Dissertation

Performance Measurement in Airline Revenue Management - A Simulation-based Assessment of the Network-based Revenue Opportunity Model

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Schriftliche Arbeit zur Erlangung des akademischen Grades
doctor rerum politicarum (dr. rer. pol.)
im Fach Wirtschaftsinformatik

eingereicht an der
Fakultät für Wirtschaftswissenschaften der
Universität Paderborn
Paderborn, im September 2010

Datum der mündlichen Prüfung: 11.04.2011

Gutachter:
1. Prof. Dr. Leena Suhl
2. Prof. Dr. Alf Kimms

Acknowledgements

This thesis is a result of a research cooperation between the *Decision Support and Operations Research Lab (DSOR)* at the University of Paderborn and Lufthansa German Airlines. It would not have been possible to complete this thesis without the valuable support of many people.

First and foremost, I want to express my gratitude to Prof. Dr. Leena Suhl for her continuous and always caring support while supervising my thesis. Moreover, I have enjoyed the open and friendly atmosphere at her research department and the help of the entire working group. In addition, I want to thank Prof. Dr. Alf Kimms for being second referee of my thesis.

I also owe a big thank you to Dr. Stefan Pölt and Dr. Michael Frank - my supervisors at Lufthansa German Airlines - for providing me with so many practical advice and introducing me into the secrets of revenue management. Furthermore, I would like to thank Martin Friedemann for our joint sessions to help me implement reasonable parts of the simulation environment.

Finally, I would like to thank my family for their encouragement and support in the course of writing this thesis. I would like to express my gratitude to my parents without their continuous encouragement this thesis would not have been possible at all. I also thank my sister Bettina, who gave me precious input in making my thoughts understandable. Lastly, I thank my wife Julia, who has always been there for me and always had trust in me.

Christian Temath
Cologne, September 2010

Contents

1. Introduction

Airlines all around the world repeatedly face difficult environments and developments in the airline market. Be it the oil crisis in the seventies or most recently the global depression in the course of the financial crisis, many external effects put tremendous pressure on airlines' profitability. Additionally, airlines nowadays face an increasing competition by the entrance of low cost carriers into the market and declining revenues caused by customers using the new opportunities to search for cheap tickets in the internet.

For many decades airlines have been applying methods of *revenue management (RM)* to maximize revenues. They basically aim at *"selling the right seats to the right customers at the right prices"* (see Smith et al., 1992) and thus to increase their revenues significantly. Lieberman (1991) and Skugge (2004) refer to additional earnings by 3 to 7 percent that are possible for companies with successful RM.

However, the question *"Am I making as much money as I should be?"* raised by Rannou and Melli (2003) is posed in many RM departments all over the world. Even though RM uses optimization techniques for the inventory control to maximize revenues, its success strongly depends on forecast accuracy. The stochasticity of the demand and the necessary manual adjustments in the course of a booking period influence the results and the quality of the revenue optimization. At the end of each booking period, the question of RM performance remains. In the past, many techniques to measure RM performance have been developed and proposed. Basic measures like *seat load factor (SLF)* or *revenue per available seat kilometer (RASK)* can easily be calculated by using data from the inventory systems. More sophisticated concepts for *performance measurement (PM)* include comparing two different time periods to analyze the performance of the *revenue management system (RMS)*. Moreover simulation plays an important role in investigating the performance of new RM methods, before implementing them into the operational RMS. Drawbacks related to the above methods are either the inability for continuous measurement or the inability to isolate RM contribution from the overall success.

A widely used technique that allows to continuously measure but also isolate the contribution of the RMS is the *revenue opportunity model (ROM)*. While adapting the ROM to major developments in RM science - i.e. the advancement from leg-based to network-based RM controls and the recent transition from independent to dependent demand structures - the question of applicability and in particular the effect of errors in the input data on the quality of the ROM became increasingly important. These new developments in RM science pose new questions and challenges on the ROM. In this thesis we model both independent and dependent demand structures in a network-based ROM and investigate main properties. Furthermore we consider different practical aspects of airline RM to enable the application of the ROM in practice.

We start with an introduction into airline RM and briefly describe some of the major developments in airline RM science in Section 1.1. In Section 1.2 we describe basic approaches to measure the performance of RM. Section 1.3 formally introduces the ROM. In addition, we describe some main properties of the ROM, elaborate the effect of major developments in airline RM science on the ROM and discuss important aspects of the application of the ROM in practice. Finally we conclude the chapter in Section 1.4 with a summary of the scope and purpose of this thesis.

1.1. Airline Revenue Management

As already described in the previous section, the main goal of RM is *"selling the right seats to the right customers at the right prices"*. This definition is also applicable to many other industries, for example the sale of empty rooms in a hotel. According to Weatherford and Bodily (1992) products or services, for whose sale the application of RM methods is useful, share three common characteristics. First, these products are *"perishable"*. This means that the product on sale is no longer available after a certain point of time and cannot be sold any more. An example is a plane leaving with empty seats. These empty seats cannot be sold any more to a customer after the departure of the plane. Second, these products have a *"fixed capacity"*. It is hardly possible to increase the number of products available for sale within a short time period and it mostly incurs high cost to extend the amount of products that can be offered. An example for limited quantity is again a plane, which has a fixed number of seats that can be sold to customers. The third characteristic is that the potential customers can be grouped into different *"segments"*. A classical segmentation at airlines is the differentiation between business travelers, who normally book their tickets shortly before departure and are not too price-sensitive, and private customers, who normally book early before the departure date, but look thoroughly at the prices. The segmentation of products is normally done with restrictions that apply to a given product. These so called *fencing rules* could be for example a purchase with a minimum of 21 days in advance or a mandatory Saturday night stay for return tickets. These two rules are typically applied to discount tickets offered to leisure customers. A business customer usually does not buy a ticket more than 21 days in advance and also does not want to stay over the weekend. Thus, these rules prevent the business customer to opt for a discount ticket. An example of how price discrimination helps to improve revenues is illustrated in Figure 1.1. If an airline would only offer a product for price p, the demand would

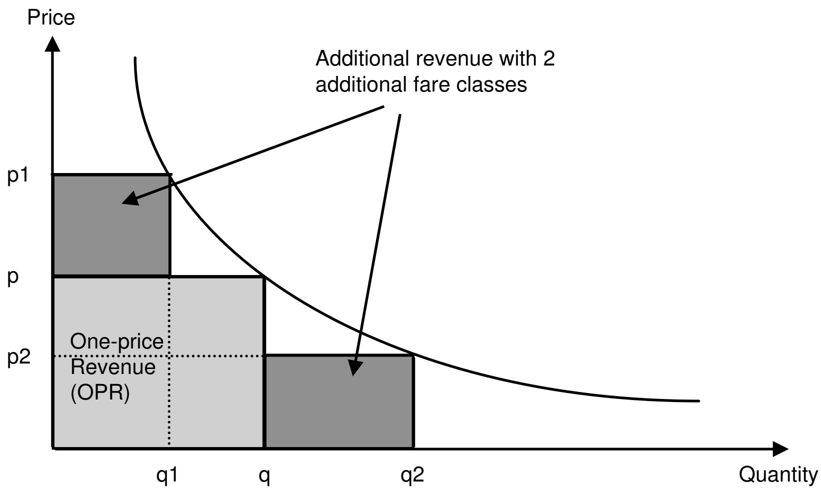

Figure 1.1.: Effect of Introducing Additional Customer Segments

be at quantity q. The resulting revenues would be $p * q$. To simplify our example we do not consider any capacity restrictions. If it is possible to create customer segments at different price levels additional revenue can be earned. For example two additional price points p_1 and p_2 would lead to additional revenues $(p_1 - p) * q_1$ and $p_2 * (q_2 - q)$. Weatherford and Bodily (1992) introduce the term *perishable-asset revenue management* to consider for the three previously mentioned main characteristics. Applications of perishable-asset revenue management or RM can be found in many industries apart from airlines, such as hotels, car rentals, cruise lines, the steel industry or in the broadcasting business.

The development of airline RM has a long history. At the beginning of the seventies airlines in Europe started offering reduced fares for seats on their flights. With the start of the *Super Saver Fares* of American Airlines in 1977 and the deregulation of the national and international air traffic in the US with the *Airline Deregulation Act* in 1978, reduced fares were introduced in the US on a large scale. As a consequence airlines had to decide if a booking for a discount ticket should be accepted or not. A major contribution to support this decision was made by *Littlewood's rule* (see Littlewood, 1972). It proposes that a booking for a reduced fare should be accepted as long as the value of the booking exceeds the expected value of a future booking for a normal fare. Starting with Littlewood's rule techniques and methods of RM have made intensive progress in the last decades. In this thesis we focus on two major developments in RM science. We illustrate them in Figure 1.2.

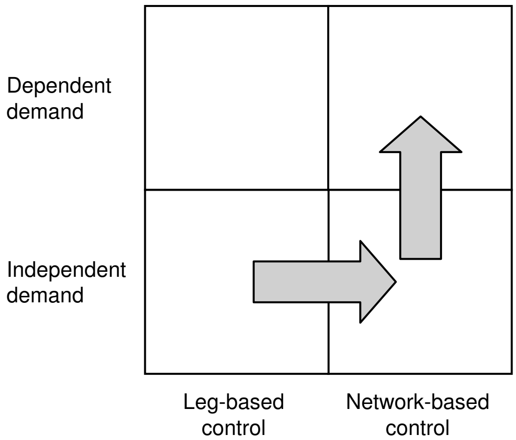

Figure 1.2.: Major Developments in RM Science

In the beginning RM methods were focussed on leg-based controls. Leg-based controls assume that a customer only demands a single resource, which in the airline case would be a single flight leg and that no interdependencies exist between the different flights offered to the customers. Thus, it was possible to manage each flight leg independently. The first major development we focus on in this thesis is the advancement from leg-based controls to network-based controls.

Since the 1980s more and more airlines established hub and spoke networks with an increasing number of passengers buying itineraries which included more than one flight leg. These so called *origin & destination (O&D)* itineraries demanded an availability decision on all flight legs contained in the itinerary at the time of a booking request. Network-based controls take the interdependencies between the flight legs into account, decide on the availability on a network level and thus help to maximize the revenues for the total flight network.

The second major development we focus on in this thesis is the change from independent to dependent demand structures. For a long time the assumption of independence of the demand between booking classes prevailed. Fencing fare rules for separating booking classes helped the airlines to uphold the assumption of the independence of the demand between the booking classes for a long time.

However, this situation has changed. Nowadays the internet offers more and more transparency about available fares. Additionally, low-cost-carriers entered the market removing fencing rules and applying restriction-free pricing. As a result, customers became increasingly price-sensitive and began to search for the lowest available fare. A lot of research has been accomplished in this field and many airlines have started upgrading their RMS to consider dependent demand structures in the last years.

The support of the availability decisions on flight legs or O&D itineraries requires a set of quite complex and sophisticated models and methods. The components of a complete RMS and the interaction with other systems such as the reservation system is presented in Talluri and van Ryzin (2004b, see Chapter 1, page 19) and in Klein and Steinhardt (2008, see Chapter 1, page 27). We show their illustration in Figure 1.3. It describes the main steps of RM for an airline: Data consolidation, forecasting and optimization. These steps will be accomplished many times during a booking period. Usually airlines recollect the actual (booking) data at a *data collection point (DCP)* and readjust the optimization settings according to the new information. At all times a manual intervention by revenue managers or analysts is possible, to react on special events or short notice changes.

In the step of data consolidation all relevant input data for RM is collected and adjusted for the upcoming RM steps. One data source contains the capacities and fares. The *fares* are set by the pricing department in a separate process and are considered to be fixed in classical, quantitative RM. Of course, fares can vary over time, but in the optimization models fixed prices are assumed. The actual *capacities* are the result of the *fleet assignment* process, which normally takes place around a year before the departure of a plane and which makes use of the results of the *network planning*. Usually airlines readjust the capacities to the current booking situation some weeks before the departure in a second fleet assignment process. Additionally *equipment changes* are possible on short notice to react on last-minute developments or events. Other than that the capacities of the planes will normally be considered as fixed in the optimization steps of RM. The other data sources contain information about historical bookings, historical *cancelations* and *no-shows*. A cancelation occurs, if a customer cancels his booking during the booking period before the departure of the plane. In contrast, a no-show occurs if a customer has a valid ticket for a flight and does not show-up at the airport when the plane departs. Usually this applies to customers with flexible tickets, who can change their reservation to a different flight without any additional cost. Additionally, the databases contain the information about the actual booking situation.

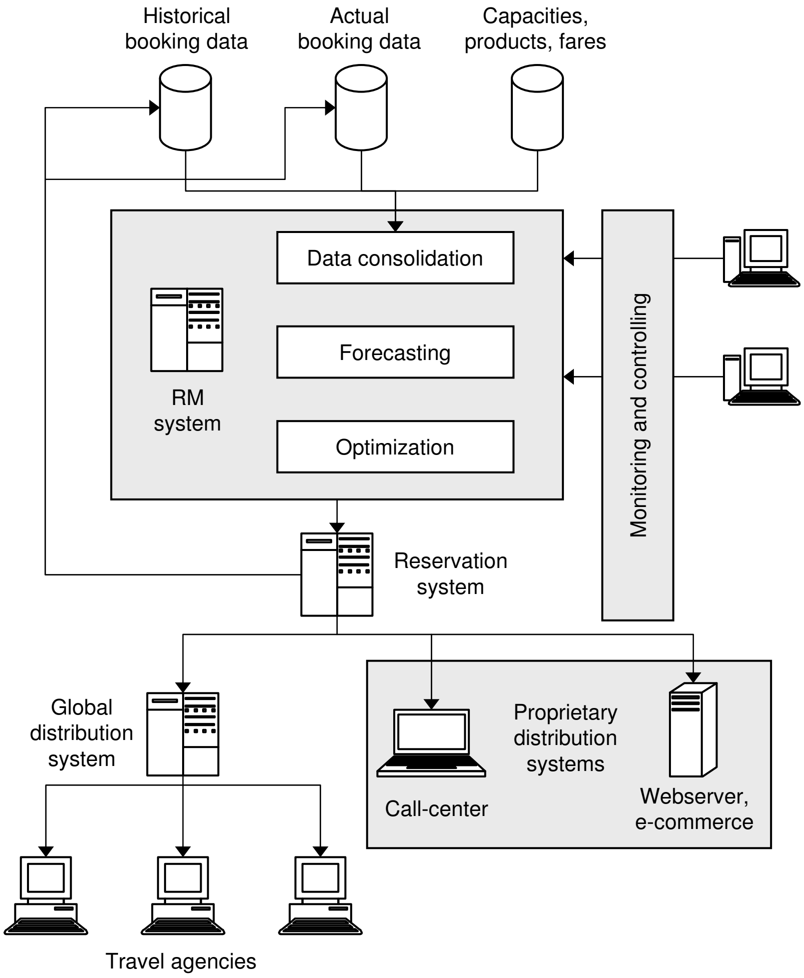

Figure 1.3.: A RMS and its Interaction with Other Systems (Adapted Illustration - See Talluri and van Ryzin (2004b) and Klein and Steinhardt (2008))

All of this data is elementary input for the forecasting methods that are performed in a second step. Typically airlines forecast the customer demand, the cancelations and the no-shows. The process of forecasting is essential in a RMS, because the forecasted data is the key input for the optimization models. Lee (1990, see page 2) for example refers to significant revenue improvements, if demand forecast accuracy increases. His analyses show that a 10% increase in forecast accuracy results in 0.5 to 3% more revenue. A main part of forecasting is *unconstraining*. Unconstraining is necessary, because an airline is not able to observe the total demand in a booking period, but only the number of bookings and the availability of booking classes. With unconstraining an airline estimates the total demand that existed for a given flight leg or O&D itinerary that has already departed.

The actual optimization takes place in the third step. During the optimization it is decided how many seats shall be reserved for which customer segment for a given product. This optimization is based on the demand forecasts, the actual booking data and the fares and capacities. To account for cancelations and no-shows and to prevent a high demand flight from leaving with empty seats, airlines apply techniques of *overbooking* during the optimization. Overbooking virtually increases the capacity of a plane to consider no-shows and cancelations. If cancelation and no-show forecasts are accurate and the overbooking optimization performs well, the real capacity will be sufficient to accommodate all passengers. However, sometimes overbooking leads to a situation in which more passengers are booked on a flight than seats are available. In this case not every customer can be boarded, which is called *denied boarding*. By civil aviation law airlines are obligated to pay a compensation for each passenger who is denied boarding. One method to prevent a denied boarding is *upgrading*: A passenger is offered a seat in a higher valued compartment than he has purchased a ticket for. Upgrading can also be applied during the booking period, if for example there is forecasted excess demand in the economy compartment and forecasted free seats in the business compartment. In this case an airline might want to virtually increase the capacity of the economy compartment to sell the surplus seats in the business compartment that might otherwise stay unsold. The results of the optimization process are reported to the reservation system, in which the seat inventory is controlled. Different parties are able to access the reservation system. A main part of the customer requests for traditional airlines is handled by a *global distribution system (GDS)*. Airlines increasingly offer their products through own sales channels, in particular their own websites, but also call centers.

1.2. Performance Measurement of Revenue Management

Since the application of RM methods in airline operations different methods to measure the *performance* of RM are prevalent. Generally, performance measures aim at describing how well the RMS in conjunction with the revenue managers were able to achieve the goal of RM, which is usually to maximize overall revenues (see McGill and van Ryzin, 1999). Talluri and van Ryzin (2004b) distinguish between *"revenue-opportunity assessment"* and *"revenue-benefits measurement"*. While the first one is usually performed before the introduction and implementation of (parts of) a RMS, the second one is usually conducted continuously after the implementation. The main motivation for revenue opportunity assessment is to estimate the potential that the introduction of a RMS is able to generate. After the implementation of the RMS or update of single components of the RMS the management and the RM department aim at justifying the investment into RM techniques. They want to know if the investment was successful and how much of the revenue potential is actually gained. Most importantly this assessment has to be performed continuously to track performance over time and to identify and eliminate weaknesses in the RMS (see also Pölt, 2001).

