, the applicable RMS decides on each day for each flight individually which booking classes are to be opened and to be closed, thus, steering the actual price offered to the customer each day. The RM techniques that apply in the different scenarios, thus, offering different prices to the passenger, will be explained in more detail in the following chapter. The passenger choice model delivers the necessary booking information as input for the RMS (compare Figure 2.1 and Figure 4.1), i.e. if a booking is done or rejected by the passenger. This decision depends on various factors as presented in depth in this chapter.

In the next section four different scenarios will be explained, each with a different RM method that applies for the NWC. Afterwards, the results of these four simulations will be presented and discussed.

V. SIMULATION RESULTS

After setting up all requirements in the last part, the following chapter leads through four different scenarios that are simulated. This simulation assumes that the LCC has already entered the market and the NWC reacted by matching fares and removing all restrictions according to LCC's unrestricted fare structure. The results within a totally unrestricted fare structure environment in terms of revenue, seat load factor (SLF) and yield will be discussed next, mainly focusing on NWC's output. Furthermore, the segregation of the two customer types and the distribution within the four booking classes of the NWC will be examined in detail and compared within the four different scenarios, thus, showing if the hybrid method leads to a better result over the other methods.

To ensure statistical confidence each simulation is run 1500 times, thereof 500 initial runs in order to let the system create historical data it can fall back to when calculating the future demand. Each run represents a single departure day. The final results presented in the following subchapters are the averaged values of all simulation runs from number 501 to 1500. Due to the fact that the NWC offers more seats in total it is clear that the overall revenue will always be higher than the LCC's revenue. However, the goal of the simulations is to examine the changes in revenue outcomes of the NWC when using different RM methods, especially if there is an increase in efficiency using RM method of hybrid forecast and optimization.

The very first scenario is the base case and indicates that both airlines in this network do not use any kind of forecast or optimization tool, this refers to a first-come-first-serve scenario. In the following three scenarios LCC uses always leg based forecast and optimization tool, i.e. all parameters of the LCC are fixed, while the NWC changes its RM method from leg based forecast and optimization to OD based and finally to hybrid forecast and optimization.

As precise forecasting for each single day into the future for each flight and each booking class on each OD would be too time consuming for each optimization, all RM systems usually use data collecting points (DCP). Each DCP represents a time frame between 360 days prior departure and the actual day of departure in which all booking and cancellation information is collected and forecasted for future flights. DCPs usually grow smaller as they approach closer to the days of departure.

Following DCPs are used by the airlines in this simulation whereas it is assumed that AA uses more DCP than LC due to their more sophisticated RMS:

DCP #	1	2	3	4	5	6	7	8	9
days prior departure	360	234	174	122	90	69	49	38	28

DCP #	10	11	12	13	14	15	16	17	18
days prior departure	22	15	10	8	6	3	1	0	-1

DCP #	1	2	3	4	5	6	7	8	9	10	11
days prior departure	360	174	69	28	15	8	6	3	1	0	-1

Table 5.1: DCP Tables of AA and LC

AA uses 18 data collection points whereas the first period between DCP one and two is 126 days while the later periods between DCP 12 and 18 last for three to one days only. The reason why the periods are getting smaller is that the number of booking and cancellation movements per day increase closer to departure, hence, the forecast per day and optimization has to be more precise here. On the other hand LC uses 11 DCPs as LC's is not as sophisticated as the NWC's.

In the following subchapters the environment of all four simulations will be explained, i.e. which RM method was used and the outcome in terms of revenue, booked passengers, yield, seat load factor as well as the distribution between low and high value passengers booked will be presented. The focus will be on the AA's performance and changes rather than on LC's as the network carrier's RM methods

are the one to investigate. Furthermore, AA's bookings class distribution will be examined closely, i.e. how many passengers booked which class in each simulation. Finally all results will be compared and discussed. As the definition of yield may alter in literature this thesis refers yield as revenue divided by booked passengers. The SLF is the quotient of booked passenger over capacity.

V.1. No RM – First Come First Serve Scenario

In this simulation both airlines do not work with any RM method; hence neither forecast nor optimization algorithms are used. The seats are assigned to the customers as requested and every booking request is accepted as long as capacity is available. The average output of simulation run 501 to 1500 can be seen in Table 5.2. It shows the overall revenue, i.e. the total revenue that is generated in this simulation for each airline. Furthermore, it shows the number of final booked passenger, yield, SLF and total capacity output.

no RM	Revenue	Booked	Yield	SLF	Cap
AA (overall)	243.865	2.124	115	88,50%	2.400
LC (overall)	162.005	1.306	124	77,74%	1.680
TTL	405.870	3.430	118	84,07%	4.080

Table 5.2: Simulation Result without RM

Without any form of RM the overall revenue results are expected to rather poor compared to later results when RM methods are used. Although the SLF is at a share of 88,50% at carrier AA, the yield is very low due to the fact that all

passengers book into the lowest class. This can be observed in Table 5.3 that provides an overview about the booking class mix of airline AA. Even high value passengers with a willingness to pay that is much greater than the offered price buy the lowest Q class as there is neither any restriction nor any availability restriction that would prevent them from doing so. Furthermore, the final booked number of both customer groups on AA as well as their contributed revenue to carrier AA and the average yield for AA's complete network can be seen. The ratio between low and high yield passengers in terms of revenue share without any RM method is 89% to 11%.

AA's Customer Type Distribution	Revenue	Booked	Yield
High Value (AA)	26.795	222	121
Low Value (AA)	217.069	1.902	114
Passenger TTL	**243.865**	**2.124**	**115**
AA's Booking Class Distribution			
Y	-	-	-
B	-	-	-
M	-	-	-
Q	243.865	2.124	115
TTL	**243.865**	**2.124**	**115**

Table 5.3: AA's Customer Type and Booking Class Mix without RM

This simulation works with neither forecast nor any optimization and represents the base case. The following subchapters will provide results with different RM methods that will be compared to this case and among each other.