One main method for revenue opportunity assessment is according to Talluri and van Ryzin (2004b) to estimate an upper bound for the achievable revenue with RM techniques using perfect hindsight information and compare it with the actual revenue. This approach reveals the potential revenue gains that are achievable with the introduction of a RMS. Although usually only a fraction of the revenue potential will be captured, even a fraction of the revenue potential surely justifies the investment into RM. A better approach according to Talluri and van Ryzin (2004b) is to assess the potential of RM methods by using techniques of simulation. With simulation the performance of a complete (or parts of a) RMS can be evaluated. In a simulation environment it is furthermore possible to thoroughly model the customer behavior and investigate the likely performance of the RM methods before implementation and operational service. In addition sensitivity and what-if analysis help to examine and to understand basic relations between the RM components and to reveal critical parts. A well known example in this field is the *passenger origin-destination simulator (PODS)* at the MIT, which is funded by a consortium consisting of seven airlines. PODS was originally developed at Boeing Company by Craig A. Hopperstad and allows to simulate a complete RM environment (see Gorin, 2000). PODS has been used by many authors to analyze the impact and performance of new RM methods and, according to Barnhart et al. (2003), is able to *"realistically simulate large networks"*. The main drawback of simulation is the clinical environment of the modules and the data, but also the fact, that user controls and influences of the revenue managers are currently not considered. Furthermore it cannot be used to continuously measure RM performance once the system and the modules are in place and operational.

To assess the revenue benefits of an operational RMS Talluri and van Ryzin (2004b) and other authors propose different methods. As a main prerequisite the revenue benefits measurement should be based on actual data from the operational RMS. As a simple classification there are usually three major categories:

- Comparison of pre and post RMS implementation performance
- Use of classical performance measures

- Assessment of the achieved revenue potential

To compare the pre and post RMS implementation performance Talluri and van Ryzin (2004b) distinguish between the comparison of two time periods - one before, one after the implementation of the RMS - and a parallel test of markets or flights - some controlled with and some controlled without the RMS. The first one is a suitable method to justify the implementation of a RMS ex-post. One major challenge for this method is to choose two time periods which are comparable in terms of overall market structure. Although the contribution of the RMS to the overall success can be isolated in that approach, it is not very well suitable to continuously measure RM performance. Another approach is the parallel test approach. It allows to examine the performance implications in the introduction phase of the new RMS. Some flights or markets will be controlled with the new RMS and others without. Positive differences in the resulting performance can be attributed to the RMS and the revenue managers. For this approach it is very important to choose comparable market situations to retrieve meaningful results from this test phase. Furthermore this approach is usually not suitable for continuous measurement as eventually the new RMS will be used to control all markets or flights.

The second category includes the continuous use of classical performance measures. Classical performance measures include SLF or RASK and are often used in the annual financial reports of an airline. Performance measures range from indicators for the overall success of the RMS to indicators of single parts of the RMS, such as forecast accuracy and quality. However, it is hard to isolate the contribution of RM from the overall success for all of these classical measures. For example, it is possible that the RM control is still equally good, but the RASK and the SLF decrease dramatically because of the entrance of a new competitor.

A widely used technique at airlines for allowing continuous measurement but also the isolation of the contribution of the RMS is the ROM. Smith et al. (1992) describe the basic idea of applying different RM control strategies to a past time period to estimate the potential revenue gains by the RMS and to investigate the achieved revenue gains accordingly. The focus of their approach in contrast to the previously mentioned revenue opportunity assessment discussed by Talluri and van Ryzin (2004b) is on the continuous examination of the revenue benefits of the RMS after the implementation. We introduce the ROM in more detail in the next section.

1.3. Measuring Performance with the ROM

This section introduces the general approach of the ROM and the necessary terminology. We focus on the main concept, neglecting the difference between leg- and network-based ROM.

1.3.1. Model Definition and Terminology

The idea of the ROM is to compare the revenue that has been actually achieved during a booking period with two reference points which are estimated at hindsight (see e.g. Smith et al., 1992). Figure 1.4 shows the three main values that are the starting point for the ROM: the *potential revenue*, the *actual revenue* and the *no RM revenue*.

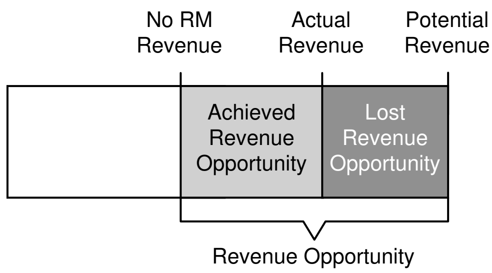

Figure 1.4.: Concept of the ROM

The first reference point is the potential revenue and is used as an indicator of how much revenue would have been potentially achievable during the past booking period. The no RM revenue as the second reference point indicates the amount of revenue the airline would have earned by not applying any RM controls and simply accepting all booking requests if capacity allows. Usually the no RM revenue is estimated using a *'first come, first served' (FCFS)* strategy assuming that no RMS and no other (manual) RM controls are in place. Both estimations use the knowledge of the estimated unconstrained demand and are deterministic as they are performed after the end of the booking period. In contrast to this, the actual revenue is the result of the joint control decisions made by the revenue managers and the supporting RMS. The main ROM measures for isolated RM performance are defined based on the potential, the actual and the no RM revenue:

- *Revenue opportunity (RO)* = Potential revenue - No RM revenue
- *Achieved revenue opportunity (ARO)* = Actual revenue - No RM revenue

- *Percentage achieved revenue opportunity (PARO)* = Achieved revenue opportunity / Revenue opportunity

The RO indicates the possible revenue gains achievable with RM techniques and the ARO shows how much of this revenue potential was actually earned. The absolute measure ARO might for example be used to compare the costs of the RMS and the revenue managers controlling the system with the gain the airlines get out of it. In contrast to the absolute measures, the PARO indicates the relative success of the RM control in comparison to its theoretical potential.

1.3.2. Main Properties of the ROM

One main property of the ROM is that it isolates the RM performance from all other revenue influencing factors, such as the overall demand during the booking period. Variations of the overall demand correlate highly with the revenue earned in a given booking period. This behavior is reflected in common performance measures like SLF and RASK. These measures usually increase in high demand situations and decrease in low demand situations. The ROM, however, takes the variations in customer demand into account as the potential and the no RM revenue change with the demand level. An example of this characteristic is shown in Figure 1.5, in which we compare the actual revenues and the PAROs of 20

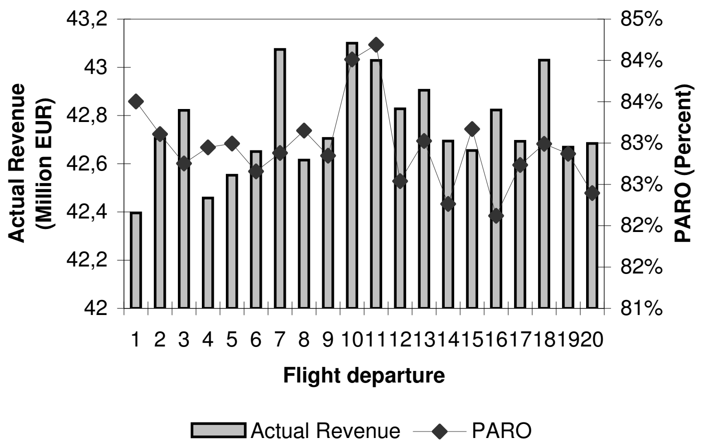

Figure 1.5.: Comparison of Actual Revenue and PARO

different flight departures. Although at some flight departures we observe higher total revenues the relative level of revenue gained by the RM controls applied decreases. Pölt (2001) presents a similar analysis and characterizes the ability to isolate the RM contribution from the overall success as one key property of the ROM.

For the ROM measures obtained in a specific situation some special cases can be observed. For example it is possible that the actual revenues fall below the estimates for the no RM revenue. This is due to the fact that a very restrictive RM control leads to the rejection of too many low-fare customers. Table 1.1 illustrates this case. In this example, we assume a plane with one compartment

Class	Fare	Forecast	Demand	Bkg limit	Act. bkgs.	No RM bkgs.	Act. rev.	No RM rev.
1	200	20	5	20	5	5	1,000	1,000
2	100	50	45	30	30	45	3,000	4,500
Sum		70	50	50	35	50	4,000	5,500

Table 1.1.: Actual Revenue Gets Less Than No RM Revenue due to Restrictive Controls

and a capacity of 50 seats. Due to the high forecasted demand for booking class one, the optimization model reserves 20 seats for booking class one. However, the real demand is only five. This leads to the rejection of many low fare customers and to very bad revenue results in comparison to the no RM revenue. As a consequence the ARO is negative. Another special case with the application of the ROM is that the RO is zero. This is the case if the potential and no RM revenue are equal. Basically this happens in low demand situations. If the estimated unconstrained demand is less than the capacity of the flight leg all bookings are accepted in the revenue estimations both for the potential and the no RM revenue. The previously mentioned special cases also have an effect on the PARO. If for example the ARO is negative, the PARO also is negative. In all situations, in which the RO is zero, the PARO cannot be determined, because of a division by zero. These special cases may occur in practical applications and should then be interpreted considering the given definition of the ROM and the current RM context.

One very important aspect of the application of the ROM is the validity of its measures. The validity of the ROM is influenced by two sources of error. We distinguish *model-related errors* from *data-related errors*. The first source of errors describes all errors that occur, because the ROM does not reflect reality correctly in the estimation of the potential and the no RM revenue. These errors are mainly due to the practical limitations of the RMS in place. The main model-related error is caused by the fact that the demand data at an airline is usually aggregated at DCP-level. Deriving the correct booking order from aggregated data is not possible and thus within the ROM definition, a decision has to be taken, which demand order is assumed in between two subsequent DCPs. If for example a FCFS strategy is used to estimate the no RM revenue the accuracy strongly depends on the real booking order. In the examples in this section we assumed a strict *low-before-high (LBH)* booking order. This means that customers willing to purchase low fare tickets are showing up first and the customers opting for high fare tickets are coming afterwards. However, in reality this will rarely be the case potentially leading to less accurate estimates for the no RM revenue.

The second source of errors are data-related errors. If we assume that the ROM reflects reality accurately, it still relies on estimated unconstrained demand, which does not match real demand due to unconstraining errors. These errors in the ROM induced by incorrect input data also lead to wrong estimations of the potential and the no RM revenue. An example of how unconstraining errors might influence the validity of the ROM measures is presented in Table 1.2. In

Class	Fare	Actual		Real demand				
		Actual bookings	Actual revenue	Demand	No RM bookings	No RM revenue	Potential bookings	Potential revenue
1	200	10	2,000	15	5	1,000	15	3,000
2	100	40	4,000	45	45	4,500	35	3,500
Sum		50	6,000	60	50	5,500	50	6,500

Resulting RO=1,000, ARO=500 and PARO=50%

		Actual		Estimated unconstrained demand				
1	200	10	2,000	17	0	0	17	3,400
2	100	40	4,000	50	50	5,000	33	3,300
Sum		50	6,000	67	50	5,000	50	6,700

Resulting RO=1,700, ARO=1,000 and PARO=59%

Table 1.2.: Errors in Unconstrained Demand Lead to Wrong ROM Measures

this example, we again assume a plane with one compartment and a capacity of 50 seats. A total of 50 bookings have been accepted by the actual RM controls with a total revenue of 6,000. The real demand is 15 for class one and 45 for class two. This leads to a no RM revenue of 5,500 if the booking requests arrive in LBH order and to an potential revenue of 6,500. According to those values, the RO is 1,000, the ARO is 500 and the PARO is 50%. If we estimate the unconstrained demand to be 17 for class one and 50 for class two, we derive different ROM values. The no RM revenue would be 5,000 and the potential revenue 6,700. This would result in a RO of 1,700, an ARO of 1,000 and a PARO of 59%. This difference between the PAROs for real and estimated unconstrained demand could lead to a misinterpretation of the results and the evaluation of the RM controls. Authors like Pölt (2001) have already considered the problem of invalid results because of errors in the estimated unconstrained demand.

1.3.3. Major Developments in Airline Revenue Management Affect the ROM

As described in Section 1.1 science in RM has made significant progress in the last decades of airline history. The two major developments not only have a significant impact on how airlines model and setup their RMS, but they also have a significant impact on the validity of the ROM. These two major developments and their impact on the ROM are a key topic in the remainder of this thesis.

The first major development - the advancement from leg-based controls to network-based controls - had a tremendous effect on the validity and applicability of the ROM. Network-based controls take the interdependencies of connecting itineraries into account and evaluate a connecting booking request as one O&D itinerary. With network-based controls, it might be revenue optimal for the network to accept a connecting passenger at a feeder flight in a low booking class. This is particularly true if the passenger connects to a long-haul flight with moderate demand. A leg-based ROM examines every flight separately and might evaluate the actual booking in the low booking class at the feeder flight as poor control. Let us assume it would have been revenue optimal for the entire flight network to accept a booking from Hamburg via Frankfurt to New York for 1,000 and the associated fare value for the flight leg Hamburg to Frankfurt is 50. In this case a leg-based ROM evaluates all rejected booking requests against bookings on flight leg Hamburg to Frankfurt with an associated fare value higher than 50 as poor RM control, because on a leg base it would for example have been better to accept a local flight from Hamburg to Frankfurt with fare value of 200. These misleading and invalid results caused many airlines with network-based seat inventory controls to stop using their leg-based ROMs.

The second main development with a major impact on the validity of the ROM is the transition from independent to dependent demand structures. In Table 1.3 a simple example is presented on how dependent demand structures influence the estimation of the no RM revenue. If we assume that demand is independent and demand for booking class one is 20 and for booking class two the demand is 30, than the no RM revenue for a flight with capacity larger than 50 is 7,000. However, out of the 20 customers demanding booking class one there are 10 customers who would buy-down into booking class two, if it is also available. This leads to a correct no RM revenue of 6,000. Similar examples can be presented for the effect of dependent demand structures on the potential revenue. Subsequently this also has a tremendous effect on the derived ROM measures like the PARO.

Class	Fare	Ind. dmd.	No RM bkgs.	No RM rev.	Dep dmd	No RM bkgs.	No RM rev.
1	200	20	20	4,000	10	10	2,000
2	100	30	30	3,000	40	40	4,000
Sum		50	50	7,000	50	50	6,000

Table 1.3.: Effect of Dependent Demand Structures on No RM Revenue

1.3.4. Consideration of Practical Aspects in the ROM

Considering practical aspects in the ROM is also very important. We start with introducing the basic process of the application of the ROM in practice. It involves four main process steps. These steps are described in detail by Chandler and Ja (2007). We illustrate these steps in Figure 1.6. The first step is to gather

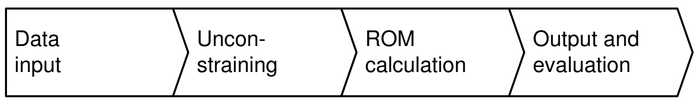

Figure 1.6.: Process of ROM Application

and input all relevant data of the booking period to be assessed. This includes actual bookings and availability information. In the second step, the main input for the ROM calculation is generated, the estimated unconstrained demand. As we laid out earlier in this thesis, this is a very important task that is discussed in detail in the remainder of this thesis. The first two steps may also be merged, if the estimated unconstrained demand can directly be taken from the forecasting module. In a third step, the ROM measures are calculated based on the estimated unconstrained demand. Lastly, the measures are analyzed and potentially split further.

In many cases, the ROM is not only used to measure the overall performance of the RMS, but also of different components or parts of it. As described earlier overbooking and upgrading play an important role in airline RM. Pölt (2001) for example proposes a split between fare-mix, overbooking and upgrading success. The choice of a specific way of considering components of the RMS strongly depends on the airline's context. We describe other potential ways to split the ROM measures in Chapter 2.

When applying the ROM to network-based controls new challenges arise. The main proposals calculate one single measure for the total network. However, for many airlines it might be very interesting to disaggregate the ROM measures for the total network to subparts of the network. Chandler and Ja (2007) for example propose a disaggregation to market level or even a single flight leg. A main challenge of this disaggregation is that usually the fares of the itineraries have to be distributed to subparts or even single flight legs of the itinerary. The distribution of the fares can be accomplished by *prorating* the fares. Methods of prorating distribute the fares of an itinerary to subparts according to a given allocation formula.

We focus on questions concerning the consideration of the practical aspects mentioned above in the ROM in Chapters 6 and 7 of this thesis.

1.4. Scope and Purpose of the Thesis

In the previous section we introduced the ROM as an important method to measure RM performance. We also described two major developments in RM science that pose new questions and challenges on the ROM. In particular the increasing importance of modeling dependent demand structures is at the center of attention in the RM departments of many airlines.

Until now, the effect of the two major developments in RM science on the ROM have not been reflected in detail. Since leg-based ROMs are not showing valid results in a network-based RM environment, the question of validity and applicability of the network-based ROM is crucial. Moreover the advancement to dependent demand structures has not been discussed in detail in the context of the ROM. In addition, we put further attention into considering practical aspects in the network-based ROM with independent and dependent demand. This being said, our main areas of interest in this thesis are:

- To assess the validity and applicability of a network-based ROM, in particular we aim at measuring the robustness of the network-based ROM
- To model dependent demand structures in a network-based ROM and to analyze the validity and robustness of the extended ROM

- To discuss and apply enhancements of the ROM to consider practical aspects

This thesis consists of eight chapters and is structured as follows. In this chapter we introduced airline RM and main methods to measure RM performance. We described the ROM with its main facets and motivated our research in this field. In Chapter 2 we give an overview of state-of-the-art methods in the field of airline RM, methods to measure RM performance, and in particular the ROM. For the state-of-the-art of airline RM science we focus on the two major developments in demand modeling and optimization. We conclude this chapter with an appraisal of research opportunities in the context of the ROM and the goals of this thesis. The concept of a novel simulation-based approach to investigate ROM properties is introduced in Chapter 3. We describe the basic approach and the components of the simulation environment. In addition, we introduce a novel method to measure the robustness of a ROM against errors in the input data. We conclude this chapter with a detailed description of the scenarios used to analyze the robustness and further properties of the ROM. The network-based ROM with independent demand will be discussed in Chapter 4. We describe main properties of the estimated potential and no RM revenue and analyze the robustness of the ROM under various scenarios. An enhancement of the ROM to dependent demand structures is introduced in Chapter 5. We describe in detail how dependent demand can be modeled in the ROM formulation and discuss main characteristics. In addition, an investigation of the ROM properties, in particular of its robustness, is conducted using our simulation environment. The consideration of practical aspects in the ROM is the focus of Chapters 6 and 7. We evaluate the possibility to disaggregate the ROM measures to single flight legs in Chapter 6. The consideration of no-shows, cancelations and subsequently overbooking and upgrading is described in Chapter 7. Furthermore we introduce an extension of the ROM to derive sub-measures for the success of single RM components, like overbooking and upgrading. We will summarize and conclude this thesis in Chapter 8 and give an outlook to further research.

2. Airline Revenue Management and Performance Measurement: State-of-the-art

In this chapter we give an overview of state-of-the-art methods for both airline revenue management and performance measurement of airline revenue management. For the airline RM part in Section 2.1 we give a brief summary about main overview literature and focus on the transition from leg-based to network-based RM controls and the advancement from independent to dependent demand structures, in particular in unconstraining and forecasting techniques. In Section 2.2 we give an overview about methods and techniques to measure the performance in RM. A thorough overview of the state-of-the-art of the ROM is presented in Section 2.3. We conclude this chapter with an appraisal of recent challenges and goals of this thesis in Section 2.4.