V.2. Flight-leg Based RM Scenario

In this scenario both carrier are using a flight-leg based RM method. While AA will change the RM technique in the forthcoming chapters, LC's technique will remain at this leg-bad RM method. It works by forecasting demand to arrive at each DCP for each flight and booking class offered by the airline. Forecasts are updated based on actual bookings at each DCP and availabilities are optimized using the EMSRb algorithm. They are re-optimized after each update of the forecast. Nested booking limits are assigned to each class and flight and sellable seats are updated whenever a booking is accepted within this method. EMSRb refers to expected marginal seat revenue method from Belobaba and is explained in Chapter II.1.3.a in more detail. Table 5.4 shows the overall revenue, final booked passengers, the average yield, the SLF and capacity of both airlines in this scenario.

leg based RM	Revenue	Booked	Yield	SLF	Cap
AA (overall)	332.641	2.127	156	88,62%	2.400
LC (overall)	170.738	1.328	129	79,02%	1.680
TTL	503.379	3.455	146	84,67%	4.080

Table 5.4: Simulation Result with leg based RM

It can be observed that the number of the final booked passengers and, thus, the SLF does not change significantly compared to the simulation without any RM method used The yield, however, increases tremendously – especially at AA – which results in a 36,4% higher revenue outcome for carrier AA and a 5,39% higher revenue result for LC. The reason for this yield growth at AA can be found in Table 5.5 that shows the distribution of both, customer types and booking classes.

AA's Customer Type Distribution	Revenue	Booked	Yield
High Value (AA)	90.968	550	165
Low Value (AA)	241.673	1.577	153
Passenger TTL	**332.641**	**2.127**	**156**
AA's Booking Class Distribution			
Y	-	-	-
B	91.713	425	216
M	134.583	789	171
Q	106.345	914	116
TTL	**332.641**	**2.127**	**156**

Table 5.5: AA's Customer Type and Booking Class Mix with leg based RM

While without any RM method passengers simply book into the lowest class according to the first-come-first-serve principle, the leg optimization reserves seats for later bookings of high value customers, especially during peak flights, as can be observed in Figure 5.1. It shows the comparison of low and high value passengers' booking behavior on airline AA in terms of time-of-booking in scenario without RM on the left versus leg based RM scenario on the right.

It clearly shows that in the scenario without forecast and optimization the low value group booking early, purchases more than 1900 tickets until approximately 20 days prior departure. At this point in time the late booking high value passengers start to fix their flight but only less than 200 passengers of this group can get a seat for their desired itinerary. In contrast, the low value type rush stops at a booking level of about 1600 in the leg based RM scenario protecting a number of seats for the later booking high value customer. The low value passenger group naturally books flights at their most preferred departure time which is usually equal to the high value passenger group, i.e. morning and early evening hours as can be seen in Figure 4.11. Due to their early booking behavior they block most of the seats on those peak flights leaving more seats empty during off-peak times. However, high value

passengers that book later have only very little demand for those off-peak flights. As a consequence of the optimization process a part of low value group is shifted to flight times during the day where the demand is not as high as during peak times in the morning and evening hours (compare Figure 4.11). The seats of those flights are in some extent protected for the passengers with a higher WTP by offering higher fare classes only. How many seats are to be protected is subject to an accurate forecast. This ends up in a great revenue contribution of high value passenger for carrier AA.
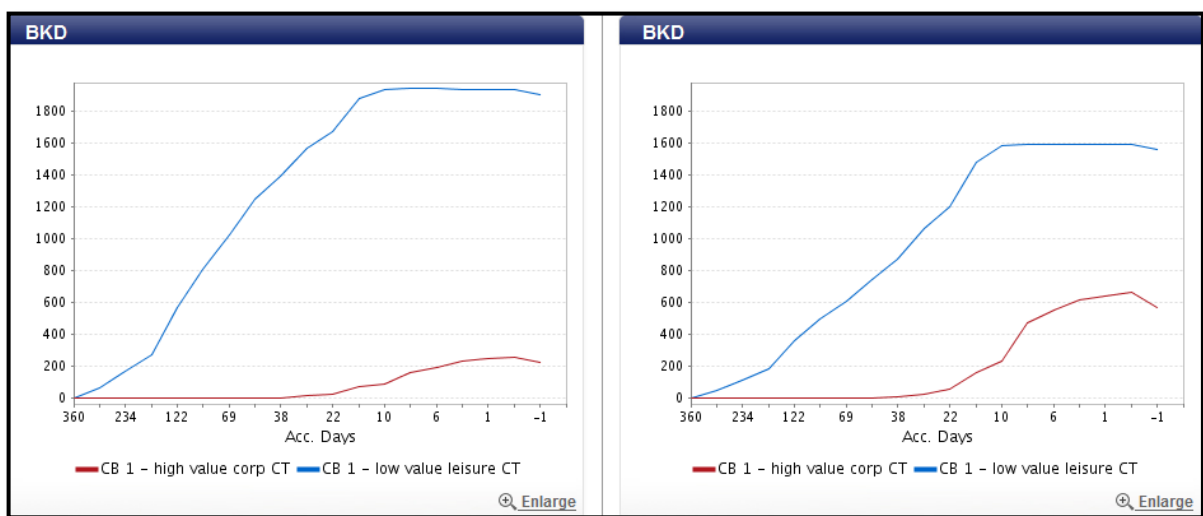
Figure 5.1: Booking behavior of Customer Types in Simulation without RM vs. Simulation with leg based RM

The revenue contribution of the high value types without optimization at AA is 26.795 in absolute figures or at a share of 11,0%. In the second scenario, however, the high yield group contributes 90.968 or 27,3% of AA's total revenues. Moreover, the booking class distribution in table 5.5 shows that leg based forecast and optimization generated an upsell from Q to higher classes M and B, therefore increasing the overall yield without the SLF to suffer. This implicates that the RM method could reflect the passengers' WTP in an appropriate manner. However, leg based RM methods prefer point-to-point over transfer passengers compared to OD

based RM methods, as explained in Chapter II.1.3, which may lead to suboptimal results. This will be examined in the subsequent chapter in more detail.

V.3. Origin-Destination Based RM Scenario

In contrast to the flight-leg based RM method an OD Based RM method works by forecasting demand to arrive at each DCP for each itinerary, respectively OD, and booking class offered by the airline. Forecasts are updated based on actual bookings at each DCP and availabilities are optimized using a combination of linear and dynamic programming. They are re-optimized after each update of forecast. The inventory control method assigns a bid price to each compartment on each flight. Only classes with a price that exceeds the bid price are available for booking. More details about Origin-Destination Control can be found in Chapter II.1.3.b. The key figures for this simulation with OD based RM are summarized in Table 5.6.