2.1. Airline Revenue Management

In the last decades numerous works have been published in the field of airline RM. A detailed introduction into the topic of RM is given by Cross (1995). An overview of the development in RM science up to the end of the 1990s is described by McGill and van Ryzin (1999). Chiang et al. (2007) present a more recent overview of the advances and recent developments in RM. Weatherford and Bodily (1992) thoroughly describe the characteristics of problems for which RM is applicable and introduce a taxonomy to classify different kinds of problems in this area. Talluri and van Ryzin (2004b) not only introduce the art of RM, but also give a detailed overview about the different aspects that RM deals with from both a theoretical and a practical perspective. Other publications that introduce RM in a detailed and structured way are e.g. Cross (1997), Klein and Steinhardt (2008) and Phillips (2005). The broad range of application areas of RM is for example discussed by Yeoman and McMahon-Beattie (2004), Kimms and Klein (2005), Chiang et al. (2007) and Talluri and van Ryzin (2004b). Kimms and

Klein (2005) describe the application of RM methods in the airline sector, the tourism industry and discuss an application in a manufacturing environment. Some very special areas of application are presented by Yeoman and McMahon-Beattie (2004). They present for example an application of RM with saunas.

The structure of this section follows the major line of developments in RM science that we presented in Section 1.1. First, we focus on the transition of optimization models from leg-based controls to network-based controls under the general assumption of the independence of the demand between booking classes in Section 2.1.1. The progression from independent to dependent demand structures is considered both in Section 2.1.2 and 2.1.3. In Section 2.1.2 we discuss the advancement in modeling customer demand to consider dependencies. In Section 2.1.3 we present optimization models that incorporate dependent demand structures. Please note that we do not provide a complete literature review in this section, but highlight major contributions and ideas in the areas that are relevant for our thesis.

2.1.1. Optimization Models with Independent Demand

Leg-based Controls

A thorough overview on publications on optimization models on a single flight leg with independent demand structures is provided by McGill and van Ryzin (1999) and Talluri and van Ryzin (2004b). The authors introduce and discuss a variety of contributions for the leg-based seat inventory control. A milestone in the development of optimization models for leg-based controls was the introduction of Littlewood's rule for the two-fare-class problem in Littlewood (1972). Belobaba (1987, 1989) extended Littlewood's rule to multiple booking classes and introduced the *expected marginal seat revenue (EMSR)* heuristic to determine booking limits for the seat inventory control. Methods to obtain *optimal booking limits* have been introduced for example by Curry (1990), Brumelle and McGill (1993) and Wollmer (1992). The EMSR heuristics, and in particular the EMSRb heuristic, are still widely in use, because they are easy to implement and deliver very satisfactory results compared to the optimal booking limits. All of the methods mentioned above share certain underlying assumptions. One assumption - next to the assumption about the independence of the demand between booking classes - is sequential booking classes. Many RM controls take advantage of a sequential order of booking classes applying a principle called *nesting*. With nesting all protected seats for a given booking class are also available for any higher booking class. This means that if a booking class is available for sale, all higher booking classes are available, too. Another main assumption is the LBH booking order, which we already introduced in the previous chapter. With the introduction of optimization methods based on *dynamic programming (DP)* the LBH booking order assumption could be neglected. Lee and Hersh (1993) for example introduce a discrete-time DP model formulation to generate optimal booking limits with batch bookings. A detailed description about applying DP in RM can be found in Talluri and van Ryzin (2004b).

Network-based Controls

Concise overviews about optimization models considering network effects are provided by Barnhart et al. (2003), McGill and van Ryzin (1999) and Talluri and van Ryzin (2004b). The main challenge with network-based controls is to account for the dependencies between the flight legs in the network, because an accept/deny decision on a booking request for an itinerary potentially involves deciding on the availability of multiple flight legs. Methods to account for network effects using adjusted leg-based optimization methods have been discussed by Williamson (1992, 1988), Smith et al. (1992), Vinod (2005) and Talluri and van Ryzin (2004b). Williamson (1992, 1988) presents the *prorated EMSR* heuristic that splits the fares of an itinerary onto the contained flight legs according to a given prorating scheme. With the prorated fares booking limits for each flight leg can be calculated. Another main approach that allows using leg-based inventory controls called *virtual nesting* is described by Smith et al. (1992), Vinod (2005), Talluri and van Ryzin (2004b) and also Williamson (1992). Virtual nesting defines virtual classes on each leg and assigns sets of itineraries to these classes. This assignment process is also known as *indexing*. If an itinerary is requested by a customer, the booking request will be accepted if all the virtual classes that the itinerary is assigned to are available.

A very simple approach to obtain booking limits on a network level using a *deterministic linear program (DLP)* is described for example in Talluri and van Ryzin (2004b) and Williamson (1988). The objective function of the DLP aims at optimizing the total network revenue, while considering the capacity constraints of the flight legs and the forecasted demand of the itineraries. The primal solution of a DLP can be used as booking limits for the respective itineraries. Among others, Talluri and van Ryzin (2004b) describe the use of bid prices as another approach for network-based RM controls. In this approach to control the seat inventory a bid price for each leg is calculated. If the fare for an itinerary exceeds the sum of the bid prices of the legs contained in the itinerary the booking request is accepted, otherwise it is rejected. A simple way to obtain bid prices is by solving a DLP and using the shadow prices on the leg capacity constraints. Different variants and characteristics of DLPs are described in detail by Talluri and van Ryzin (2004b). One drawback of the DLP is that it only considers mean demand. Talluri and van Ryzin (1999) propose an extension of the DLP called the *randomized linear program (RLP)*, which accounts for variance in demand and results in better bid prices.

However, bid prices have to be updated regularly within the booking period as every accepted booking and change in forecasted demand has the potential to change the adequate bid price. Bertsimas and Popescu (2003) basically propose to solve the DLP for each incoming booking request and call their approach *"certainty equivalent control"*. Other methods to obtain better bid prices include the application of DP. Due to the fact that the state space of a DP even for small networks grows enormously, these methods usually apply a decomposition of the network problem to multiple leg problems such as the virtual nesting control. Talluri and van Ryzin (2004b) describe two widely used approaches. The first approach is used to improve the indexing process in a method called *displacement adjustment virtual nesting (DAVN)*. The other approach calculates bid price vectors, that contain an appropriate bid price for each number of remaining seats.

Methods that do not make use of decomposition but of simulation-based approaches to improve bid prices are presented by Klein (2007), Bertsimas and de Boer (2005) as well as van Ryzin and Vulcano (2008b). Klein (2007) introduces a heuristic for self-adjusting bid prices considering the current booking situation. Bertsimas and de Boer (2005) and van Ryzin and Vulcano (2008b) propose simulation-based approaches to improve bid prices that do not make use of a decomposition approach either and show reasonably good results with adequate computing time. Möller et al. (2004) propose a stochastic programming formulation for network-based RM controls. The method shows good revenue results on small network instances, but is currently computationally infeasible for flight networks that are used in practice.

2.1.2. Modeling, Unconstraining and Forecasting Customer Demand

The problem of modeling and forecasting customer demand is one of the most important areas in RM research. The assumptions about customer behavior, for example the LBH booking order or the independence of demand between booking classes are integral decisions for the optimization models applied. Furthermore the question of forecast accuracy for a given demand model significantly corresponds to the RM success. A concise overview about the different aspects of handling and modeling customer demand is provided by Ratliff et al. (2008), Cleophas (2009) and Cleophas et al. (2009a). In the following we use a categorization of demand models introduced by Ratliff et al. (2008). The authors mainly distinguish between three major model types. They refer to *single-class*, *multiple-class* and *multiple-flight* models. In this section we focus in particular on major demand models and approaches to unconstrain and forecast demand for these three types.

Independent Demand Models

One classic assumption in modeling customer demand is to assume independence of the demand between booking classes. Among others Talluri and van Ryzin (2004b) describe the independent demand model. Basically this simplifying assumption was justified with the application of fencing rules as described in Section 1.1. Although this assumption was never completely appropriate, it was and is still widely applied by both researchers and practitioners. Ratliff et al. (2008) refer to the independent demand model as the single class model.

For all forecasting methods, the handling of *censored booking data* is an elementary part. The actual bookings for a booking period usually do not reflect the overall demand that existed in the market. This is due to the fact that some booking classes are closed during the booking period according to the results of the optimization. A booking request for these booking classes cannot be seen in the actual bookings. Thus airlines strive to unconstrain the demand in those time periods, in which the booking classes have not been available. The process of unconstraining plays an important role in forecasting.

One of the seminal works on unconstraining for independent demand structures is provided by Zeni (2001). The author describes and compares major methods like *booking profile method*, *mean imputation method*, *projection detruncation* and *expectation maximization*. Another detailed introduction into unconstraining is given by Pölt (2000). Crystal et al. (2007) introduce another unconstraining method called *double exponential smoothing*. Other important publications that deal with unconstraining are provided by Zeni (2003), Zeni and Lawrence (2004), Talluri and van Ryzin (2004a) and Weatherford and Pölt (2002). Weatherford and Pölt (2002) describe and quantify the positive revenue effect, that occurs when the unconstraining quality increases.

Among others Lee (1990) and Talluri and van Ryzin (2004b) discuss different approaches for demand forecasting. A widely used method is *exponential smoothing*, because it is simple, robust and obtains a good forecast accuracy. The idea of exponential smoothing is to calculate the new forecast based on the historical forecast and actual observations weighted with a smoothing factor α. The higher the smoothing factor α is, the higher the share of the actual observations in the new forecast gets. Talluri and van Ryzin (2004b) discuss the effect of different levels of α. The actual observations used in this approach is usually the estimated unconstrained demand for the given booking period.

The forecasting of demand on itineraries in a flight network is more difficult than the forecasting of the demand on single flight legs. Williamson (1992) points out that due to the high number of itineraries offered by an airline, a significant portion of them has a probability to be traveled near or equal to zero. This characteristic makes forecasting for these itineraries very difficult. According to McGill and van Ryzin (1999) airlines tackle this problem by grouping these itineraries. In addition to just using the booking numbers from the inventory system Neuling et al. (2004) for example propose an analysis of the *passenger name records* to improve the quality of forecasts on itineraries. Analyses on the positive effect of better forecast accuracy were for example accomplished by Lee (1990) and Weatherford and Belobaba (2002).

However, the assumption of the independence of demand between booking classes is increasingly inadequate. Moreover Cooper et al. (2006) describe the so called *spiral down effect*. This effect in particular occurs when classical RM environments that assume independent demand are confronted with a *price-sensitive* customer behavior and fare structures with no restrictions. In such a situation a price-sensitive customer looks for the lowest available fare of a ticket. This behavior leads to increased bookings in the lower booking classes and decreased bookings in the upper booking classes. The forecaster incorporates this information into the new forecasts and the optimization model reserves less seats for higher booking classes. This feedback loop repeats and the revenue results decrease further. Eventually, the forecasts only predict demand for the lowest available fare. As a remedy against this behavior demand models that incorporate dependencies have been proposed.

Dependent Demand Models

To react to the effects described by Cooper et al. (2006) models for dependent demand structures have been introduced. A thorough overview about available literature is provided by Ratliff et al. (2008), Cleophas et al. (2009a) and Cleophas (2009). In this section we focus on selected dependent demand models and relevant methods for unconstraining and forecasting dependent demand. We both discuss multiple class and multiple flight models. Single-class models have already been described in the previous section.

Main demand models for dependent demand include *sell-up models*, *hybrid demand* and *customer-choice models*. Sell-up models are based on independent demand and incorporate a sell-up probability describing a customer purchasing a ticket in a higher booking class, if his first choice is not available. Talluri and van Ryzin (2004b) give a comprehensive introduction into sell-up models. A combination of *product-oriented* and *price-oriented* customers is modeled with hybrid demand. The product-oriented or *yieldable demand* is expected to have no dependencies to other booking classes, i.e. a customer will not sell-up or buy-down into another booking class. The yieldable demand matches the independent demand described in the previous section. The other part is the price-oriented or *priceable demand*. This demand is a consequence of *restriction-free-pricing* and models customers that have a certain willingness-to-pay. According to their willingness-to-pay they will opt for the cheapest booking class available. Hybrid demand models are described intensively by Fiig and Isler (2004), Boyd and Kallesen (2004), Walczak et al. (2010) and Fiig et al. (2010). A general extension of the hybrid demand model is the model described by Winter (2010). The demand is modeled using a directed acyclic buy-down graph. For each booking class the *buy-down* into a lower booking class is estimated. The buy-down occurs, if the lower booking class is available. In the graph the buy-down is modeled with buy-down arcs. Additionally, for each booking class the *total demand* is estimated, if all buy-down can be prevented. It is possible to show, that the demand models described by Fiig and Isler (2004), Boyd and Kallesen (2004), Walczak et al. (2010) and Fiig et al. (2010) are a special case of the model introduced by Winter (2010). A general description of customer demand that takes into account multiple criteria for selecting a ticket is modeled using so-called customer-choice models. These models define the choice behavior according to preferences in categories like price, travel time, strategic behavior, offers by competitors and so forth. Kimms and Müller-Bungart (2006) for example give a comprehensive introduction into customer-choice behavior. A detailed overview on available literature is given by Cleophas (2009). Customer-choice behavior is modeled formally using *binary probit*, *binary logit* or *multinomial logit* models (see e.g. Talluri and van Ryzin, 2004b). We refer the interested reader to the publications mentioned above to learn more about customer-choice models.

Ratliff et al. (2008) present a concise overview about methods to unconstrain and forecast demand for multiple classes. Mishra (2003) for example introduces a method called *cumulative expected bookings*. It is primarily used to estimate dependent demand in restriction-free fare environments. An application of the expectation maximization algorithm is introduced by McGill (1995). Skwarek (1996) investigates unconstraining and forecasting with sell-up behavior. Another method is *Q-forecasting.* Authors like Cleaz-Savoyen (2005), Belobaba and Hopperstad (2004), Gorin and Belobaba (2004), Kambour et al. (2001) and Reyes (2006) describe the method in detail. Q-forecasting is mainly applied in the PODS context and primarily used to estimate the priceable demand part in hybrid demand models.

The multiple-flight models are also covered by several publications. Ratliff et al. (2008) introduce a recapture heuristic to estimate the unconstrained demand based on actual bookings for multiple flights. Stefanescu (2009) and Stefanescu et al. (2004) describe a multivariate demand model and present a method to unconstrain and forecast correlated demand based on censored sales data. The expectation maximization approach to unconstrain dependent demand for multiple flights is described and applied by Talluri and van Ryzin (2004a), Vulcano et al. (2010) and Vulcano et al. (2009). Ja et al. (2001) apply a regression-based demand and recapture estimation to unconstrain and forecast demand for connected flights.

2.1.3. Optimization Models with Dependent Demand

In this section we introduce some major optimization models that consider hybrid demand or customer-choice based demand models. We primarily focus on some major models that are relevant for our analyses. As a starting point we refer to Weatherford and Ratliff (2010). The authors discuss existing approaches to deal with dependent demand structures in optimization.

Optimization models using hybrid demand are getting increasingly common. Authors like Fiig and Isler (2004), Boyd and Kallesen (2004), Cleaz-Savoyen (2005), Belobaba and Hopperstad (2004), Reyes (2006), Walczak et al. (2010) and Fiig et al. (2010) discuss these kind of optimization models. The main idea behind these approaches is the application of *fare adjustment* or *fare transformation* and *demand transformation.* The fare transformation incorporates the opportunity cost of potential buy-down into the fares. With demand transformation the hybrid demand consisting of yieldable and priceable demand is changed into an equivalent yieldable demand. Walczak et al. (2010) lay out that this transformation from a dependent demand model into a transformed independent demand model leads to the same optimization results. The main advantage is that the existing optimization methods, i.e. the operational optimization systems at an airline, can still be used. For details on the transformation and the characteristics of this optimization approach we refer to Walczak et al. (2010) and Fiig et al. (2010).

Optimization models for general customer-choice demand models are discussed by Brumelle et al. (1990), Gallego et al. (2009), Bront et al. (2009), van Ryzin and Vulcano (2008a) and Talluri and van Ryzin (2004a). Brumelle et al. (1990) propose a method to allocate seats between stochastically dependent demands. Gallego et al. (2009) extend the EMSR heuristic to consider choice-based customer behavior for single-leg RM with demand dependencies. A column generation algorithm for choice-based network RM is presented by Bront et al. (2009). A customer-choice demand model to compute virtual nesting controls in a network-based environment is considered by van Ryzin and Vulcano (2008a). Talluri and van Ryzin (2004a) introduce an optimization approach for customers with general choice behavior.

2.2. Performance Measurement of Revenue Management

Until now, a variety of sophisticated methods to measure the performance of RM has been introduced. In this section we introduce the most common approaches. We also refer to the motivation of PM, highlight some main approaches and contributions, exemplify the broad variety of methods available and take a broader view on RM performance by discussing some organizational challenges for successful RM. A summary of the state-of-the-art of the ROM use is presented in the next section. As a good starting point for literature that covers PM of RM we refer to Chiang et al. (2007). The authors give a detailed overview about existing approaches.

The motivation to measure performance in RM is explained by numerous authors. Talluri and van Ryzin (2004b) mention the assessment of the revenue potential of a RMS and the continuous measurement of captured benefits. After stressing the importance to justify the investment into the RMS they also highlight the importance of continuous improvement of the RM process and methods. Vinod (2006), among others, names the validation of the performance of a recently introduced RMS and *"getting the most out of revenue management in a steady-state operating environment"*. One argument in favor of PM according to Curry (1992) is the fact that continuously measuring performance is able to prevent costly mistakes. He adds that in the course of a booking period revenue managers or the RMS in use can make wrong decisions and methods of PM are able to detect them. Additionally it can help companies to fine-tune their RMS, as PM tools allow to display in which areas of the system further revenue can be generated. As a basic property PM methods for RM should therefore be able to isolate the contribution of RM from the overall success. Pölt (2001) adds that

PM also helps to track the RM performance over time, which is key for continuous improvement of the RM controls. This not only facilitates the identification of weaknesses in the RMS but it also allows to quantify and objectify the impact of RM decisions.

Applications of simulation to analyze the performance of RM methods are widely spread and used for different purposes. A major contribution in this field is PODS. Many authors used the PODS environment to assess the performance of different RM components in a realistic environment. In the following we will just name some of these assessments and do not account for completeness. Among others Skwarek (1996), Reyes (2006), Carrier (2003), Cleaz-Savoyen (2005), Gorin (2000), Zickus (1998) and Gorin and Belobaba (2004) used the PODS environment to accomplish research on forecasting models, hybrid forecasting, fare adjustment and other topics.