OD based RM	Revenue	Booked	Yield	SLF	Cap
AA (overall)	361.369	2.202	164	91,76%	2.400
LC (overall)	170.636	1.335	128	79,45%	1.680
TTL	532.005	3.537	150	86,69%	4.080

Table 5.6: Simulation Result with OD based RM

The first significant difference to the leg based scenario is that both, yield and booked passengers, and hence SLF and total revenue could be increased with OD based RM for AA. With this method this carrier's revenue has raised to 361.369, a 48,2% increase over the base case's revenue level and even another 8,6% increase over the leg based RM scenario. This increase is not only a consequence of an even better passengers' WTP reflection but also because point-to-point is not

preferred over transfer traffic as already discussed in Chapter II.1.3 and will also be explained in more detail in the following paragraphs.

The revenue share of the high value customer type is 36,3% equaling 131.133 in absolute figures and represents an augmentation over the leg based RM scenario. The raised share is on cost of the low value passengers' revenue contribution. However, this decline is smaller than the gain of high value customer. The booking class mix in this simulation shows that an upsell even to the highest class could be obtained which influences the yield in a positive way. The overall yield in an OD based RM simulation is 5,2% higher compared to the leg based RM scenario and 42,6% higher than in the base simulation. The detailed figures of this scenario's distribution of customer types and booking classes are presented in Table 5.7.

AA's Customer Type Distribution	Revenue	Booked	Yield
High Value (AA)	131.133	596	220
Low Value (AA)	230.236	1.606	143
Passenger TTL	**361.369**	**2.202**	**164**
AA's Booking Class Distribution			
Y	60.076	178	338
B	65.808	282	233
M	108.802	651	167
Q	126.683	1.091	116
TTL	**361.369**	**2.202**	**164**

Table 5.7: AA's Customer Type and Booking Class Mix with OD based RM

Both results imply that OD based RM method reflects passengers' WTP even better than leg based RM does. Moreover, another fact leads to the improved result of OD based RM over leg optimization: as already described in Chapter II.1.3.a and II.1.3.b the leg based RM method tends to prefer point-to-point over transfer passengers in bottleneck situation leading to suboptimal results. However, OD RM

amends this drawback due to a more sophisticated approach. Having a look in Table 5.8 one can see that this is also true in this scenario as this network also has a bottleneck situation in the morning hours during peak demand times between 6 and 8 a.m. and 5 to 7 p.m. The table compares AA's revenues made by point-to-point versus transfer passengers in both scenarios: leg based RM as well as OD based RM.

AA's RevenueDistribution (P2P vs transfer)	leg based RM	OD based RM
Revenue: P2P	209.186	208.978
Revenue: Transfer	123.455	152.390
Total Revenue	**332.641**	**361.369**

Table 5.8: P2P and Transfer Revenue mix: leg based vs. OD based RM

While the revenue produced by point-to-point traffic remains almost stable, transfer revenue is increased by 23,4% in the scenario using OD based RM method. Exactly this advantage leads to an overall increase of both factors positively influencing the revenue, AA's yield and SLF, by stimulating transfer traffic through granting more availability in lower booking classes and selling up point-to-point traffic into higher booking classes. Taking into consideration that this scenario has a very small network with one hub and only three more destinations, the expected benefit of an OD based RM method over a leg based, will be rather small. The gain of OD based optimization clearly increases with a greater and more complex network, e.g. a multi-hub network.

V.4. Hybrid Forecast RM Scenario

Similar to the OD based RM the hybrid forecast RM method works by forecasting demand to arrive at each DCP for each itinerary – point-to-point as well connecting ODIs – and fare class offered. As discussed in detail in Chapter III.2.1 there are two different sets of demand forecasted: price-oriented and product-oriented. While product-oriented customers request to book one specific booking class regardless of other classes availability, price-oriented passengers always request to book the cheapest class available. Sell-up indicators are calculated for this hybrid RM technique as described in Chapter III.2.1 depending on the share of priceable customers. As in the last simulations, forecasts are updated based on actual bookings at each DCP. Availabilities are optimized using the same combination of linear and dynamic programming that is applied in the OD based RM method scenario. They are re-optimized after each update of the forecast and the inventory assigns a bid price to each compartment on each flight as well. Hence, only classes with a price exceeding the bid price are available for bookings.

Hybrid RM	Revenue	Booked	Yield	SLF	Cap
AA (overall)	373.892	1.911	196	79,61%	2.400
LC (overall)	181.731	1.448	125	86,20%	1.680
TTL	555.624	3.359	165	82,32%	4.080

Table 5.9: Simulation Result with Hybrid RM

Table 5.9 presents the overall results of this simulation where carrier AA uses the hybrid forecast model. An interesting fact is that the number of final booked passengers on AA in this scenario is lower than in any other simulation before ending at an overall SLF of 79,6% only. Still, the AA's revenue outcome is the highest of all simulation results with a total amount of 373.892 due to an overall average yield of 196. Interestingly, LC also has the highest revenue in this scenario and a significant higher SLF result than in other simulations while LC's yield