More applications of simulation can be found in Weatherford (2004b, 2002, 2004a), Belobaba and Weatherford (1996), Weatherford and Belobaba (2002) and Weatherford and Pölt (2002). Similar to PODS, these authors also investigate different aspects of RMS components. The topics range from evaluating the impact of different optimization and forecasting models on the RM success to comparing the performance of different methods of unconstraining.

Variants of simulation studies focussing on single regional markets are for example provided by Oliveira (2003) and Eguchi and Belobaba (2004). In his study Oliveira (2003) assesses the consequences of RM application in the Brazilian airline market. Eguchi and Belobaba (2004) analyze the impact of RM methodologies on the domestic airline market in Japan.

A novel approach to apply a simulation environment to investigate forecast performance is presented by Cleophas (2009) and Cleophas et al. (2009b). The authors apply a simulation-based approach based on a decomposition of the single components of a RMS to evaluate the performance of forecasts and classical measures of forecast accuracy considering customers with a choice-based demand model. Furthermore simulation environments are being used to examine strategic decisions or to train the revenue managers. Basumallick and Singh (2009), for example, propose a simulation environment that is fed and calibrated with data from the operational RMS to analyze the impact of strategic RM decisions. Gerlach and Frank (2010) introduce the *revenue management training for experts (ReMaTE)* simulator. In this simulation setup the revenue managers are able to replay real life situations to better understand the influencing factors for RM success. The simulator basically reflects the operational RMS with the same underlying RM methods and control screens used. ReMaTE furthermore allows to simulate competition against other airlines in selected markets.

Core principles in the implementation of a RM simulator can be found for example in Talluri and van Ryzin (2004b), Frank et al. (2008) or Vinod (2006). Vinod (2006) describes a *"passenger simulation model"* and states that using this model can help airlines to point out the revenue gains through the application of RM. Talluri and van Ryzin (2004b) and Frank et al. (2008) describe basic principles about setting up a RM simulation environment.

Various methods of PM using actual data from the operational RMS are proposed in the RM community. The comparison of two time periods is described by Williams (1995), Jain and Bowman (2005) as well as Lieberman and Raskin (2005). Williams (1995) uses a multi-regression analysis to evaluate the positive effect of RM on the overall performance. Jain and Bowman (2005) introduce a method to measure the performance of a length-of-stay control for the hotel industry. The authors conclude that this model provides accurate results by removing the influence of internal and external factors. Lieberman and Raskin (2005) introduce a method named *"comparable challenges"* which normalizes market conditions and provides an indicator of the efficiency of RM decisions. However, although the contribution of the RMS to the overall success can be isolated in these approaches, they are not well suitable for continuous measurement. One application of parallel testing of old and new RM methods using actual data is introduced by Talluri et al. (2010). The authors propose a method called *"sandbox testing"* to evaluate the revenue potential of a new RM methodology.

Another method to assess the success of RM called *"performance monitor"* is introduced by Anderson and Blair (2002, 2004). The first article deals with assessing the relative performance of a location to benchmarks gathered from different locations, markets and also time periods. In their second article they describe a disaggregation of the lost revenue opportunities to single components.

Vinod (2006), Pölt (2001) and Talluri and van Ryzin (2004b) present a comprehensive overview of classical or traditional performance measures, which can easily be calculated using data from the operational RMS. Vinod (2006) and Pölt (2001) focus on the airline industry, while Talluri and van Ryzin (2004b) name common performance measures used in other industries. Vinod (2006) also proposes to distinguish between pre- and post-departure measures. Pre-departure measures give an indication of how well the RM is performing within the booking period. A major pre-departure measure is the *booked seat load factor*. Post-departure measures are calculated after the departure of the plane and describe retrospectively the overall success or the isolated contribution of the RMS. Widely used classical measures are *RASK* or *SLF*. Phillips (2005) names the RASK as the key classical measure as it not only incorporates the revenue gained, but also considers the supply that was offered - namely the seat kilometers that have been offered to customers. Beyond focussing on monetary performance or the utilization of the plane several measures are known to measure forecast accuracy. In a seminal work about forecasting, Armstrong (2001) provides a comprehensive overview of common measures to examine forecast accuracy and performance.

According to authors like Skugge (2004) and Lieberman (1991) meeting the organizational requirements is key for a successful implementation of RM (see e.g. Lieberman, 1991). Based on an empirical test, Crystal (2007) identifies the *"technical capability"* and the *"social support capability"* as key drivers of RM success. Lieberman (1991) proposes ten guidelines for a successful application of RM including the importance of training the employees. Skugge (2004) also emphasizes the relevance of training as a main driver for RM performance particularly the use of interactive case studies and simulation tools. One previously mentioned example in this area is the ReMaTE simulator described by Gerlach and Frank (2010). This simulation tool intends to train the revenue managers to obtain the full possibilities of RM. In his article Lieberman (2003) concludes that six key criteria exist for successful RM: *"measuring performance"*, *"developing supporting business policies and processes"*, *"ensuring decision-making authority and accountability"*, *"integrating RM with other departments"*, *"knowing the limits of the RMS"* and *"providing career path support and progression"*. In addition, Wishlinski (2006) discusses the organizational requirements for successful RM in detail.

2.3. The ROM

Leg-based ROMs have been applied at many airlines and some publications can be found covering the topic. First ideas to apply perfect RM controls in hindsight were presented by Kempka (1991) and Smith et al. (1992). Kempka (1991) proposes a model for calculating the optimal revenue on a single leg. Smith et al. (1992) discuss different hindsight control strategies in detail and provide a comprehensive introduction to the ROM in a leg-based airline RM environment. Daudel and Vialle (1992, p. 110) also propose to compare the actual revenues with estimates for perfect hindsight and no RM revenues. Pölt (2001) provides a thorough summary of the leg-based ROM. Rannou and Melli (2003) use a procedure very similar to the ROM to evaluate the performance of a RMS in the Western European hotel-industry. Similar to Smith et al. (1992) they define and discuss various control strategies to estimate the potential and no RM revenue in hindsight. For the no RM revenue estimate they propose not only to apply a FCFS strategy, but to assume certain (rule-based) user interactions that lead to higher revenues.

Adler (1993) describes several major issues that arise when a leg-based ROM is applied in a network-based RM environment and suggests to introduce adjusted variants of the ROM. Proposals for network-based ROMs are introduced by Talluri and van Ryzin (2004b), Vinod (2006), Chandler and Ja (2007) and Temath et al. (2009). Talluri and van Ryzin (2004b) and Vinod (2006) propose to use a LP-formulation to determine the optimal revenue for independent demand at hindsight. Chandler and Ja (2007) describe the whole process of ROM application at an airline and introduce the approaches used to estimate the potential and no RM revenue for a network-based ROM in detail. Temath et al. (2010) present computational results on ROM robustness for the network-based ROM with independent demand.

Adler (1993) points out that the ROM is only able to measure *"within the current infrastructure"*. Chandler and Ja (2007) examine this characteristic for the assumption of the independence of the demand between booking classes and describe the negative implications on the potential revenue estimations if dependent demand structures are not considered. Temath et al. (2009) introduce an extension of the network-based ROM to dependent demand structures to account for this problem.

Some authors comment on main properties of the ROM. Curry (1992) introduces the notion of *"achievable opportunity"* to consider forecast errors during the booking period and its implications on the ROM results. Adler (1993) names the ability to isolate the RM contribution of the overall success as one main property. The importance of accurate estimates for the unconstrained demand for the ROM is emphasized by Chandler and Ja (2007), Adler (1993), Pölt (2001) and Zeni (2001, 2003). Pölt (2001) shows an analysis in a leg-based airline RM context in which he investigated the effect of an independent and unbiased unconstraining error on the validity of the ROM. He points out that the effect in that context is minor and can be neglected since the ROM errors balance out at an aggregated level. Adler (1993) states that the ROM is "is only as good as the unconstrained demand forecasts". Zeni (2001, 2003) also emphasizes this problem in his detailed work on unconstraining.

The practical applications of the ROM plays an important role in ROM discussions as well. Cross (1995) characterizes the ROM as a very useful method to keep the revenue managers *"focussed"* and to search for continuous improvements. Bach (1999) presents an analysis which shows a positive correlation between the performance of revenue managers and their ROM results. Adler (1993) and Pölt (2001) consider the relation between ROM measures and classical performance measures. Adler (1993) proposes the *"key performance measures basket concept"*, to achieve the best results using performance measures. Pölt (2001) suggests to use ROM measures in combination with other performance measures to increase reliability.

Ideas to customize the ROM to investigate single components of RM control are presented by Smith et al. (1992), Pölt (2001) and Chandler and Ja (2007). Smith et al. (1992) describe two variants of the ROM, which focus on specific parts of RM. On the one hand they describe the overbooking ROM, which estimates the contribution of overbooking to the overall success. On the other hand they present the discount allocation ROM that describes the performance of reserving seats for different price categories. One key challenge for the customized use of the ROM measures according to Smith et al. (1992) is to *"avoid double counting benefits"*. Pölt (2001) adds to that and identifies upgrading, overbooking and fare-mix as potential areas of investigation. Chandler and Ja (2007) propose to split the ROM measures into *"dilution"* and *"spoilage"*. With the analysis of dilution they aim at assessing the revenue mix of the passengers accepted. The analysis of spoilage in contrast aims at investigating the revenue loss caused by empty seats that could have been sold to customers. For the network-based ROM the authors propose to disaggregate the ROM measures for the total flight network to market or leg level.

Beyond the application of the ROM to continuously measure the performance of an operational RMS, some authors use the ROM to describe the performance of new RM methods in simulation studies. In the following we present some examples. Mak (1992), for example, uses the ROM to evaluate the performance of different optimization techniques in a simulation study. Dar (2006) uses a no RM control strategy to measure performance improvements achieved by different RM methods in a PODS study. An examination of customer lifetime value considerations in RM is presented by von Martens and Hilbert (2010). They utilize the ROM to determine upper and lower bounds for the achievable revenue. Imhof et al. (2010) use revenues based on a simulated FCFS strategy and ex-post optimal revenues to classify the performance of different approaches to optimize the availability of rental cars considering upgrades.

2.4. Research Opportunities and Goals of the Thesis

In the previous sections we gave an overview about current literature in airline RM, performance measurement of RM and the ROM. While revisiting the existing literature we identified some research opportunities.

Performance measurement is an important facet of the application of RM at airlines. Among other approaches discussed in literature the ROM allows to continuously measure and to isolate the contribution of RM from the overall success. The ROM is well documented in leg-based environments. Authors like Smith et al. (1992) and Pölt (2001) discussed the ROM and its properties intensively. In particular the effect of errors in the input data on the ROM is considered the main driver for validity of the ROM. However, a systematic evaluation of the implications of unconstraining errors on the robustness of the ROM has not yet been presented. In addition the airline market and subsequently the airline RM has significantly changed. The advancement from leg-based to network-based RM controls and the consideration of dependent demand models instead of independent demand models are becoming increasingly important. As Barnhart et al. (2003) point out, applications of network-based controls with independent demand in airline RM are nowadays common with airlines using hub and spoke networks. On the contrary the necessity of applying forecasting and optimization models for dependent demand strongly increased in the last decade caused by low-cost-carries removing fare-restrictions and the ability to search the internet for cheap fares. Research in this field has made tremendous progress and as Weatherford and Ratliff (2010) point out, a lot of work exists in this field which prove applicable in practice. Only a limited number of publications exist covering the necessary modifications and adjustments of the ROM to consider these new developments. Proposals to apply the ROM in a network-based RM environment with independent demand have been described for example by Chandler and Ja (2007). However, an enhancement of the ROM to dependent demand structures and a concise analysis of the effect of dependent demand structures is missing. Proposals to consider practical aspects, for example to integrate overbooking and upgrading into the ROM, have been made so far, but no detailed analysis has been presented.

Building on the research work accomplished so far and the developments airline RM is heading at, we derive some research opportunities and goals for this thesis. First, we want to thoroughly assess the effect of errors in the unconstrained demand on the robustness of the network-based ROM. Therefore we aim at implementing a simulation environment that reflects reality in the best possible way and to develop a novel approach to measure the robustness of the ROM. In addition we plan to assess the properties of the ROM with the help of different scenarios and sensitivity analysis. The simulation environment should be capable to allow those kinds of analyses. In a second step, we want to use the novel simulation-based approach to investigate the properties of the network-based ROM with independent demand. A special focus will be on the comparison of data- and model-related errors and on the robustness of the ROM against errors in the unconstrained demand. Another main goal of this thesis is to consider the latest developments in RM science and to enhance the network-based ROM with independent demand to dependent demand structures. Therefore we want to make use of a state-of-the-art dependent demand model and an optimization method which is able to handle dependent demand. We aspire to enhance the given formulation of the ROM to dependent demand structures. Similar to the ROM with independent demand questions about the robustness of the ROM with dependent demand are to be analyzed. As a last goal we strive to consider practical aspects in the ROM. The disaggregation of the ROM measures to subparts of the flight network seems to be useful in practice. We will investigate if this can be done and how reliable the results are. At last the assessment of single RM components needs to be discussed. In particular we aim to integrate common RM components into the ROM and to explore ways of splitting the overall success to single parts of the RMS.

3. A Novel Simulation-based Approach to Investigate ROM Properties

In this chapter we present our novel simulation-based approach to investigate ROM properties. The simulation environment introduced in this chapter is an essential part of our assessment of the ROM. As written earlier, we aim at testing the robustness, but also at investigating further properties of the ROM in an environment which reflects the real life applications and network structures of a large network carrier as realistically as possible. The potential to use the ROM to measure RM performance strongly depends on the evaluation of the revenue managers that it delivers valid results. To assess if the network-based ROM with independent demand and dependent demand is able to deliver valid results, a special simulation environment has to be set up. Most notably a systematic way to analyze the robustness of the ROM against errors in the estimated unconstrained demand has to be implemented.

In this chapter we describe the structure of our simulation environment and the interaction of the core modules applied in Section 3.1. In the same section we also provide a detailed description of the components of the simulated RMS. In Section 3.2 we introduce our novel simulation-based approach to measure ROM robustness. Details on the simulation scenarios in which we investigate the properties of the ROM are provided in Section 3.3. We conclude this chapter with Section 3.4.

3.1. The Simulation Environment

For our investigation of the properties of the network-based ROM we use the simulation environment presented in Figure 3.1. Basically we simulate a complete RMS and add an additional module to calculate and evaluate the ROM. The setup of the simulated RMS follows the principles of a RM simulator that are presented in Frank et al. (2008) and is based on an existing simulation environ-

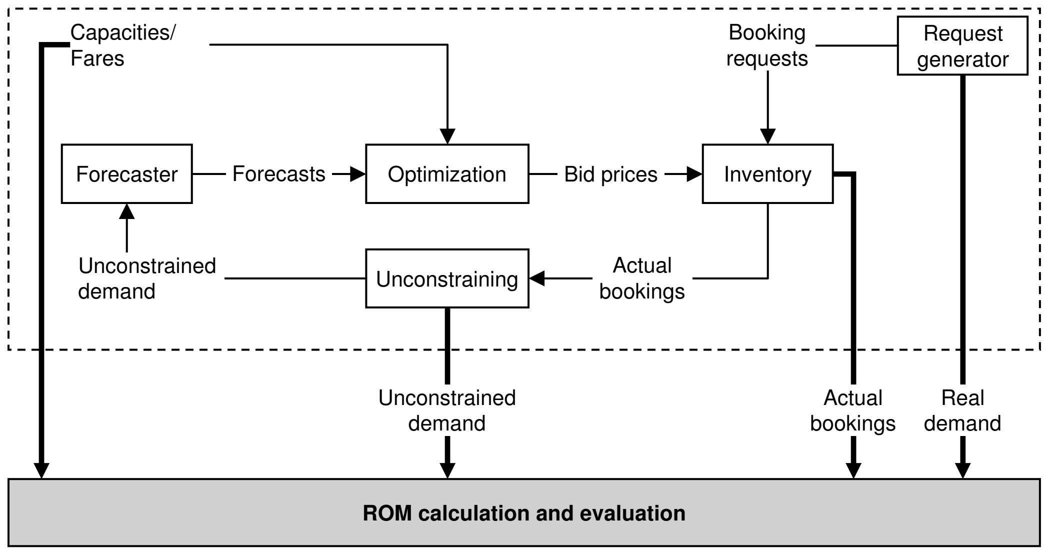

Figure 3.1.: The Simulation Environment to Investigate ROM Properties

ment available at Lufthansa German Airlines. For our simulation environment we apply a decomposition approach very similar to the approach introduced by Cleophas (2009). This allows us to perform various scenarios and analyses to investigate the effect on the ROM. Therefore, the existing simulation environment is extended and revised in most components, for example to implement the different simulation scenarios. In addition, the RMS used in this thesis reflects all main components and used RM methods of a large network airline, in particular regarding state-of-the-art demand modeling and optimization models. In addition we calibrate the input data to be as realistic as possible to achieve results that allow a transfer of the findings to the operational RM controls.

In order to generate a sufficient number of observations numerous simulation runs are applied, i.e. simulated consecutive booking periods. Before the first simulation run some data structures are initialized with default values, for example the forecaster with an initial forecast. At the beginning of each simulation run all booking requests for the simulation run are generated and stored. After the request generation the flow of the simulation is very similar to an operational RMS. At the beginning of each simulation run the current forecast is used in the optimization module to calculate bid prices for the inventory control. The optimization also incorporates the fares for the itineraries and capacities of the compartments of the flight legs. Within a simulation run the booking requests are handled by the inventory and either accepted or rejected. At predefined DCPs the bid prices are reoptimized to react to the current booking situation. After the simulation run the actual bookings and availability information are used in the unconstraining module to estimate the unconstrained demand. The unconstrained demand together with the old forecast is the base for the forecast of the next run.

After each simulation run four data streams are provided to the module that calculates and evaluates the ROM. In the first data stream the capacities of the flight legs and the fares of the itineraries are provided. The second data stream are the booking requests from the request generator, which serve as the real demand in the following calculations. The actual bookings from the inventory not only serve as a key input to the unconstraining module, but they also define the third data stream used in the ROM calculation. The fourth input stream is the estimated unconstrained demand from the unconstraining module. We provide a detailed description of the different modules and data streams in the following sections.

3.1.1. Modeling Customer Demand and Request Generation

In this section we start with a formal definition of the applied models of independent and dependent demand in our simulation. Afterwards we describe how the customer requests are generated in the request generator and how they are handled in the simulation.

Basic Notation and Independent Demand Model

Let us start this section with some general definitions. Let I denote the set of all itineraries i offered. These O&D itineraries contain the flight legs that are traversed to get from an origin to a destination. The available flight legs l are stored in set L, whereas L_i contains only those legs l that are part of an itinerary i. In analogy to the last definition J_i contains the set of all available booking classes j on itinerary i. M denotes the set of all compartments m and the set M_l the compartments that are available in leg l. The respective compartment for a booking on leg l in booking class j is labeled with $m_{l,j}$. The physical capacity of such a compartment m in leg l is named $cap_{l,m}$. In addition, T denotes the set of all time periods t and S the set of all available simulation runs s. The sets J_i, T, M_l and S are sequentially ordered. For example $t = 1$ defines the first time period, whereas $t = |T|$ defines the last time period in T. The successor of a given time period t is marked with $t + 1$. The sequential order of the booking classes is based on their respective fares. The successor of a booking class j is defined as $j + 1$. The highest available booking class in a compartment m for itinerary i is denoted with $j^+_{i,m}$ and the lowest available booking class with $j^-_{i,m}$. The same order applies to compartments. The highest compartment of a leg l is defined as m^+_l. The next simulation run from a given run s is denoted with $s+1$.

As described in Section 2.1.2 an independent demand model describes the customer demand without considering any dependencies to other available products. The assumption of the independence of the demand increasingly loses importance, since more and more models to handle dependencies have been introduced and proven in practical applications. However, many airlines still use independent demand models and some state-of-the-art optimization methods transform and reduce dependent demand models back to equivalent independent demand models. To model the independent demand in our simulation we refer to a classic definition, which is widely used in the airline world. In the following $d_{i,j,t,s}$ represents the mean demand for itinerary i for booking class j in time period t in simulation run s. s is only appended in the subscript if we have to differentiate between two simulation runs s. If s is omitted, $d_{i,j,t}$ describes the independent demand in the current simulation run. This also applies to all other definitions for which we have values for each simulation run.

Dependent Demand Model

We introduced some state-of-the-art dependent demand models in Section 2.1.2. For our simulation of the effect of dependent demand structures on the ROM we refer to the model definition by Winter (2010). Like the dependent demand models described by Walczak et al. (2010) and Fiig et al. (2010) and in accordance to the classification by Ratliff et al. (2008), it models the dependencies of the demand between the booking classes for a single itinerary. A wide range of practical applications is available for these kinds of models as well as numerous optimization models that are based on these model definitions. One advantage of the model definition by Winter (2010) is the fact that it allows more degrees of freedom to model dependencies of the demand.

The basic idea of the definition introduced by Winter (2010) is to model the demand using a buy-down graph. The graph models the customer-choice options in an acyclic directed graph. This means that a logical ordering of buy-down behavior is given. Buy-down can occur from one booking class to another, but not in reverse direction. In Figure 3.2 we provide an example of such an acyclic directed buy-down graph. The graph illustrates the dependencies between the booking classes. As a basic assumption the availability of booking classes is often sequentially ordered. The sequential opening order is defined by *feasible actions*. In our example there are five feasible actions. It is only possible to make the

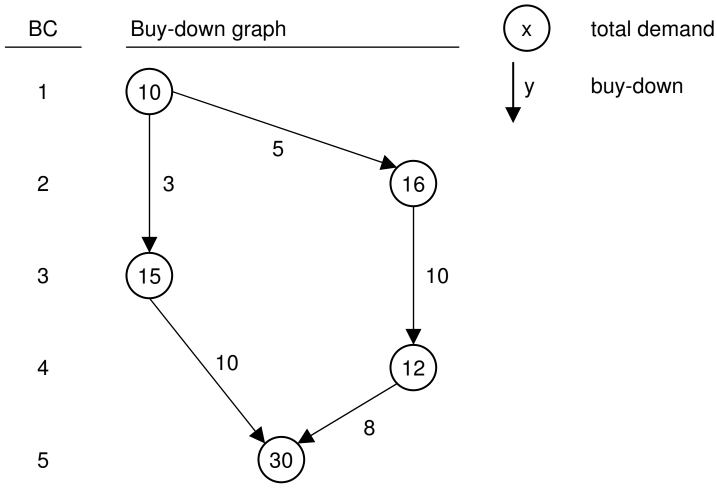

Figure 3.2.: Dependent Demand Modeled in an Acyclic Directed Buy-down Graph

next booking class available in the given sequential order. It is for example not possible to have booking class one and three available, but booking classes two, four and five unavailable. The *realized demand* we observe in a booking class is the total demand minus the buy-down into other booking classes. In our example the total demand of booking class one is ten. If only booking class one is available this is also the realized demand. However, a buy-down will materialize if booking class two or additionally three are also available. The buy-down from booking class one to booking class two is five. Given the feasible action of making booking classes one and two available the realized demand for booking class one is five and for booking class two it is 16. We list the realized demands in Table 3.1.

	Realized demand in BC					
BCs open	1	2	3	4	5	$\sum$
1	10	-	-	-	-	10
1,2	5	16	-	-	-	21
1,2,3	2	6	15	-	-	23
1,2,3,4	2	6	15	12	-	35
1,2,3,4,5	2	6	5	4	30	47

Table 3.1.: Realized Demand According to Opened Booking Classes

We formalize this model with the following definitions. The total demand for itinerary i for booking class j in time period t is denoted with $d^{td}_{i,j,t}$ and the buy-down for itinerary i for booking class j into a lower booking class j' in time period t with $d^{bd}_{i,j,j',t}$. With yieldable demand we describe the demand for a booking class, if all buy-down occurred. A formal definition is given in Equation 3.1.

$$d^{yd}_{i,j,t} = d^{td}_{i,j,t} - \sum_{j' \in J_{i,j}} d^{bd}_{i,j,j',t} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{3.1}$$

In the given equation $J_{i,j}$ describes the set of all booking classes that are lower than booking class j and for which a buy-down relation exists. A cross compartment buy-down is not considered in this thesis. Please note that the total demand contains the buy-down into lower booking classes and thus cannot be used to estimate the total number of customers in the market.

In this thesis we differentiate between different types of demand. The estimated unconstrained demand is indicated by $d_{i,j,t}$. It refers to the estimated unconstrained demand that is generated in the unconstraining module. $r_{i,j,t}$ denotes the real demand. The real demand is taken from the request generator and is described in detail in the next section. The forecasted demand as the basic input for the optimization module is named $f_{i,j,t}$.

Request Generation

A main part of each simulation environment is the generation of customer requests. The booking requests in our simulation environment are generated according to the proposal of Frank et al. (2008). Customer requests are assumed to be Poisson distributed and generated using a non homogeneous Poisson process. For a detailed description about the application of a non homogeneous Poisson process we refer the interested reader to Kimms and Müller-Bungart (2007). The intensity of the Poisson distribution may vary over time and is based on historical demand profiles for each itinerary and booking class used in the simulation. In the case of independent demand we generate customer requests for a given itinerary i in a given booking class j within a given time period t. The number of all customer requests for itinerary i in booking class j and time period t is denoted with $c_{i,j,t}$. Although not used in the notation, we assume, that a customer request can occur at any given point in time and we are able to use this information for a special analysis. No-show behavior is applied to a customer request using a no-show probability and a Bernoulli process to determine whether a customer request ends up being a no-show or not. The information about no-show probability are also taken from historical observations in the operational RMS. Cancelations could be modeled in the same manner, but are not considered in this thesis. It is also possible to consider seasonal demand deviations in the historical demand profiles. This allows us to simulate realistic demand profiles known from the operational RMS.

In the case of dependent demand structures an additional information to each customer request is applied. Given a probability that a customer would also be willing to purchase the next higher booking class, a Bernoulli process is applied to determine the number of booking classes the customer is willing to sell-up. The sell-up order of our customer requests is sequentially along the booking classes. In analogy to the definition with independent demand the number of customer requests for a given itinerary i within a given time period t is denoted with $c_{i,j,j',t}$. Booking class j refers to the highest booking class the customer would purchase and booking class j' refers to the lowest booking class the customer would opt for.

The booking requests from the request generator module are not only handled by the inventory availability decision, but they also reflect the real demand. This is one key input stream for our analysis setup. For our standard analysis we will use aggregated real demand information. For some analysis however, we make use of the single customer requests because they contain the exact information, at which time point the requests occur. With independent demand the definition of $r_{i,j,t}$ is simple. It equals $c_{i,j,t}$ in all cases, as presented in Equation 3.2.

$$r_{i,j,t} = c_{i,j,t} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{3.2}$$

With dependent demand the transformation from customer requests to the aggregated real total demand, yieldable demand and buy-down is a bit more complicated. Using the definitions made before, Algorithm 3.1 describes, how the values of $r^{td}_{i,j,t}$, $r^{yd}_{i,j,t}$ and $r^{bd}_{i,j,j',t}$ are generated.

First, all values of $r^{yd}_{i,j,t}$ and $r^{bd}_{i,j,j',t}$ are set to zero (Lines 3 to 6). Afterwards for all potential combinations of customer requests in which the customers are willing to purchase a ticket within the range from booking class j to j' the values of the real yieldable demand and buy-down are determined. The values of the yieldable demand are increased for the lowest booking class the customers are looking for (Line 10). From this booking class no buy-down is intended. For all booking classes in between (j to $j' - 1$) buy-down into a lower booking class can occur and thus the values of $r^{bd}_{i,j,j',t}$ are increased (Line 12). At the end the total real demand $r^{td}_{i,j,t}$ is determined as the sum of the real yieldable demand and buy-down (Line 15).

Algorithm 3.1: Generating Real Demand out of Single Booking Requests

foreach $t \in T$ **do**
  foreach $i \in I$ **do**
    set values to zero
    foreach $j \in J_i$ **do**
      $r^{yd}_{i,j,t} = 0$
      $r^{bd}_{i,j,j+1,t} = 0$
    determine real aggregated yieldable demand and buy-down
    foreach $j \in J_i$ **do**
      for $j' = j$ **to** $|J_i|$ **do**
        $r^{yd}_{i,j',t} = r^{yd}_{i,j',t} + c_{i,j,j',t}$
        for $j'' = j$ **to** $j' - 1$ **do**
          $r^{bd}_{i,j'',j''+1,t} = r^{bd}_{i,j'',j''+1,t} + c_{i,j,j',t}$
    determine real aggregated total demand
    foreach $j \in J_i$ **do**
      $r^{td}_{i,j,t} = r^{yd}_{i,j,t} + r^{bd}_{i,j,j+1,t}$

3.1.2. Unconstraining and Demand Forecasting

All common unconstraining methods make use of actual bookings and information about the availability of booking classes as a basic input. $b_{i,j,t}$ denotes the number of actual bookings and $a_{i,j,t}$ the availability information of itinerary i for booking class j in time period t. Many unconstraining methods also use average historical bookings, which are labeled with $h_{i,j,t}$.

Independent Demand

In Section 2.1.2 we listed several commonly used unconstraining methods such as additive pick-up, expectation maximization or projection detruncation. As we investigate the effect of different levels of unconstraining errors on the ROM robustness later in this thesis, the choice of a specific unconstraining method is not important. We apply the additive pick-up unconstraining method and estimate the unconstrained demand using Equation 3.3.

$$d_{i,j,t} = \begin{cases} b_{i,j,t} & a_{i,j,t} = 1 \\ max(h_{i,j,t}; b_{i,j,t}) & a_{i,j,t} = 0 \end{cases} \quad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{3.3}$$

This definition also adheres to one basic proposition, which is that the lower bound of the demand estimates for a given time period are the actual bookings $b_{i,j,t}$. We formalize this assumption in Proposition 3.1.1. Keeping this proposition in mind, the basic idea of our unconstraining approach is to use all booking observations in those time periods in which the booking classes were available all the time. For all other time periods we use the maximum of the average historical bookings $h_{i,j,t}$ and the actual bookings $b_{i,j,t}$.

Proposition 3.1.1 $d_{i,j,t} \geq b_{i,j,t} \quad \forall i \in I, \forall j \in J_i, \forall t \in T$

In addition to the unconstrained demand we also recalculate the average historical bookings and the forecast for the next simulation run. For both updates we use exponential smoothing, which is described in detail in Talluri and van Ryzin (2004b, Chapter 9.3.1.2 Exponential Smoothing, page 436). Equation 3.4 shows, how the average historical bookings are updated.

$$h_{i,j,t,(s+1)} = \begin{cases} \alpha * b_{i,j,t,s} + (1-\alpha) * h_{i,j,t,s} & a_{i,j,t,s} = 1 \\ h_{i,j,t,s} & a_{i,j,t,s} = 0 \end{cases} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{3.4}$$

$$f_{i,j,t,(s+1)} = \alpha * d_{i,j,t,s} + (1-\alpha) * f_{i,j,t,s} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{3.5}$$

To update the average historical bookings we use all time periods in which the booking class was available the whole time. The bookings of these time periods are learned using exponential smoothing with smoothing factor α. If the booking class was not available for sale in a time period, the old value is kept for the next simulation run. The forecast for the next simulation run $s+1$ simply integrates the estimated unconstrained demand with the same smoothing factor α as shown in Equation 3.5.

Dependent Demand

The unconstraining and forecasting of dependent demand is a very challenging task compared to the independent demand case. The estimation of independent unconstrained demand is able to directly make use of actual observations or of historical observations. Thus, the accuracy of the estimated unconstrained demand is usually quite good. For dependent demand structures it is not possible to estimate the unconstrained demand based on direct observations with the same accuracy. In particular the buy-down is hard to estimate. As presented in Section 2.1.2 some methods have been proposed to solve this challenging task. The approach we apply in this thesis uses some simplifying assumptions. One simplifying assumption is that we only estimate buy-down from one booking class j to the next booking class $j+1$ which corresponds to the customer demand we generated in the request generator. The unconstraining method is first and foremost intended to support us in our research objective at assessing the impact of different levels of unconstraining errors on the ROM. For the dependent demand case we are also able to define a basic proposition. It is depicted in Proposition 3.1.2.

Proposition 3.1.2 $d^{td}_{i,j,t} \geq b_{i,j,t} \quad \forall i \in I, \forall j \in J_i, t \in T$

It states, that the total demand for a booking class is greater than or equal to the actual bookings. In addition, we consider the average historical bookings to be the average historical yieldable demand in the case of dependent demand structures. According to our model these values are easy to observe in comparison to the total demand and the buy-down.

The unconstraining process is described in detail in Algorithm 3.2. It basically consists of three steps. First, the yieldable demand is estimated. This is done in Lines 4 to 16. According to our demand model we assume that all buy-down for a booking class j materialized, if booking class j was open and also booking class $j+1$. If this was not the case we use historical average yieldable demand as an estimator. The buy-down and total demand are estimated by using the estimations for the total demand of a booking class $j+1$ and the help of an estimated sell-up rate $\theta_{i,j,t}$ in a second step. These steps are described in Lines 17 to 24. To adhere to Proposition 3.1.2 the total demand in a booking class is always estimated to be greater than or equal to the bookings we observed. If this is not the case in the first place the difference between the two estimators is attributed to the yieldable demand and buy-down using coefficient ω. The third step is enforcing consistency. It is possible that after the first two steps the estimations of the buy-down into a lower booking class are greater than the total demand in the lower booking class. This is not possible by definition and will be corrected in a similar way we described before (Lines 25 - 34). At the end of the algorithm we have estimations for $d^{td}_{i,j,t}$, $d^{yd}_{i,j,t}$ and $d^{bd}_{i,j,j',t}$.

The historical average yieldable demand is updated in a very similar way to the average historical bookings for the independent demand model. If for a booking class j it holds true that it was a) the last booking class $j^{-}_{i,m}$ in a compartment m and it was available or b) it was not the last booking class in a compartment m and both booking classes j and $j+1$ were available, then we assume that we observed the yieldable demand. This observation is then learned by using

Algorithm 3.2: Process to Unconstrain Dependent Demand

```
foreach t ∈ T do
    foreach i ∈ I do
        foreach m ∈ M_i do
            Estimate yieldable demand
            for j ← j^+_{i,m} to j^-_{i,m} do
                if (j = j^-_{i,m}) then
                    if ((a_{i,j,t} = 1) ∨ (b_{i,j,t} > h_{i,j,t})) then
                        d^{yd}_{i,j,t} = b_{i,j,t}
                    else
                        d^{yd}_{i,j,t} = h_{i,j,t}
                    d^{td}_{i,j,t} = d^{yd}_{i,j,t}
                else
                    if ((a_{i,j,t} = 1) ∧ (a_{i,(j+1),t} = 1)) then
                        d^{yd}_{i,j,t} = b_{i,j,t}
                    else
                        d^{yd}_{i,j,t} = h_{i,j,t}
            Estimate buy-down and total demand
            for j ← j^-_{i,m} - 1 downto j^+_{i,m} do
                d^{bd}_{i,j,(j+1),t} = d^{td}_{i,(j+1),t} * θ_{i,j,t}
                d^{td}_{i,j,t} = d^{bd}_{i,j,(j+1),t} + d^{yd}_{i,j,t}
                if d^{td}_{i,j,t} < b_{i,j,t} then
                    d^{bd}_{i,j,(j+1),t} = d^{bd}_{i,j,(j+1),t} + ω * (b_{i,j,t} - d^{td}_{i,j,t})
                    d^{td}_{i,j,t} = b_{i,j,t}
                    d^{yd}_{i,j,t} = d^{td}_{i,j,t} - d^{bd}_{i,j,(j+1),t}
            Enforce consistency to observed bookings
            for j ← j^+_{i,m} to j^-_{i,m} - 1 do
                if d^{td}_{i,(j+1),t} < d^{bd}_{i,j,(j+1),t} then
                    if (j + 1) < j^-_{i,m} then
                        d^{bd}_{i,(j+1),(j+2),t,s} =
                         d^{bd}_{i,(j+1),(j+2),t,s} + ω * (d^{bd}_{i,j,(j+1),t} - d^{td}_{i,(j+1),t})
                        d^{td}_{i,(j+1),t} = d^{bd}_{i,j,(j+1),t}
                        d^{yd}_{i,(j+1),t} = d^{td}_{i,(j+1),t} - d^{bd}_{i,(j+1),(j+2),t,s}
                    else
                        d^{td}_{i,(j+1),t} = d^{bd}_{i,j,(j+1),t}
                        d^{yd}_{i,(j+1),t} = d^{td}_{i,(j+1),t}
```

exponential smoothing. A formal definition is given in Equation 3.6.

$$h_{i,j,t,(s+1)} = \begin{cases} \alpha * b_{i,j,t,s} + (1-\alpha) * h_{i,j,t,s} & (j < j^{-}_{i,m} \wedge a_{i,j,t,s} = 1 \\ & \wedge a_{i,(j+1),t,s} = 1) \vee \\ & (j = j^{-}_{i,m} \wedge a_{i,j,t,s} = 1) \\ h_{i,j,t,s} & Otherwise \end{cases} \tag{3.6}$$
$$\forall i \in I, \forall j \in J_i, \forall t \in T$$

The process of forecasting is the same as with independent demand. Again we use exponential smoothing as depicted in Equations 3.7 - 3.9.

$$f^{td}_{i,j,t,(s+1)} = \alpha * d^{td}_{i,j,t,s} + (1-\alpha) * f^{td}_{i,j,t,s} \tag{3.7}$$
$$\forall i \in I, \forall j \in J_i, \forall t \in T$$
$$f^{yd}_{i,j,t,(s+1)} = \alpha * d^{yd}_{i,j,t,s} + (1-\alpha) * f^{yd}_{i,j,t,s} \tag{3.8}$$
$$\forall i \in I, \forall j \in J_i, \forall t \in T$$
$$f^{bd}_{i,j,j',t,(s+1)} = \alpha * d^{bd}_{i,j,j',t,s} + (1-\alpha) * f^{bd}_{i,j,j',t,s} \tag{3.9}$$
$$\forall i \in I, \forall j \in J_i, \forall t \in T$$

3.1.3. Optimization Models and Seat Inventory Control

Optimization with Independent Demand

In the optimization module, we use a bid price control, which uses shadow prices from a DLP and a decomposition approach to multiple leg problems in conjunction with DP to generate bid prices as described in Talluri and van Ryzin (see 2004b, Chapter 3.4.4). Based on the given forecasts bid prices $\pi_{l,m}$ are calculated for each compartment m on leg l. $\pi_{l,m}$ denotes the current valid bid price for one seat in compartment m and leg l. Usually airlines store bid price vectors containing values for each number of seats left. As in practice, the bid prices are recalculated at selected DCPs. In the inventory for each booking request the fare is evaluated against the sum of the current bid prices. If the fare is greater than the sum of the bid prices, the booking request is accepted, otherwise rejected. We have chosen this optimization approach because it is common in practical applications of network-based RM at airlines and thus supports us in assessing the ROM in a realistic environment.