remains stable. Here, AA obviously protects more seats for passengers with higher WTP which leaves more low value passengers for low cost competition. A comparison of all revenue and SLF results in one chart is presented in Figure 5.2.
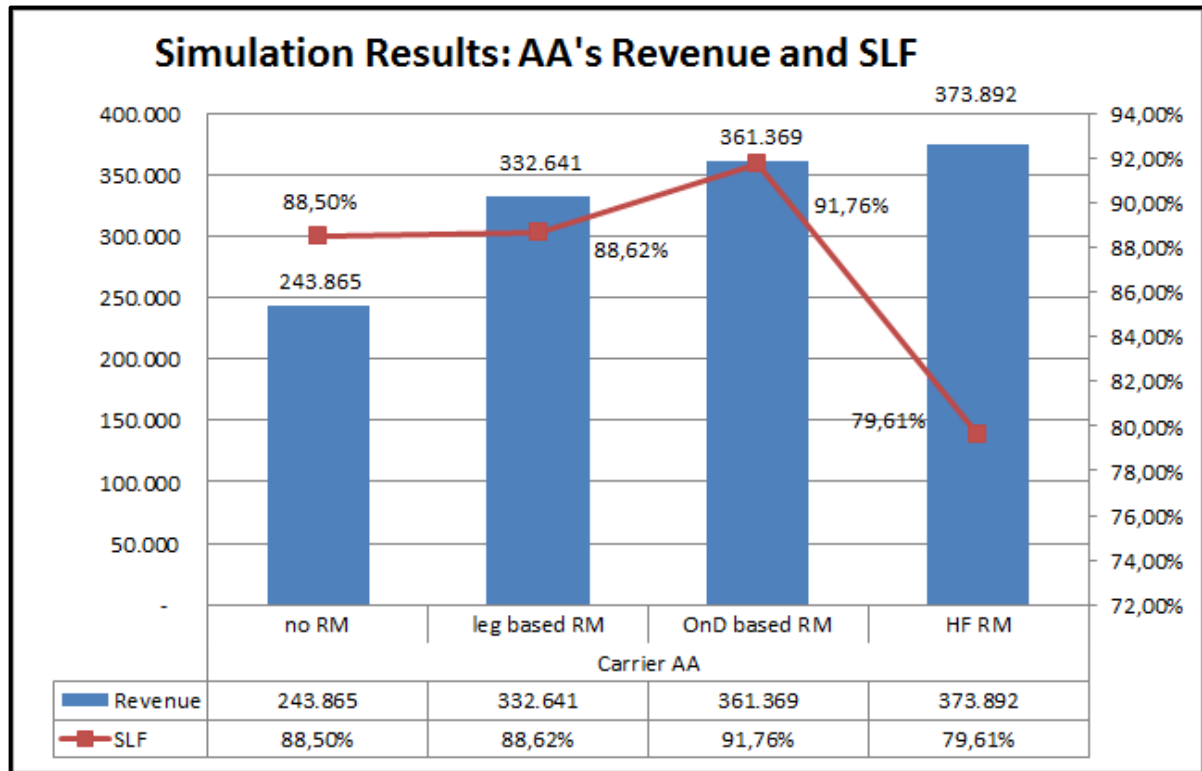

Figure 5.2: Comparison of all Simulation Results: Revenue and SLF

Highest Revenue with lowest SLF indicates that the revenue quality, i.e. the average yield, is the highest one in this scenario. HF seems to be able to model passengers' WTP better than other RM techniques in an environment of unrestricted fares. The customer type mix and the booking class distribution in this HF RM scenario (as seen in table 5.10) support this theory too. The revenue share of the high yield customer group is higher than the one from low value passengers, i.e 52% or 195.122 of all revenues contributed by high value group. The booking class mix shows that both, revenue and booked passengers in the highest classes Y and B have increased compared to the other scenarios, mostly due to the calculated up-sell of HF RM method.

AA's Customer Type Distribution	Revenue	Booked	Yield
High Value (AA)	195.122	900	217
Low Value (AA)	178.770	1.011	177
Passenger TTL	**373.892**	**1.911**	**196**
AA's Booking Class Distribution			
Y	62.861	188	334
B	133.463	583	229
M	137.155	816	168
Q	40.414	324	125
TTL	**373.892**	**1.911**	**196**

Table 5.10: AA's Customer Type and Booking Class Mix with HF RM

The following figures present comparisons of AA's customer type and booking class distribution results among all four simulations. While Figure 5.3 shows the customer type mix in terms of revenue and the overall yield for each simulation, Figure 5.4 presents the booking class mix. Not surprisingly, the scenario without any RM method, where first-come-first serve applies has simple outputs which result in hardly any customer type mix and no booking class mix at all. As no seat allocation optimization process takes place all bookings are done in lowest class Q and, hence no protected seats for late booking high yield passengers. Additionally, one can observe that by using higher sophisticated RM methods the revenue distributions are improving in terms of overall revenue maximization. Better forecast and optimization methods force passengers to book into higher booking classes that rather correspond to their true WTP. Bookings in highest fare classes Y only occur in the OD based and in the HF RM simulation. Especially the HF RM method increases the revenue generated in higher booking classes significantly, this however, on cost of Q class revenue, and thus, resulting in a higher total yield as seen in Figure 5.3 at the left scale on the second axis. HF achieves the overall averaged highest yield with a value of 196 due to a more balanced customer type and booking class mix (Figure 5.4).

AA's Customer Type Distribution and Yield

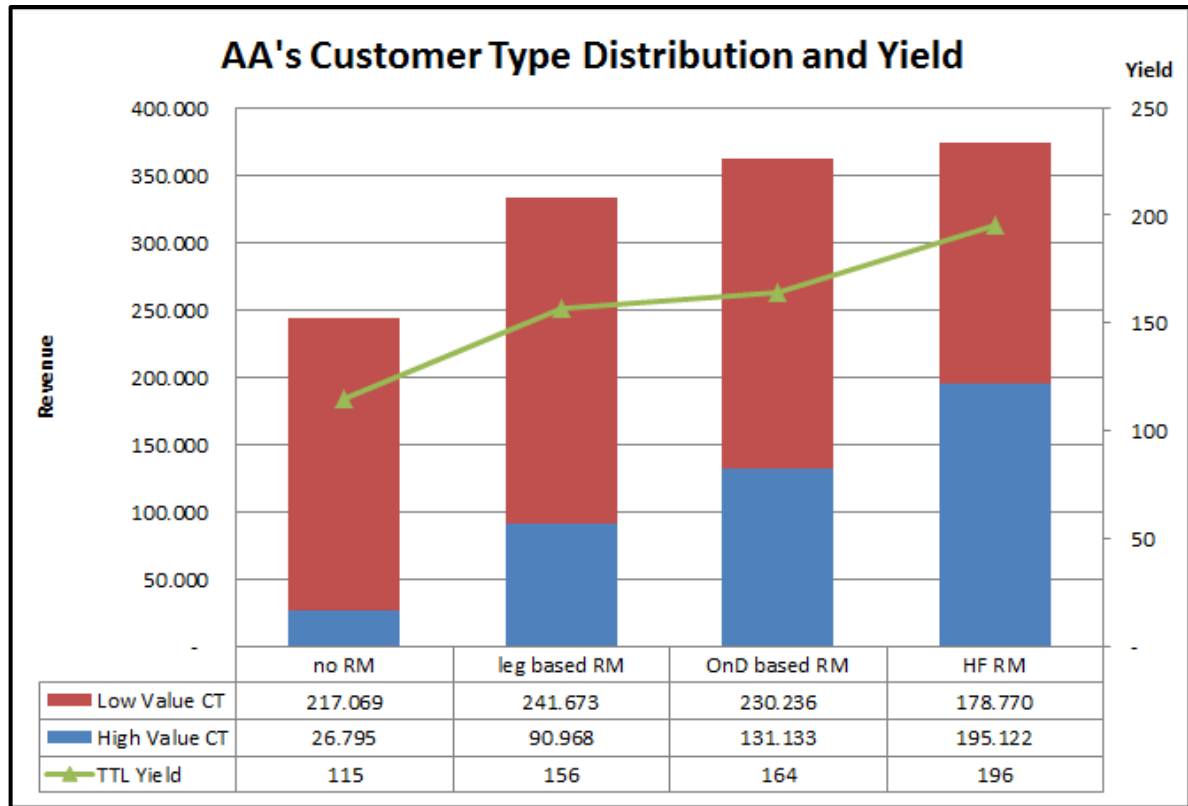|	no RM	leg based RM	OnD based RM	HF RM
Low Value CT	217.069	241.673	230.236	178.770
High Value CT	26.795	90.968	131.133	195.122
TTL Yield	115	156	164	196