Optimization with Dependent Demand

In case of dependent demand structures we will use a hybrid optimization approach as described by Fiig et al. (2010) and Walczak et al. (2010) with fare and demand transformation which is common in practical RM applications and nowadays becoming increasingly important for airlines. One advantageous feature of this approach is that it allows to further use the previously mentioned optimization model with independent demand because the dependent demand is transformed to an equivalent independent demand.

For the inventory two adjustments have to be performed. First, instead of comparing the bid prices against the original fare of a booking request, their sum is evaluated against the transformed fare. If the transformed fare is greater than the sum of the bid prices the booking request is accepted, otherwise rejected. And secondly, the booking request contains a range of booking classes in which the customer is willing to buy a ticket as described with the request generation. Thus, starting with the the lowest booking class j' all booking classes between j' and j are evaluated until the booking request is accepted or eventually rejected.

Applying Upgrading and Overbooking

In our simulation environment we also able to apply upgrading and overbooking. These two RM components play a crucial role at an airline to consider no-shows and cancelations. For these two components of RM many sophisticated methods have been described in literature and used in practice. Because we also apply different scenarios of the overbooking and upgrading controls, we have implemented simple methods.

If upgrading is applied in our simulation environment, we follow a basic approach presented by Pölt (2002). We determine an adjusted virtual capacity $cap^U_{l,m}$ for each compartment m on a leg l. The capacity $cap^U_{l,m}$ of a compartment m is increased if there is excess demand for compartment m and there is forecasted spare capacity in the next higher compartment $m-1$. If the capacity is adjusted according to this principle, $cap^U_{l,(m-1)}$ is decreased by the same number of seats. This ensures that the RM control does not offer more seats for a flight leg than actually available.

If overbooking is applied, the capacity of the compartments is virtually increased. A simple way in calculating the adjusted virtual capacity of a compartment is depicted in Equation 3.10 (see Talluri and van Ryzin, 2004b, Chapter 4.2.2 for details)

$$cap^O_{l,m} = round(\frac{cap_{l,m}}{q_{l,m}}) \qquad \forall l \in L, \forall m \in M_l \tag{3.10}$$

The capacity of each compartment m on a given leg l is divided by the estimated show-up rate $q_{l,m}$ for this compartment. The adjusted capacity $cap^O_{l,m}$ is rounded to an integer value, because the capacity of a compartment cannot take fractional values by definition. If both upgrading and overbooking are applied, the upgrading is performed first and afterwards the overbooking. Equation 3.11 changes the definition of $cap_{l,m}^{O,U}$ accordingly.

$$cap_{l,m}^{O,U} = round(\frac{cap_{l,m}^{U}}{q_{l,m}}) \qquad \forall l \in L, \forall m \in M_l \tag{3.11}$$

Virtually increasing the capacity of a compartment can lead to a situation, in which more bookings than the total capacity of the plane are accepted. This might in particular result in denied boardings. We discuss this matter in more detail in Chapter 7.

3.2. Measuring ROM Robustness

A key prerequisite for a ROM to present valid performance measures is that it reflects the general method of the RMS in place, e.g. network-based controls. Furthermore the question of robustness against errors in the input data is a main determinant for its validity. For this reason we present in this section a simulation-based approach to measure the robustness of a ROM. Although we focus on the application of this approach to airline RM, the approach can easily be applied to different industries and scenarios.

An operational RMS observes the actual bookings and estimates the unconstrained demand based on these bookings. The estimated unconstrained demand serves as the input to calculate ROM measures. Since the estimated unconstrained demand contains errors, there will be errors in the ROM measures as well. However, we do not know how severely the error in the estimated unconstrained demand affects the quality and validity of the ROM measures. To analyze this effect we take advantage of the previously defined simulation environment. Figure 3.3 illustrates the principle of our approach. In our simulation environment, we do not only have the actual bookings and thus the estimated unconstrained demand at hand, but also the real demand. This allows us to quantify the degree of error between estimated unconstrained and real demand, as well as the degree of similarity between the ROM measures that are calculated based upon this underlying estimated unconstrained and real demand. In such an environment, we are also able to incorporate further scenarios - for example different forecast error levels - and to simulate the implications they have on the similarity of the ROM measures. To decide whether or not to consider the ROM robust against input errors, we define two thresholds. One threshold is a *minimum level of similarity*, which defines the minimum degree of similarity

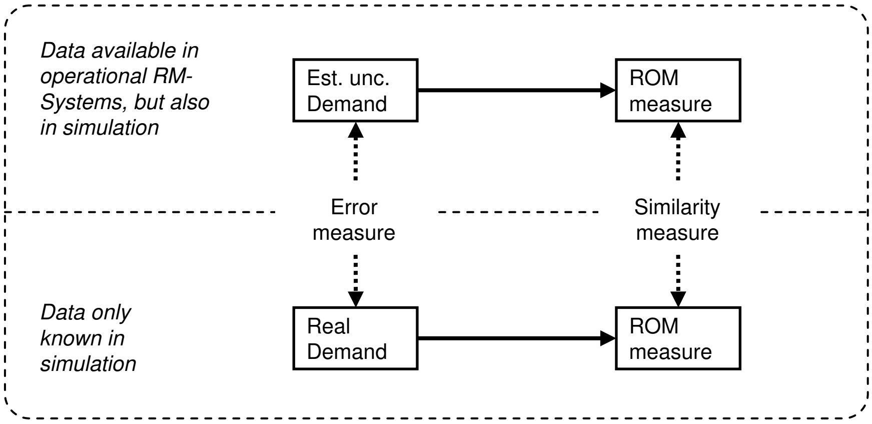

Figure 3.3.: Simulation-based Approach to Measure ROM Robustness

between the ROM measures that we consider sufficient to apply the ROM in real life applications. We also define a *maximum error level* in the estimated unconstrained demand based upon our worst case expectations in reality. By the use of sensitivity analysis we examine whether the similarity measures are above our threshold for given error levels up to the defined maximum error level and even beyond. If for all error levels applied up to the defined worst case expectations the similarity measures are above the required level, we consider the ROM robust against errors in the input data. Please note that the decision whether or not to consider the ROM robust heavily depends on the scenarios and the assumptions on the real world used in the simulation. In the next sections, we will give formal definitions of error and similarity measures.

3.2.1. Error Measures

Many methods and measures to quantify the error level between correct and estimated figures are available. Armstrong (2001) discusses several error measures in the area of forecasting in detail. In our approach, we use the *mean absolute error (MAE)* and the *percentage mean absolute error (PMAE)* as error measures. These measures are defined in Equations 3.12 and 3.13. The MAE^D defined in Equation 3.12 measures the average absolute error between the real demand and the estimated unconstrained demand. The definition makes use of the cumulated estimated unconstrained demand $D_{i,j}$ and real demand $R_{i,j}$ for itinerary i for booking class j up to the end of the booking period. In comparison to the MAE^D the $PMAE^D$ defined in Equation 3.13 determines the relative error level between the sum of absolute errors and the total real demand: The higher the error measures, the higher the error level for a certain scenario. These two measures are common in practical applications and thus we are able to define maximum error levels for different error scenarios by considering the worst case. We will come back to these error levels in Section 3.3.

$$MAE^D = \frac{\sum_{i\in I}\sum_{j\in J_i}|D_{i,j} - R_{i,j}|}{\sum_{i\in I}|J_i|} \tag{3.12}$$

$$PMAE^D = \frac{\sum_{i\in I}\sum_{j\in J_i}|D_{i,j} - R_{i,j}|}{\sum_{i\in I}\sum_{j\in J_i}R_{i,j}} \tag{3.13}$$

With dependent demand we do not only have to consider yieldable demand, but also buy-down and the resulting total demand. In our simulation environment we are able to measure the unconstraining or forecast error for all demand components, because we know them from the demand generation. This is of course not possible in reality, but in our simulation environment it helps us, to perform different kinds of sensitivity analysis. The formulas to determine the error measures on total demand, yieldable demand and buy-down are the same as presented in Equations 3.12 and 3.13. The only change is using the respective real and estimated unconstrained demand figures (i.e. $D^{td}_{i,j}$, $R^{td}_{i,j}$, $D^{yd}_{i,j}$, $R^{yd}_{i,j}$, $D^{bd}_{i,j}$ and $R^{bd}_{i,j}$).

3.2.2. Similarity Measures

The proposed simulation environment generates pairs of ROM measures for each run, one ROM measure calculated based on real demand and one calculated based on the estimated unconstrained demand. These ROM measures include values not only for the potential and no RM revenue, but also for the RO, the ARO and the PARO. In our definition of similarity measures, we use the PARO as one example. However, the similarity measures are easily applicable to the other ROM measures. In the following, $PARO^R$ denotes the PARO calculated with the real demand and $PARO^D$ denotes the PARO calculated with the estimated unconstrained demand. We illustrate our definitions with an example in Figures 3.4 and 3.5, in which we compare $PARO^R$ and $PARO^D$ out of 20 simulated flight departures per run and in a scatter plot.

In case of perfect similarity, we would observe $PARO^R = PARO^D$ for all runs. However, this will rarely be the case in reality and is not the case in our example. To measure the degree of similarity, we propose a combination of quantitative measures and a visual inspection of the scatter plot. The first measure we propose is the mean absolute error between $PARO^R$ and $PARO^D$. A low MAE^{PARO} implies a high similarity between $PARO^R$ and $PARO^D$. For example, if MAE^{PARO}

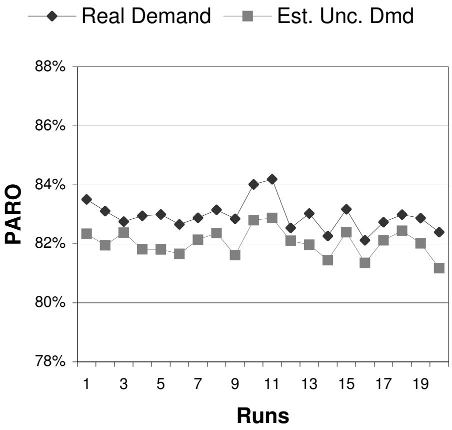

Figure 3.4.: Comparing PAROs per Run

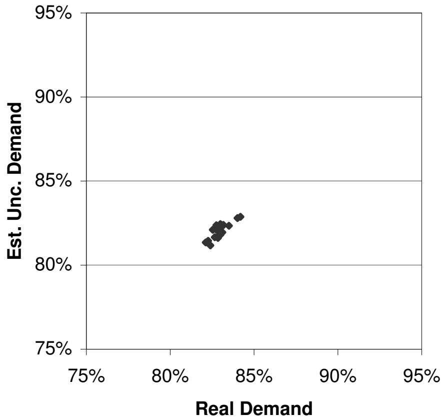

Figure 3.5.: Comparing PAROs in a Scatter Plot

is zero then all pairs are identical and we observe perfect similarity. In practice all values for MAE^{PARO} below 5% indicate a very high similarity. In cases in which MAE^{PARO} does not indicate a high degree of similarity we could still be able to observe a linear relation between $PARO^R$ and $PARO^D$, for example because of a biased over- or underestimation of $PARO^D$. In this case, there could be a high degree of similarity, which cannot be measured with the MAE^{PARO} as the MAE^{PARO} will by definition increase with the level of bias in this case. By a visual inspection of the scatter plot, we would be able to observe this linear relation. If there still exists a linear relation values of MAE^{PARO} up to 15% are considered sufficient to indicate a high degree of similarity. To quantify the linear relation between $PARO^R$ and $PARO^D$ and to introduce the second measure for similarity we propose the Pearson's correlation coefficient and denote it with r^{PARO}. Pearson's correlation coefficient is a basic measure of linear relations between two paired sets of values. Values of r^{PARO} range between -1 and 1 and values greater than 0.5 indicate a good linear correlation. In those cases in which the MAE^{PARO} does not indicate a good similarity but in which there is a good linear relation between $PARO^R$ and $PARO^D$, Pearson's r^{PARO} helps us to quantify the quality of this linear relation. As a conclusion, we propose to use the MAE^{PARO}, the Pearson's correlation coefficient r^{PARO} in combination with a visual inspection of the scatter plot to determine the level of similarity. For the MAE^{PARO} we define 5% - 15% as the minimum level of similarity depending on the values for r^{PARO}. We consider 0.5 as the lower bound for r^{PARO}. In our example, MAE^{PARO} is 0.9% and r^{PARO} is 0.83. These values indicate a high level of similarity.

3.3. The Simulation Scenarios

To measure the robustness of the ROM as described in the previous section and to investigate further properties of the ROM we apply different scenarios. Besides simulating various unconstraining errors, the scenarios include the possibility to adjust the forecast errors, to apply different kinds of seasonality to the customer demand, to adjust the bid prices to simulate open or restrictive RM controls and to adjust the overbooking and upgrading controls. All scenarios are performed ceteris paribus. Besides the module, in which an adjustment is applied, all other modules work under normal conditions. A detailed description of the scenarios is given in the following sections.

3.3.1. The Base Case

The starting point of all of our investigations is a base case that reflects the reality of a large network carrier in the most realistic way possible. We consider nine booking classes (two business and seven economy classes). The flight network consists of 728 continental and intercontinental flights and includes 1,605 different itineraries which are taken from a realistic flight network. The demand level applied leads to an average SLF of around 75%, which varies according to an observed seasonality in reality by around 10% over time. The share of connecting passengers is around 30%. On continental flights, the capacity can be flexibly distributed between business and economy class bookings. The fares and capacities are kept constant within a simulated booking period. We simulate one network day for each scenario. The number of total runs for each scenario is 180, out of which 150 runs are used for the analyses. 30 preliminary runs in a start-up phase are not considered in the final evaluation. If dependent demand is applied we assume 30% as an average sell-up rate. If no-shows are applied, an average no-show rate of around 6% is assumed as observed in reality. The smoothing factor α is set to 15%.

For some analyses we change the structure of our realistic flight network and set the share of connecting passengers to 0%. We keep the demand level on the flight legs constant compared to the base case defined on the realistic flight network. We refer to this network as the *no-connecting-traffic flight network*.

3.3.2. Adjusting the Unconstraining Error

One main focus of this thesis is to assess the robustness of the ROM against errors in the estimated unconstrained demand. Therefore we apply various unconstraining error scenarios and measure the effect on the ROM measures. In this section we describe how we adjust the unconstraining error based on the base case. All of the following approaches have in common, that they influence the forecast of the next simulation run and thus the results of the optimization module. These feedback loops are well-known in reality; a special case was described with the spiral-down effect.

Independent Demand

For the unconstraining error we assume that we only apply errors in those time periods in which the booking classes were closed. Furthermore Proposition 3.1.1 still holds. Equation 3.14 depicts the adjusted principle.

$$d_{i,j,t} = \begin{cases} b_{i,j,t} & a_{i,j,t} = 1 \\ max((1 \pm \epsilon_{i,j,t})h_{i,j,t}; b_{i,j,t}) & a_{i,j,t} = 0 \end{cases} \quad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{3.14}$$

$\epsilon_{i,j,t}$ describes a random error factor from a uniform distributed interval $[\epsilon^l - \epsilon^d..\epsilon^l + \epsilon^d]$. ϵ^l describes the average error level and ϵ^d the error deviation. In our simulation setup, we are able to apply a biased overestimation, a biased underestimation and an unbiased error for the unconstrained demand in the case of a closed booking class. If we apply a biased overestimation the value of $\epsilon_{i,j,t}$ always increases the estimated unconstrained demand. The contrary is true for a biased underestimation. When using the unbiased error the estimated unconstrained demand is randomly increased or decreased with the same probability. In our scenarios we set ϵ^d to 10% and apply three different error levels ϵ^l: 30%, 60% and 90%. Based on observations in practice[1] we define the 60% error level to be the worst case in reality. Furthermore we expect the unbiased unconstraining error to be more common because a strong bias into one direction is usually prevented by the forecasting modules in an operational RMS.