Figure 5.3: Simulation Comparison of AA's Revenue Distribution per Customer Type and total Yield

Figures 5.5 and 5.6 compare the outputs among the different scenarios. Figure 5.5 presents the changes in percentage of revenue, final booked passengers and yield of each simulation over the base case where no RM method was used. The final booked passengers show no significantly changes when comparing flight-leg based or OD based RM methods. This number, however, is reduced by 10% compared to the base case when HF RM technique is being used. The most significant change among all simulation is the yield increase that can be obtained in the simulations where HF RM is used.
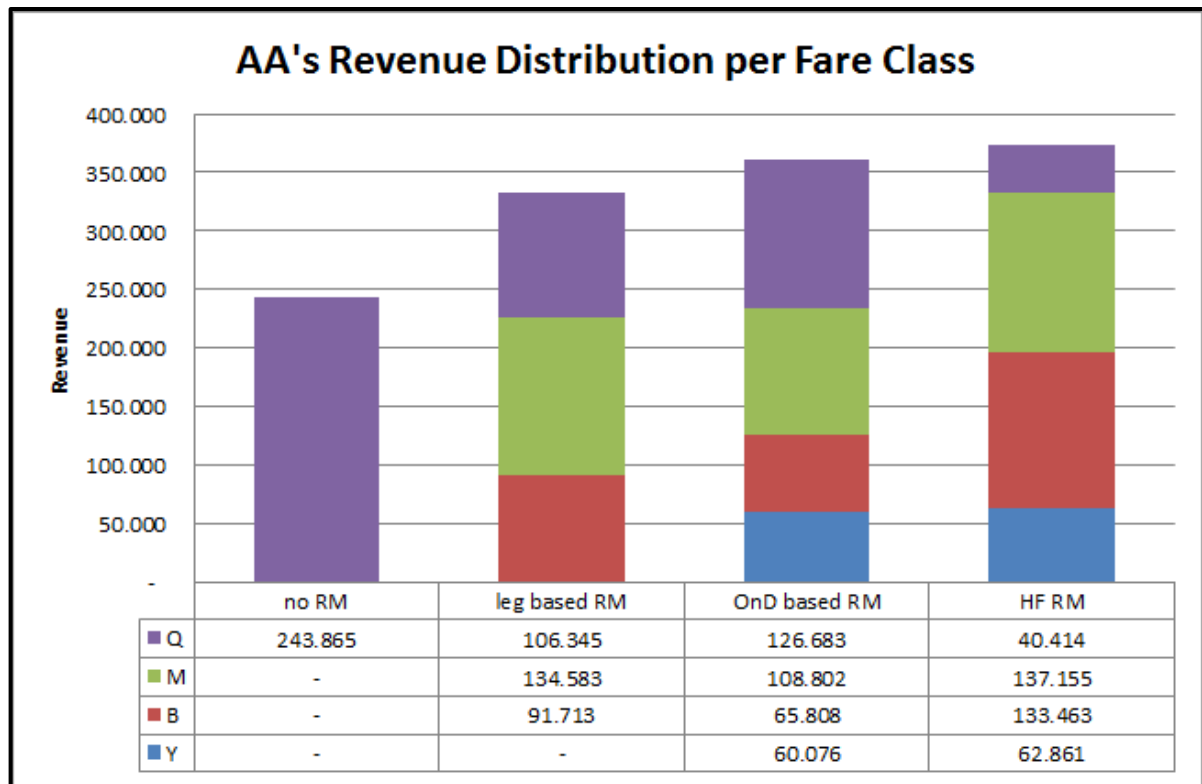
Figure 5.4: Simulation Comparison of AA's Revenue Distribution per Booking Class

The highest overall yield of 196 in the HF RM method scenario – an increase of 70% towards the base case – even overcompensates the lowest SLF of 79,6% (i.e. 10% less than in the base case), still leading to an overall revenue that is higher than in any other simulation. This means that HF RM finds the optimal seat allocation that maximizes revenue within the different methods presented by granting fewer seats in total but to higher prices.

Figure 5.6 shows the improvements of HF over all other RM methods in percentage of total revenue only. Hybrid forecast method delivers 53% more revenue for AA than in the same scenario where no RM is used. Furthermore, HF even outperforms the other two methods, leg based and OD based RM, by an increase in total revenue by 12% respectively 3%. Obviously, the best output can be achieved with HF RM method with which indicates that HF is the best RM method among these