Dependent Demand

The application of additional error to the estimated unconstrained demand and the forecast is done in a similar way with dependent demand structures. As a first

[1] Based on information discussed in personal communication with Dr. Pölt - Lufthansa German Airlines

step we estimate the unconstrained demand using Algorithm 3.2. Afterwards we apply an error to the yieldable demand or the buy-down in a two-stepped approach. First, the demand estimates are adjusted. The yieldable demand is adjusted according to Equation 3.15 and the buy-down is adjusted in correspondence to Equation 3.16.

$$
\begin{aligned}
d^{yd}_{i,j,t} &= \begin{cases} d^{yd}_{i,j,t} & (j < j^{-}_{i,m} \wedge a_{i,j,t,s} = 1 \\ & \wedge a_{i,(j+1),t,s} = 1) \vee \\ & (j = j^{-}_{i,m} \wedge a_{i,j,t,s} = 1) \\ (1 \pm \epsilon_{i,j,t}) * d^{yd}_{i,j,t} & Otherwise \end{cases} \qquad (3.15) \\
& \quad \forall i \in I, \forall j \in J_i, \forall t \in T \\
d^{bd}_{i,j,j',t} &= (1 \pm \epsilon_{i,j,t}) * d^{bd}_{i,j,j',t} \qquad (3.16) \\
& \quad \forall i \in I, \forall j \in J_i, \forall t \in T
\end{aligned}
$$

The definition of $\epsilon_{i,j,t}$, ϵ^l and ϵ^d is the same as in the independent demand case. The main difference between the error for the yieldable demand and for the buy-down is, that in the buy-down case the error is applied for every booking class, whereas for the yieldable demand it is only applied, if for a booking class j it holds true that it was a) the last booking class $j^{-}_{i,m}$ in a compartment m and it was available or b) it was not the last booking class in a compartment m and both booking classes j and $j+1$ were available. After adjusting the yieldable demand and buy-down in the described way, the total demand is preliminary set to $d^{td}_{i,j,t} = d^{yd}_{i,j,t} + d^{bd}_{i,j,j',t}$. Afterwards the consistency check of Algorithm 3.2 in Lines 25 - 34 is performed to enforce Proposition 3.1.2. The applied scenarios are like with independent demand a biased overestimation, a biased underestimation and an unbiased error for either the unconstrained yieldable demand or the unconstrained buy-down. The error levels ϵ^l remain the same with 30%, 60% and 90% and the same worst case assumption.

3.3.3. Further Scenarios

Besides analyzing the robustness of the ROM with the help of sensitivity analyses with different error scenarios in the estimated unconstrained demand, we apply further scenarios to assess the properties of the ROM.

Adjusting the Forecast Error

The application of an additional forecast error increases the effect of a simulated unconstraining error. By increasing the forecast error we expect that the quality of the RM control will decrease further and in particular we expect that it will decrease stronger than in the unconstraining error scenario. The adjustment of the forecast error with independent demand follows the same principle as the modification of the unconstrained demand. The only difference is that we do not consider whether the booking classes were available or not, but apply the additional error in all cases. With dependent demand the only change is that the error for the yieldable demand is applied to every booking class, no matter if the booking class was available or not. For the forecast error we also apply a biased overestimation, a biased underestimation and an unbiased error with error levels ϵ^l of 30%, 60% and 90%.

Adjusting the Seasonality of Customer Demand

As described in Section 3.1.1 we are able to apply seasonality to the demand generation. In Section 3.3.1 we explained which kind of seasonality we assume for the base case scenario. Beyond that we apply a seasonality with less or stronger deviation in customer demand. Another kind of seasonality that we apply is a demand deviation that follows a saw tooth curve. Within five simulation runs we decrease the demand level from 130% to 70% and jump back to 130%. Another saw tooth curve scenario describes a decrease from 120% to 80% demand level within five simulation runs. The adjustment of the seasonality aims at assessing the effect of different kinds of seasonality on the robustness of the ROM. Moreover we want to assess how the overall RM control is affected by different kinds of seasonality.

Adjusting the Bid Prices

In addition, it is possible to influence the RM control to be either more open or more restrictive. In the scenario for the less restrictive RM control, we decrease the bid prices $\pi_{l,m}$ from the optimization module by a certain percentage β. For more restrictive control, we increase the bid prices respectively. Equation 3.17 provides a formal definition of the modification of the bid prices.

$$\tilde{\pi}_{l,m} = (1 \pm \beta) * \pi_{l,m} \qquad \forall l \in L, m \in M_l \tag{3.17}$$

As we are not applying any additional error to the estimated unconstrained demand or the forecasted demand we expect to observe effects in the overall RM success, but no significant effects on the robustness of the ROM.

Adjusting the Overbooking and Upgrading Levels

As part of the scenarios in which we applied overbooking we are also able to adjust the overbooking level. Equation 3.18 shows the formal definition of the modification. Basically we apply an adjustment level β to the overbooking level obtained from the overbooking control. We are able to increase and to decrease $cap^{O}_{l,m}$.

$$cap^{O}_{l,m} = round((1 \pm \beta) * cap^{O}_{l,m}) \qquad \forall l \in L, m \in M_l \tag{3.18}$$

In the scenario presented before we only considered overbooking in the RM simulation. If the RM control considers only upgrading, the virtual capacity of the compartments $cap^{U}_{l,m}$ is adjusted according to Equation 3.19. In case both upgrading and overbooking are applied Equation 3.20 is to be used to modify $cap^{O,U}_{l,m}$.

$$cap^{U}_{l,m} = round((1 \pm \beta) * cap^{U}_{l,m}) \qquad \forall l \in L, m \in M_l \tag{3.19}$$
$$cap^{O,U}_{l,m} = round((1 \pm \beta) * cap^{O,U}_{l,m}) \qquad \forall l \in L, m \in M_l \tag{3.20}$$

3.4. Summary

In this chapter we described a novel simulation-based approach to investigate ROM properties. The simulation environment makes use of state-of-the-art demand modeling and optimization methods for both independent and dependent demand structures in a network-based RM context. They are similar to those methods applied at large network carriers. Common RM components in practice such as overbooking and upgrading are also incorporated. In addition we calibrated the input data to reflect the reality of a network carrier as well as possible. The simulation environment furthermore allows us to perform sensitivity analyses on the robustness of the ROM by adjusting the unconstraining error in different ways. With our simulation environment we are also able to assess many other additional scenarios and the subsequent effect of these scenarios on the ROM. This enables us to apply a holistic simulation-based assessment of the network-based ROM.

4. The Network-based ROM with Independent Demand

In this chapter we focus on the network-based ROM with independent demand. We describe the estimation of the potential, actual and no RM revenue in detail. Furthermore we highlight some main properties of the network-based ROM with independent demand with a special focus on model- and data-related errors. We put a main emphasis on investigating the robustness of the ROM against errors in the estimated unconstrained demand. Therefore we present and analyze computational results on the effect of different (error) scenarios on the validity and robustness of the network-based ROM.

4.1. Model Definition

The basic idea of a network-based ROM was described in detail by Chandler and Ja (2007). We follow their approach and define the potential, the actual and the no RM revenue used in the ROM according to their proposal. The potential revenue is calculated by solving a DLP. As described in Section 1.3.2 this *linear program (LP)* does not take into account any stochasticity and simply maximizes the potential revenue for the past booking period under the given constraints of the model. In this chapter we do not consider any no-shows or cancelations of passengers. As a consequence overbooking or upgrading are also not applied. However, we extend the described model to no-shows, cancelations and the application of overbooking and upgrading by some modifications to the demand inputs and the LP formulation in Chapter 7.

$$Max \sum_{i \in I} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,t} * x^{+}_{i,j,t} \tag{4.1}$$

$$\sum_{i \in I_l} \sum_{j \in J_{i,l,m}} \sum_{t \in T} x^{+}_{i,j,t} \leq cap_{l,m} \qquad \forall l \in L, \forall m \in M_l \tag{4.2}$$

$$0 \leq x^{+}_{i,j,t} \leq d_{i,j,t} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{4.3}$$

The objective function 4.1 maximizes the revenue as the sum of fare $p_{i,j,t}$ times accepted bookings $x^{+}_{i,j,t}$ over all itineraries $i \in I$ with booking class $j \in J_i$ in time period $t \in T$. Constraint 4.2 ensures that the capacities of the compartments are not exceeded. $J_{i,l,m}$ denotes the set of all booking classes j that are booked into compartment m of flight leg l. Finally, Constraint 4.3 ensures that the number of accepted bookings is bound by the estimated unconstrained demand. The potential revenue Rev^+ corresponds to the solution of the objective function. Rev^+ can also be deducted by taking the solution of the $x^+_{i,j,t}$ variables applied to Equation 4.4.

$$Rev^+ = \sum_{i \in I} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,t} * x^+_{i,j,t} \tag{4.4}$$

To estimate the no RM revenue, we simulate a FCFS strategy over the booking period for each itinerary. The estimated unconstrained demand $d_{i,j,t}$ is available as curves over $|T|$ time periods within the booking period, which are defined by $|T|+1$ DCPs. As we do not have any information on the booking order between two DCPs, we assume that booking requests arrive in a LBH order within each single time period t defined by two subsequent DCPs. Thus, we first sort all booking requests for an itinerary i in booking class j by their fare ascending within each single time period t defined by two DCPs and store them in $\mathbb{P}_t$. Then, starting with the first time period in the booking period, all booking requests that still fit into the given capacity of the associated planes are accommodated. Algorithm 4.1 describes the process to estimate the no RM revenue in detail. First, the free capacity $cap^f_{l,m}$ of all compartments is set to the capacity of the compartments $cap_{l,m}$. Then for each booking request the number of seats left sl are determined and the remaining capacity is adjusted. After the algorithm has been applied the estimations for the bookings are used to determine Rev^-, which is formally defined in Equation 4.5.

$$Rev^- = \sum_{i \in I} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,t} * x^-_{i,j,t} \tag{4.5}$$

As we do not assume any no-shows or cancelations, the actual revenue is calculated as the sum of all accepted bookings $b_{i,j,t}$ times their fares $p_{i,j,t}$. This information is available in the inventory system. Rev is formally defined in Equation 4.6.

$$Rev = \sum_{i \in I} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,t} * b_{i,j,t} \tag{4.6}$$

Based on the calculated values for the potential, the actual and the no RM revenue, the other ROM measures are deducted. According to the definition in

Algorithm 4.1: Estimation of No RM Revenue

Input: $\mathbb{P}_t \ \forall t \in T$

foreach $l \in L$ **do**
    foreach $m \in M_l$ **do**
        $cap^f_{l,m} = cap_{l,m}$

for $t = 1$ **to** $|T|$ **do**
    foreach $(i, j) \in \mathbb{P}_t$ **do**
        Determine seats left
        $sl = \infty$
        foreach $l \in L_i$ **do**
            $sl = min(sl, cap^f_{l,m_{l,j}})$
        Take seats
        $x^-_{i,j,t} = x^-_{i,j,t} + min(sl, d_{i,j,t})$
        foreach $l \in L_i$ **do**
            $cap^f_{l,m_{l,j}} = cap^f_{l,m_{l,j}} - min(sl, d_{i,j,t})$

Section 1.3.1 we define RO, ARO and $PARO$ formally in Equations 4.7, 4.8 and 4.9.

$$RO = Rev^+ - Rev^- \tag{4.7}$$

$$ARO = Rev - Rev^- \tag{4.8}$$

$$PARO = \frac{ARO}{RO} \tag{4.9}$$

4.2. Main Properties of Network-based ROM with Independent Demand

By definition the network-based ROM with independent demand isolates the RM contribution from the overall success. The estimated unconstrained demand is the key input data to determine the potential and the no RM revenue and thus the ROM measures consider demand deviations.

Moreover, without the application of any enhancements or further analyses the network-based ROM with independent demand generates only one aggregated set of measures for the entire flight network for each booking period considered. This means that we obtain one estimate of the potential and the no RM revenue and derive from that the RO, the ARO and the PARO. It is unlikely, that we observe the special cases mentioned in Section 1.3.2, i.e. that the RO is zero or the ARO is negative.

A main focus in this chapter is on the validity of the ROM measures. The validity is strongly driven by data-related errors, i.e. the accuracy of the estimated unconstrained demand used in the revenue estimations. We analyze the robustness against errors in the input data in detail in the following section. Our definition of the network-based ROM with independent demand also incurs model-related errors. As already described in Section 1.3.2 model-related errors denote errors in the ROM measures caused by incorrect modeling of the reality in the revenue estimations. One source of errors is the LP-relaxation. Bookings in reality are integer. This means that the number of bookings never takes fractional values. However, we have defined the potential revenue estimation as an LP, which relaxes the integer constraint. Besides reasons of solvability, this is mainly due to the fact that demand estimations are representing mean demand values, which in most cases are fractional. These values cannot simply be rounded or transformed into integer demand. An example of how the LP-relaxation leads to different results is depicted in Figure 4.1. Let us assume we have a flight net-

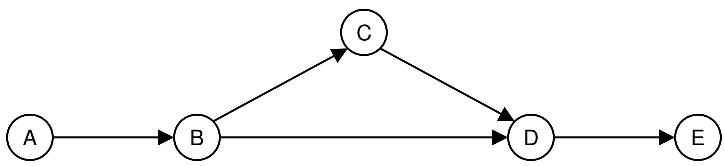

Figure 4.1.: Effect of LP-relaxation on Potential Revenue Estimate

work which consists of 5 flight legs AB, BC, BD, CD, and DE each with a capacity of one. The itineraries offered to the customers are ABCD, ABDE, and BCDE. If we assume a demand for each itinerary of one and a fare of 500, the optimal integer solution is 500, because only one itinerary can be sold to customers. The solution of the LP is 750 (each itinerary is taken 0.5 times). This is of course an extreme case to illustrate that there might be deviations between the IP and LP solution. In our simulations however, we observed no differences between the IP and LP solutions and expect the effect of the LP-relaxation to be very minor on a large network.

Another main source of model-related errors is the assumed booking order. One main assumption that is usually made for the no RM revenue is the LBH booking order. This assumption was also one key assumption at the beginning of RM research. In a leg-based ROM this would automatically lead to a decreased revenue estimate. For a network-based ROM however, this is not always the case. In Table 4.1 we describe an example with three different booking orders and the effect on the no RM revenue estimates. We assume that we have a very simple

		Booking order					
Itinerary	Fare	LBH	Revenue	Real 1	Revenue	Real 2	Revenue
AB-1	100	AB-2	50	AC-2	505	BC-1	1,000
AB-2	50	AB-1	rejected	AC-1	rejected	AB-1	100
BC-1	1000	BC-2	500	BC-2	rejected	BC-2	rejected
BC-2	500	AC-2	rejected	AB-1	rejected	AC-1	rejected
AC-1	1010	BC-1	rejected	AB-2	rejected	AC-2	rejected
AC-2	505	AC-1	rejected	BC-1	rejected	AB-2	rejected
		Sum	550	Sum	505	Sum	1,100

Table 4.1.: No RM Revenue Depending on Booking Order

network with destinations A, B and C. The available itineraries are AB, BC and AC, which means there are two local itineraries and one connecting itinerary. If we now suppose that the capacity on each flight (AB and BC) is limited to one, we could observe very different estimations for the no RM revenue. If we apply a LBH booking order - which is indicated in column 'LBH' - the request for 'AB-2' comes first, followed by 'AB-1' and so forth. The request for 'AB-2' will be accepted, the request for 'AB-1' rejected and finally the request for 'BC-1' accepted. All other remaining booking requests have to be rejected due to the capacity constraints. Both accepted requests lead to a total revenue of 550. If the real booking order is as presented in column 'Real 1', then the no RM revenue is different. The request for 'AC-2' will be accepted and all other requests rejected. This only leads to a total revenue of 505. If we apply the booking order 'Real 2', the total demand goes up to 1,100. As we can see, the total revenue according to a given order can be higher or lower than the total revenue estimated with a LBH booking order. However, this is an extreme example. Most likely the correct total revenue will be higher than the total revenue estimated with the LBH assumption. This effect decreases significantly if the whole booking period is split into multiple time periods. Usually airlines divide their booking periods in 20-25 time periods. Theoretically this model-related effect completely disappears if we divide the booking period in so many time periods that in each time period only one booking occurs. In the following section we compare the influence of the main model-related errors with the data-related errors in the ROM.

4.3. Computational Results

In this section, we investigate the properties and in particular the robustness of the network-based ROM with independent demand. We start with a comparison of the effect of model- and data-related errors, followed by a detailed inspection of the main data-related error, i.e. errors in the estimated unconstrained demand. We also assess the effect of other relevant scenarios on the validity and the results of the ROM. For each scenario we apply 180 simulation runs out of which we discard the first 30 runs. The base case as defined in Section 3.3.1 serves as the starting point of our analysis. Based on the base case we derive all further scenarios.

4.3.1. Comparing Model- vs. Data-related Errors

In Section 4.2 we discussed one main model-related source of errors in the ROM. We described the effect of a wrong assumption on the booking order on the no RM revenue. In this section, we present a detailed analysis to compare the magnitude of this effect against the effect of the data-related errors, i.e. the errors in the estimated unconstrained demand. We make use of the simulation-based environment to investigate ROM properties. In particular we examine the base case introduced in Section 3.3.1 and the scenarios to simulate unconstraining errors introduced in Section 3.3.2. In our simulation environment we are not only able to adjust and measure unconstraining errors, but we are also able to utilize the single booking requests generated in the request generator (see also Section 3.1.1 for further details). This allows us to determine the no RM revenue using the correct booking order. In our flight network the correct no RM revenue based on a real FCFS booking order is on average 39.3 million. If we use the aggregated real demand in conjunction with Algorithm 4.1 presented in Section 4.1, we obtain a slightly smaller average no RM revenue of 39.0 million. We observe that the gap between the two no RM revenues with real demand is marginal with 0.3 million or 0.8%.

In a second analysis, we investigate the effect of errors in the unconstrained demand on the no RM revenue estimation derived with Algorithm 4.1 compared to the average no RM revenue obtained with real demand ($\overline{Rev}^{-,R}$). Detailed results can be found in Table 4.2. In the first two rows we describe the different error scenarios and the error level. We start with the base case in the second column and continue with the three main error scenarios: An error with a biased underestimation, an error with a biased overestimation and an unbiased error of the estimated unconstrained demand. For all error scenarios, we apply error

	Base	Biased			Biased					
	Case	underestimation			overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
Deviation to $\overline{Rev}^{-,R}$ (million)	0.0	0.8	1.8	2.7	-0.8	-1.4	-2.0	-0.1	-0.1	-0.1
Deviation to $\overline{Rev}^{-,R}$ (%)	-0.1	2.1	4.5	7.0	-2.1	-3.7	-5.1	-0.2	-0.2	-0.3

Table 4.2.: Deviations in No RM Revenue Estimates Caused by Errors in Unconstrained Demand

levels of 30%, 60% and 90%, out of which we assume 60% to be the worst case as already described in Chapter 3. In the third row the absolute deviations between the average no RM revenue obtained with the corresponding estimated unconstrained demand using the simulated FCFS-strategy are listed. The relative deviations are presented in the subsequent row. We observe that with the base case - which already contains unconstraining errors as defined before - and the unbiased unconstraining errors the deviations are lower than the deviation caused by the model-related error. However, the deviations are by far higher with a biased over- or underestimation of the estimated unconstrained demand.