four to reflect true passengers' WTP accurately and, hence, is a better RM technique for NWC when competing against a LCC in an unrestricted environment.
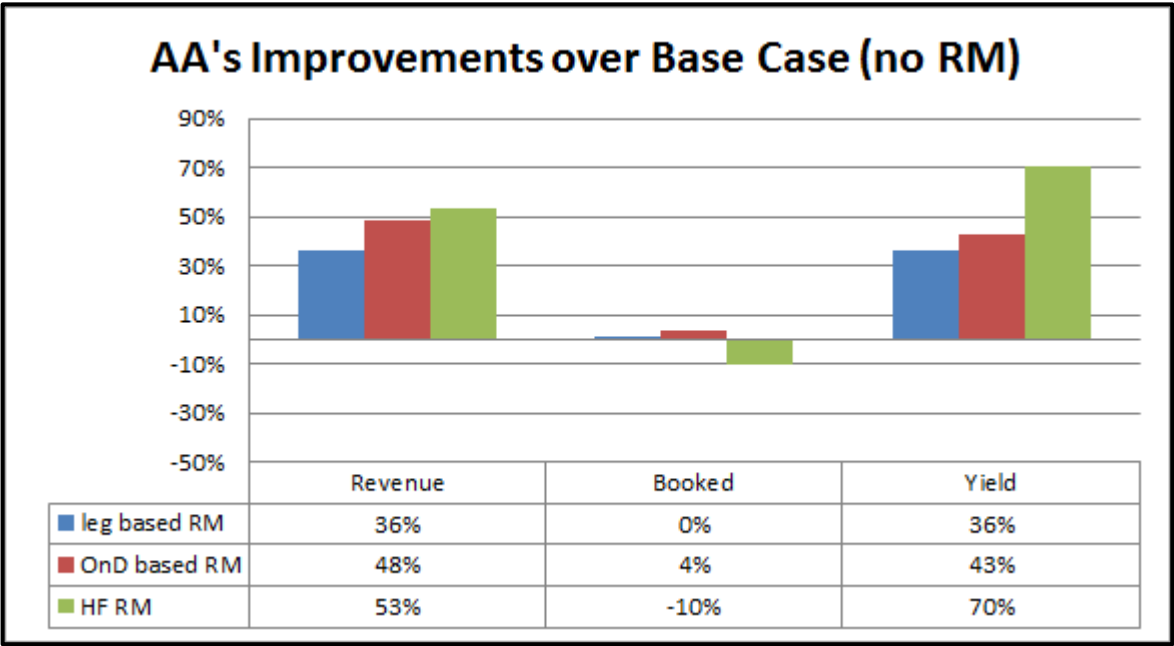

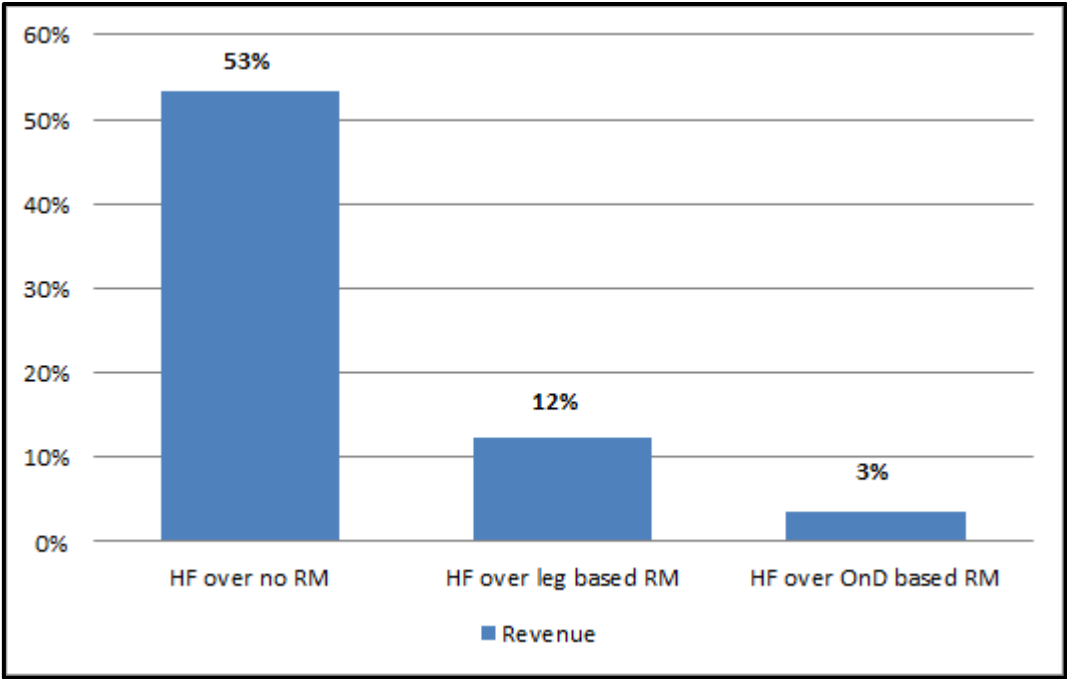Figure 5.5: Improvements over Base Case with no RM method

Figure 5.6: Revenue Improvements of Hybrid RM method over other RM techniques

V.5. Chapter Summery

In this section the results of all four different simulations were presented and discussed with a focus on carrier AA's overall revenue, the customer type mix and the booking class distribution. The chapter began providing the results of the base case, i.e. the simulation where no RM method was used by AA and continued with the simulation results of the scenarios where RM methods were used: leg based RM, OD based RM and HF RM. While the base case delivered total revenue of 243.865 this result could be increased with each further simulation as the methods became more sophisticated and ended up at 373.892 by using HF method. Although, the number of final booked passengers clearly decreased in this simulation using HF RM, the overall yield could be increased so that the total revenue exceeded the other scenario's results. The reason for the better yield can be found in the better customer mix and booking class distribution passenger finally booked, i.e. more high yield customer booked into higher fare classes when using HF. The conclusion of those findings will be discussed in the subsequent chapter.

VI. CONCLUSION

After the entrance of the low cost carrier in many markets worldwide the airline industry and especially network carrier faced heavy yield declines. This yield decline was caused by the fact that low cost carrier removed all fare restrictions in all booking classes down to the lowest one. Fare restrictions such as minimum stay, Saturday or Sunday rule, advanced purchase and often also restrictions to rebook or refund tickets were important for traditional carrier to segregate demand into low yield and high yield target groups. Hence, without these restrictions every customer suddenly was able to buy the lowest class available, leading to an undesirable down sell. Forecast of traditional RM systems learned quickly that demand in lowest booking classes had increased and granted even more availability in those classes; a down sell spiral started that traditional RM systems could not handle. The effect of this tremendous yield decline hit network carrier even harder as they faced higher costs than their low cost competition. New RM systems were developed as a consequence, including the model of hybrid forecast and optimization. This thesis was set up in order to examine the potential benefits on revenue development network carrier may face when using the revenue management method of hybrid forecasting and optimization. The personal contribution of the author was to develop a small network with two airlines competing against each other – one traditional network carrier and one low cost carrier – in a realistic environment regarding demand and competition behavior and, thus, to evaluate the effectiveness of hybrid forecast over traditional RM methods. Therefore the simulation tool REMATE was used to develop and test this theory using four different scenarios. In each scenario the NWC used another RM method, including hybrid forecast, and the overall revenue results of the NWC was compared.

The first and the second chapter of this thesis present an overview about the history of airline revenue management including the deregulation in the US and its impact.

Moreover, traditional RM tools and methods are described as well as the low cost carrier business model and the reason of the lower cost they face. Within the third chapter the down sell spiral is explained in detail, concluding with the hybrid forecast RM method, which was developed as a reaction of the new environmental and competitive challenges in the airline business. This RM method distinguishes the demand into two categories, yieldable and priceable demand, and forecasts each separately per flight and booking class. The Q forecasting is discussed additionally as it is used to estimate the sell-up probability of priceable demand. Yieldable demand, in contrast, can be forecasted with ordinary pick-up forecasting methods. Furthermore, a brief insight into FA as another RM method of the new competitive environment is presented.

Chapter four introduces the simulation tool REMATE explaining all the basic requirements that are needed for the simulation. The exact schedules of both airlines are presented as well as their pricing structure offered to the passengers. Furthermore the two customer types with all possible attributes are discussed that should represent leisure and business traveler and their booking behavior and the final demand generation.

Findings of the simulations are finally presented and discussed in Chapter five. In each of the four different scenarios another RM method is used by the NWC AA but the first one. This base case, where no RM method applies, simulates a first-come-first-serve scenario, obviously resulting in the lowest revenue outcomes. The three other scenarios provide results when AA is using leg based RM, OD based RM and, finally, HF RM method against its low cost competition. Results show that using a RM method increases NWC's revenue significantly compared to the base case, where all passengers book the lowest Q class only and where seats are allocated mainly to the low value early bookers. The scenarios when RM methods are in use by the NWC shows that upsells to higher class are generated and seats are protected for late booking passengers. This is a better reflection of the passengers' WTP and hence increases the yield and moreover even the overall revenue output of carrier AA. The leg based and OD based RM simulation deliver very similar

results in terms of overall revenue. However, it is shown that OD RM method increases the revenue contributed by transfer passengers which further improves the overall network revenue maximization compared to the leg-based RM technique. Hence, it can be assumed that in a bigger and therefore, more complex network than provided in this thesis, the revenue results have even more potential to improve by the means of using OD RM.

When focusing on the results of the simulation where HF is used as RM method by carrier AA, two interesting effects can be observed. There are significant changes in SLF and yield output compared to the results of previous simulation with leg based and OD based RM method. While the overall SLF drops down to 79,6%, the total yield increases to a level of 196, thus, overcompensating the fewer passengers in terms of overall revenue. HF RM simulation increases the total revenue of carrier AA by 3%, respectively 12% compared to the OD based and flight-leg based RM method. Figure 6.1 provides an overview of the simulation results.
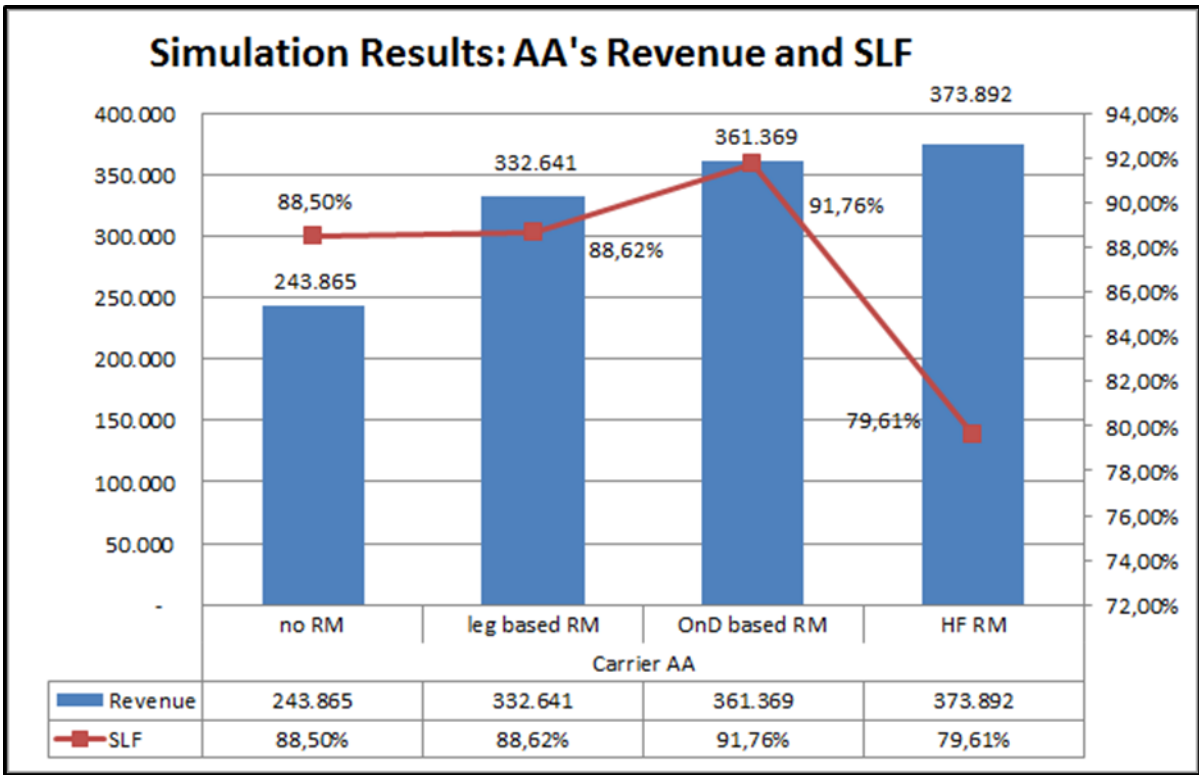

Figure 6.1: Comparison of all Simulation Results: Revenue and SLF

All four simulation scenarios have the same precondition of an unrestricted fare structure. This means a demand separation into high and low yield customers cannot be done by means of fare rules but with accurate forecasting only. Although HF RM simulation has the lowest SLF and final booked passenger number, it delivers the highest revenue output through high yield as a result of a better customer type and booking class mix. That indicates that HF can reflect true passengers' WTP even better than the other RM methods tested in this thesis. This further suggests that HF is an appropriate RM tool to segregate passenger demand in unrestricted market environments, thus, maximizing an NWC's revenue. Moreover, the simulation results support the theory that HF can counter-steer against the spiral down effect NWC face when competing against LCC in unrestricted markets.

Although this thesis supports the theory that HF outperforms compared to traditional RM methods in unrestricted environments, it should be considered that the simulation environment consists of a small network with one hub and three more destinations. In order to obtain further evidence of this theory a possible enhancement could be to enlarge carrier's network. Furthermore, only one day of operation was simulated I this thesis. Another possible enhancement could be an extension of the simulation over more days.

List of Abbreviations

A319 – aircraft Airbus 320

A320 – aircraft Airbus 320

AA – name of the NWC in this thesis' simulation

B737 – aircraft Boing 737

BER – Berlin

BRU – Brussels

C – total cost factor

CT – customer type

DBD – days before departure

DCP – data collecting points

FA – fare adjustment

HF – hybrid forecast

LC – name of the LCC in this thesis' simulation

LCC – low cost carrier

MOW – Moscow

NWC – network carrier

OD / OnD – origin-(and)-destination

ODF – origin-destination fare

ODI – origin-destination itinerary

OCP – operating carrier preference factor

RM – revenue management

RMS – revenue management system

RoW – Rest of the World

SLF – seat load factor

TD – travel distance

VIE – Vienna

WTP – willingness to pay

WTPF – willingness to pay factor

WTPE – willingness to pay error factor

Abstract (English version)

Over the last decades airline revenue management (RM) has become a very sophisticated and complex topic that was subject to big changes during the recent years. Due to the growth of the low cost carriers and their new approach of low and unrestricted fares, traditional revenue management tools used by legacy network carriers suddenly became invalid. Traditional carriers used to separate and forecast passenger demand through certain restrictions as a crucial precondition of their revenue optimization process. These restrictions have been removed in low cost competition, thus, inhibiting revenue maximization with the common systems. Consequently, this led to a new generation of revenue management tools; one of these new approaches is Hybrid Forecasting seeking to maximize revenues in an unrestricted or semi-restricted fare environment by segregating passenger demand in priceable and yieldable demand. Once having this "hybrid" demand separate a hybrid forecast, i.e. separate forecast for yieldable and priceable can be created as a precondition for revenue optimization process in a low cost carrier environment.

This thesis starts with a brief historical insight over airline revenue management including the impact of deregulation in US and Europe. Furthermore, the low cost carrier business model is described and the consequences of their worldwide rise for legacy carries' RM systems. It continues examining the different RM tools that airlines are using in order to maximize revenue, especially the new method of Hybrid Forecasting will be explained in more detail.

In the second part of the thesis the simulation tool REMATE which was developed at Lufthansa together with the University of Berlin is presented. REMATE is used to create and develop a certain scenario, i.e. a small network with one hub and three legs where a traditional network carrier competes against a low cost carrier. Assuming that the legacy carrier has already matched fares and conditions of the low cost carrier the revenue outcome of the network carrier is simulated using different revenue management methods. These are First Come First Serve RM, leg

based optimization, Origin-Destination (OD) based optimization and, finally, Hybrid Forecast RM. The results will be presented and discussed afterwards. The goal of this thesis shall be to examine – with a simplified model – if Hybrid Forecast is an appropriate RM tool for traditional network carriers to steer against the down-sell and revenue dilution that usually occurs when a low cost carrier enters the market.

Abstract (German version)

Während der letzten Jahrzehnte veränderte sich Airline RM stetig hin zu einem immer komplexer werdenden Themengebiet. Vor allem in den letzten Jahren gewann RM erheblich an Bedeutung auf Grund des rasanten Wachstums der Low Cost Carrier und deren neuartiges Geschäftsmodell. Dieses sah neben der niedrigeren Preise auch eine Aufhebung der Tarifkonditionen vor. Diese Restriktionen werden bei Netzwerkcarrier mit traditionellen RM-Systemen jedoch dazu verwendet Kunden entsprechend ihrer Zahlungsbereitschaft zu segmentieren – eine unerlässliche Voraussetzung für den Ertragsoptimierungsprozess. Durch die Entfernung genau jener Restriktionen wurden traditionelle RM Systeme ausgehebelt, was dazu führte, dass eine neue Generation von RM Techniken notwendig wurde. Eine dieser neuen Techniken ist der sogenannte „Hybrid Forecast", entwickelt um die Nachfrage auch in einem Umfeld ohne Tarifrestriktionen zu segmentieren. Passagiere werden demnach nach der Kategorien „priceable" und „yieldable" unterschieden. Diese neue „Hybrid"-Methode die diese Unterscheidung möglich macht, dient wieder als Voraussetzung für den Ertragsoptimierungsprozess in einem Umfeld, wo Netzwerkcarrier mit Low Cost Carrier konkurrieren.

Zu Beginn dieser Diplomarbeit wird kurz auf die Geschichte der Ertragssteuerung in der Airline Branche eingegangen, unter anderem auch auf die Auswirkungen der Liberalisierung des Airline Sektors in den U.S.A und Europa. Des Weiteren wird das Business Model der Low Cost Airlines beschrieben, sowie die dadurch weltweit entstandenen Konsequenzen auf traditionelle RM Systeme. Danach werden die verschiedenen Komponenten eines traditionellen RM Systems beschrieben, darunter auch detailliert die neuartige Technik des „Hybrid Forecasts".

Im zweiten Teil der Arbeit Simulationsprogramm REMATE präsentiert. Dieses wurde von Lufthansa gemeinsam mit der Universität Berlin entwickelt. REMATE wird in dieser Arbeit dazu benutzt ein kleines Netzwerk zu entwickeln, um darin verschiede RM Techniken zu simulieren und deren Auswirkungen zu studieren. Das Netzwerk besteht aus einem „Hub" und drei anzufliegenden Destinationen, in dem zwei Fluglinien nebeneinander konkurrieren: ein traditioneller Netzwerkcarrier und eine Low Cost Carrier. Es werden vier verschiedene Situationen simuliert, in denen der Netzwerkcarrier jeweils eine andere RM Technik zur Ertragsoptimierung einsetzt. Bei der „First-Come-First-Serve" Methode wird keine Optimierung eingesetzt. Des Weiteren wird streckenbasierte Optimierung, OD-basierte (Origin-Destination); Optimierung und schließlich Hybrid Forecast-Optimierung simuliert. Dabei wird vorausgesetzt, dass der Netzwerkcarrier bereits die Preise und Tarifkonditionen an die der Low Cost Konkurrenz angeglichen hat. Danach werden die Ergebnisse der unterschiedlichen Szenarien präsentiert. Als Ziel dieser Diplomarbeit soll untersucht werden, ob Hybrid Forecast eine angemessene RM Technik für Netzwerkcarrier darstellt, um in einem Umfeld hoher Konkurrenz zu bestehen und dem Ertragsverfall entgegenzusteuern.

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