We conclude that the model-related error induced by an incorrect assumption on the booking order has a minor effect on the validity of the no RM revenue estimate. On average the errors induced by incorrect estimations of the unconstrained demand are significantly higher. In the remainder of this thesis, we will focus on the analysis of the effect of errors in the estimated unconstrained demand. Thus, we use the no RM revenue estimate for real demand obtained with the simulated FCFS algorithm to avoid overlapping error effects. Furthermore, in practice the correct booking order is unknown and an assumption in the ROM has to be made that leads to reasonable results.

4.3.2. Analyzing the Effect of Unconstraining Errors

In this section, we analyze the main data-related error in the ROM. We investigate the effect of different unconstraining errors on the validity of the ROM and determine its robustness. We analyze the general average effect of the different unconstraining error scenarios on the potential and no RM revenue estimates and furthermore the resulting effect on the two derived absolute ROM measures RO and ARO. Afterwards we focus on the PARO and in particular assess its robustness against errors in the input data.

The first analysis we conduct is comparing the estimations of the potential and the no RM revenue between the different scenarios already introduced in the previous section. Figure 4.2 compares the potential and no RM revenue estimates for the base case and the nine unconstraining error scenarios. The error scenarios

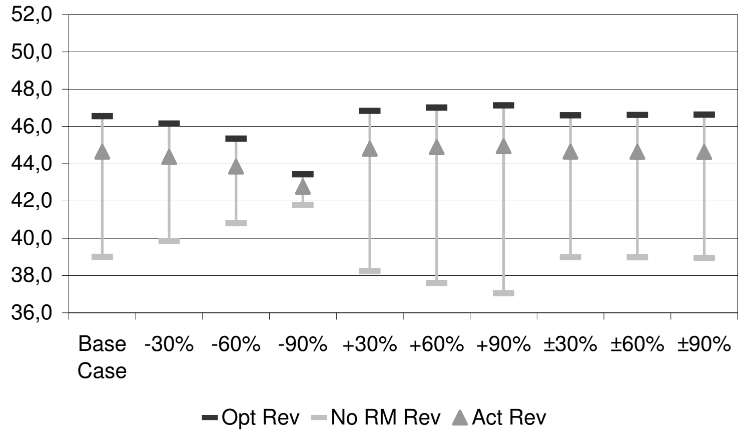

Figure 4.2.: Effect of Unconstraining Errors on the Potential and No RM Revenue

of a biased underestimation are marked with a minus (e.g. -30%), the error scenarios of a biased overestimation with a plus (e.g. $+30\%$) and the unbiased unconstraining error scenarios are marked with a plus/minus sign (e.g. $\pm30\%$). We observe that for an unbiased error the effect on the revenue estimates is minor. Both the estimates of the potential and the no RM revenue remain more or less constant. However, if we overestimate the unconstrained demand the potential revenue increases and the no RM revenue decreases. An underestimation of the unconstrained demand leads to contrary results. The potential revenue estimate decreases and the no RM revenue estimate increases. We also observe that the RO as the difference between potential and no RM revenue deviates to a significant degree from the base case scenario if a biased under- or overestimation of the unconstrained demand is given. The effect on the potential revenue, the no RM revenue and subsequently on the RO and the ARO is examined in detail in Table 4.3. In the first three data rows the table shows the average potential revenue for both real ($\overline{Rev}^{+,R}$) and estimated unconstrained demand ($\overline{Rev}^{+,D}$) and the difference between them. The average actual revenue $\overline{Rev}$ is listed in the fourth data row. The subsequent data rows present the average no RM revenue, the average ARO and the average RO calculated with the real demand and the estimated unconstrained demand ($\overline{Rev}^{-,R}$, $\overline{ARO}^{R}$ and $\overline{RO}^{R}$) and with estimated

	Base	Biased			Biased					
	Case	underestimation			overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{Rev}^{+,R}$ (million)	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5
$\overline{Rev}^{+,D}$ (million)	46.6	46.2	45.3	43.4	46.8	47.0	47.1	46.6	46.6	46.6
Diff. (million)	-0.1	0.3	1.2	3.1	-0.3	-0.5	-0.6	-0.1	-0.1	-0.1
$\overline{Rev}$ (million)	44.6	44.4	43.8	42.8	44.8	44.9	44.9	44.6	44.6	44.6
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.0	39.8	40.8	41.8	38.2	37.6	37.1	39.0	39.0	38.9
Diff. (million)	0.0	-0.8	-1.8	-2.8	0.8	1.4	1.9	0.0	0.0	0.1
$\overline{ARO}^{R}$ (million)	5.6	5.3	4.8	3.7	5.8	5.8	5.9	5.6	5.6	5.6
$\overline{ARO}^{D}$ (million)	5.6	4.5	3.0	1.0	6.6	7.3	7.9	5.7	5.7	5.7
Diff. (million)	0.0	0.8	1.8	2.7	-0.8	-1.5	-2.0	-0.1	-0.1	-0.1
$\overline{RO}^{R}$ (million)	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5
$\overline{RO}^{D}$ (million)	7.5	6.3	4.5	1.6	8.6	9.4	10.1	7.6	7.6	7.7
Diff. (million)	0.0	1.2	3.0	5.9	-1.1	-1.9	-2.6	-0.1	-0.1	-0.2

Table 4.3.: Effect of Errors in the Unconstrained Demand on RO and ARO

unconstrained demand ($\overline{Rev}^{-,D}$, $\overline{ARO}^{D}$ and $\overline{RO}^{D}$) and the respective differences. The error scenarios are still the same. Besides assessing the base case we again investigate the three main unconstraining error scenarios. As already indicated in Figure 4.2 the average RO remains constant with an unbiased unconstraining error. It increases with a biased overestimation and strongly decreases with a biased underestimation. This is in particular due to the effect that a strong biased underestimation leads to an estimated total demand which is only slightly above the total number of bookings. Additionally, we observe that the ARO mainly shows the same characteristics as the RO. However, we furthermore conclude that the ARO can be used to justify the application of a RMS. For all error scenarios up to the expected worst case of 60%, the average ARO is pretty stable. In particular the values for the unbiased unconstraining error are very stable, which is the most likely scenario of an unconstraining error in reality. Thus, an indication of the absolute revenue contribution of the RM controls applied at an airline can be given by the ARO.

After having assessed the basic average effects of the different unconstraining errors on the revenue estimates and the absolute ROM measures, in the following we investigate the robustness of the PARO in detail. We analyze the base case scenario and additionally the unconstraining error scenarios as already introduced before. In the base case, we compare the $PARO^R$ with the $PARO^D$, which is derived from the unconstraining module without applying any additional error in this case. In the scatter plot presented in Figure 4.3, each dot represents a pair of PARO values generated in a single simulation run. For the x-value, we

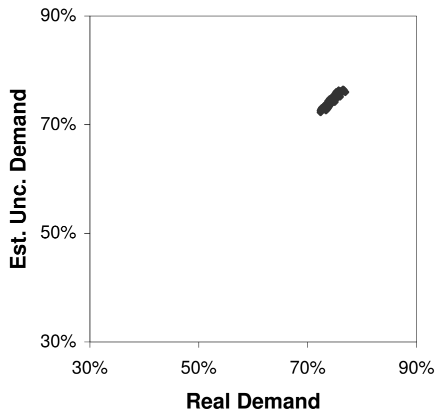

Figure 4.3.: Base Case with Independent Demand

take the $PARO^R$ values and for the y-value, we take the $PARO^D$ values. As the PAROs range from 30% to 90% for most of the scenarios analyzed, we only use this scale in the graphs to improve visibility and comparability. In case that the PARO values are not within this graphs we adjust the range accordingly and point to the adjustment. In Table 4.4, we list the key metrics of the base case and the error scenarios on the unconstrained demand. The columns are the

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	74.7	71.0	64.1	49.6	76.8	78.0	78.7	74.8	74.6	74.5
$\overline{PARO}^D$ (%)	74.7	71.6	66.9	59.4	76.3	77.4	78.2	74.4	74.0	73.9
$\overline{MAE}^{PARO}$ (%)	0.3	0.6	2.8	9.8	0.5	0.6	0.6	0.4	0.6	0.7
r^{PARO}	0.94	0.87	0.75	0.64	0.97	0.97	0.96	0.94	0.90	0.86
$\overline{R}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{D}$ (thousand)	87.2	79.8	72.6	65.4	95.1	102.9	110.7	87.5	87.8	88.2
$\overline{MAE}^D$	0.56	0.73	1.11	1.55	0.76	1.17	1.66	0.75	1.15	1.62
$\overline{PMAE}^D$ (%)	9.3	12.0	18.2	25.6	12.6	19.4	27.5	12.3	18.9	26.8

Table 4.4.: Effect of Unconstraining Errors on PARO

same as listed in the previous tables. The results for the base case are presented in column two. In the first two data rows we present the average values for the PAROs calculated with real and estimated unconstrained demand in the following denoted with $\overline{PARO}^R$ and $\overline{PARO}^D$. According to these underlying PARO values, the two subsequent data rows show the values for the derived similarity measures $\overline{MAE}^{PARO}$ and r^{PARO}. The average total real demand $\overline{R}$ and the average total estimated unconstrained demand $\overline{D}$ are shown in data rows five and six. The values of the error measures $\overline{MAE}^D$ and $\overline{PMAE}^D$, which were derived by comparing the total real and the estimated unconstrained demand for each itinerary are presented in the last two data rows. For the following unconstraining error scenarios, we present the results using similar scatter plots and tables. For the base case, the $\overline{MAE}^{PARO}$ is very low with 0.3%. By inspecting the scatter plot, we are also able to observe a very strong linear relation between $\overline{PARO}^R$ and $\overline{PARO}^D$. This visual observation is supported by a high value of the correlation coefficient $r^{PARO} = 0.94$. The levels of total demand are very similar, and, for the error measures, we observe $\overline{MAE}^D = 0.56$ and $\overline{PMAE}^D =$ 9.3%. The values for the error measures seem to be low compared to error levels we normally observe for forecasts in real-life applications. This is because of the fact that for unconstraining we only have to estimate the demand for those time periods in which the booking classes were closed. In this and also in the following scenarios, this was the case in about 20% of the time periods, which is comparable to what we observe in reality. This circumstance reduces the error potential of the unconstraining significantly. Overall, we observe similarity measures indicating a very high similarity combined with moderate error levels for the base case.

Besides the base case we also investigated the error scenarios on the unconstrained demand. We again analyzed an error with a biased underestimation, an error with a biased overestimation and an unbiased error of the estimated unconstrained demand. The results are listed in Table 4.4 and the scatter plots for the respective scenarios can be found in Figures 4.4, 4.5 and 4.6. Overall, because of the average error levels applied, the error measures approximately tripled compared to the base case from 0.56 to around 1.60 for the $\overline{MAE}^D$ and from 9.3% to around 27% for the $\overline{PMAE}^D$. However, for all error scenarios the similarity measures indicate a very high resemblance. For the biased underestimation of the unconstrained demand, we observe a significant effect on the ROM measures. With increasing error level, the $\overline{MAE}^{PARO}$ increases from 0.3% for the base case to 9.8% for the highest error level. We also observe a strong decrease in overall RM success, which is indicated by a decrease of the values for $\overline{PARO}^R$. Please note that for the highest error level, the average total demand $\overline{D}$ decreased to around 65.4 thousand. This is only slightly above the average number of actual bookings, which is, by definition, the absolute lower bound for the estimation of the unconstrained demand (see Proposition 3.1.1). However,

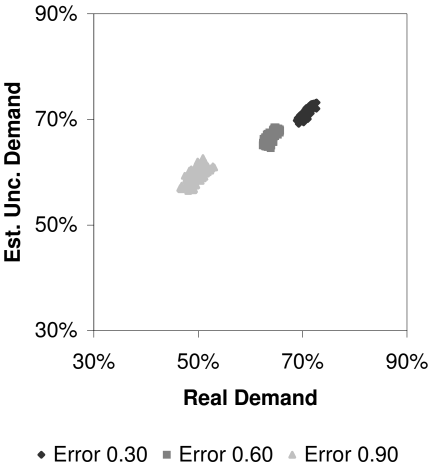

Figure 4.4.: Effect of a Biased Underestimation of Unconstrained Demand on PARO

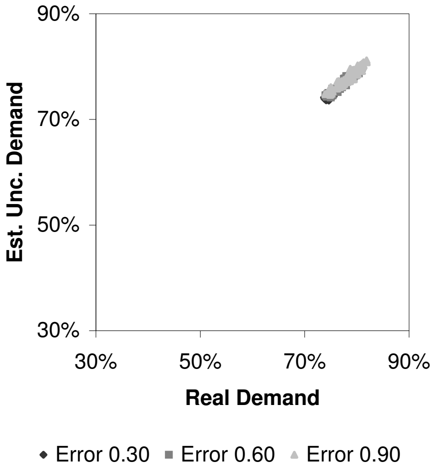

Figure 4.5.: Effect of a Biased Overestimation of Unconstrained Demand on PARO

we still observe a linear relation in the scatter plot shown in Figure 4.4 and the correlation coefficient remains above our minimum level of similarity with r^{PARO} at 0.64, even at an error level of 90%. In our worst-case scenario at 60% error level, the similarity measures indicate a very high resemblance. The application of a biased overestimation and an unbiased error on the unconstrained demand do not have a significant effect on the similarity measures. Although the error measures strongly increase, the similarity measures indicate a high similarity. The $\overline{MAE}^{PARO}$ stays below 1% and the correlation coefficient r^{PARO} is larger than 0.86 for all cases. The results of our scenarios also validate the analysis of the effect of an unbiased unconstraining error on the ROM accomplished by Pölt (2001) in a leg-based airline RM context.

4.3.3. Analyzing the Effect of Further Scenarios

Besides analyzing the robustness of the ROM - in particular the PARO - against errors in the unconstrained demand, we apply additional scenarios to investigate the ROM properties. In the following we analyze the effect of forecast errors, open/restrictive RM control and adjusted seasonality on the ROM and on its robustness.

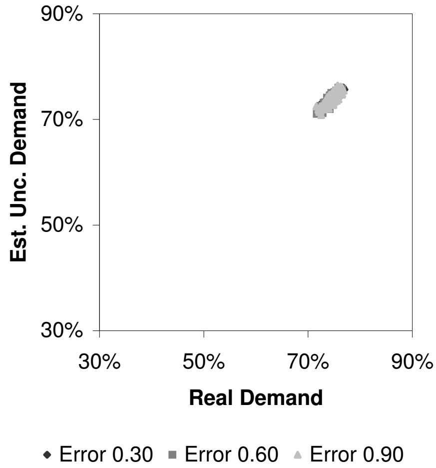

Figure 4.6.: Effect of an Unbiased Unconstraining Error on PARO

Effect of Forecast Errors on ROM

We start by analyzing the effect of forecast errors on the ROM. The applied scenarios are described in detail in Section 3.3.2. Compared to the unconstrained demand scenarios we expect the error and similarity measures to be quite similar, but we also expect a decreased overall RM success, which is indicated by the values for $\overline{PARO}^R$. The detailed results are presented in Table 4.5. Figures 4.7 and 4.8 show the scatter plot for the biased over- and underestimation of the forecasted demand. Please note, that the 90% error scenarios are not in the range of the graphs. The scatter plots showing these error scenarios and the scatter plot of the unbiased forecast error can be found in the appendix. In the table we added a data row with the average forecasted demand $\overline{F}$ and two data rows with the measures for the forecast error $\overline{MAE}^F$ and $\overline{PMAE}^F$. A first observation is that the similarity measures of the PARO are basically the same as those with the error on the unconstrained demand scenario. For example the values of r^{PARO} develop in the same direction throughout the error scenarios, whereas they decrease a bit stronger than with the unconstraining error scenarios. However, the values of r^{PARO} are above 0.76, except for the 90% underestimation of the forecast. Moreover, the values of $\overline{MAE}^{PARO}$ remain moderate in most cases. Another main observation is that the increase in the forecast error leads to worse RM results as it was expected during the scenario setup. The values for $\overline{PARO}^R$ decreased for each forecast error scenario. By looking at the forecast error it becomes obvious that applying an error on all booking classes leads on average

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	74.7	65.0	43.2	15.1	69.0	53.8	35.5	74.7	74.4	73.9
$\overline{PARO}^D$ (%)	74.7	67.4	52.1	33.4	69.3	57.3	44.0	74.3	73.8	73.2
$\overline{MAE}^{PARO}$ (%)	0.3	2.4	8.9	18.3	0.4	3.5	8.5	0.4	0.6	0.8
r^{PARO}	0.94	0.81	0.76	0.49	0.99	0.99	0.98	0.93	0.89	0.84
$\overline{R}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{D}$ (thousand)	87.2	80.0	72.7	65.2	95.1	104.6	115.6	87.5	87.8	88.2
$\overline{F}$ (thousand)	87.1	61.2	35.2	8.9	112.9	138.5	163.8	87.1	87.1	87.1
$\overline{MAE}^D$	0.56	0.75	1.13	1.57	0.78	1.31	2.02	0.75	1.15	1.63
$\overline{PMAE}^D$ (%)	9.3	12.3	18.6	25.9	12.9	21.7	33.4	12.3	19.0	26.9
$\overline{MAE}^F$	1.83	2.37	3.76	5.47	2.50	3.85	5.44	1.89	2.05	2.29
$\overline{PMAE}^F$ (%)	30.3	39.0	62.0	90.2	41.4	63.7	90.0	31.2	33.9	37.7

Table 4.5.: Effect of Forecast Errors on PARO

to the applied forecast error defined in the error scenario both for a biased over- and underestimation. The unbiased forecast error scenario shows smaller forecast errors, due to the fact that the forecast is updated using exponential smoothing and the error method applied randomly overestimates or underestimates it. This behavior is expected to be more realistic than a constant overestimation of one part of the itineraries and a constant underestimation of the other part.

Effect of Adjusted RM Control and Seasonality on ROM

Apart from analyzing the robustness of the ROM against unconstraining and forecast errors in various scenarios and biases, we studied the effects of poor - i.e., very open or very restrictive - RM controls on the PAROs. Therefore, we increased and decreased the bid prices by a certain percentage. The adjustment levels applied were 25% and 50%. In contrast to the forecast error scenario we expect the overall RM success to decrease, but the errors in the unconstrained demand should remain basically constant. Detailed results can be found in Table 4.6. We also show the scatter plot for the open RM control scenario in Figure 4.9. The scatter plot for the restrictive RM control case can be found in the appendix. As we adjusted the final bid prices, not the forecasts in the simulation runs, we observe similar error levels in the estimated unconstrained demand compared to the base case. Furthermore, the similarity measures indicate a very high similarity in all cases. We not only observe high similarity of the PAROs for both the open RM control and the restrictive RM control scenario. Moreover the results of

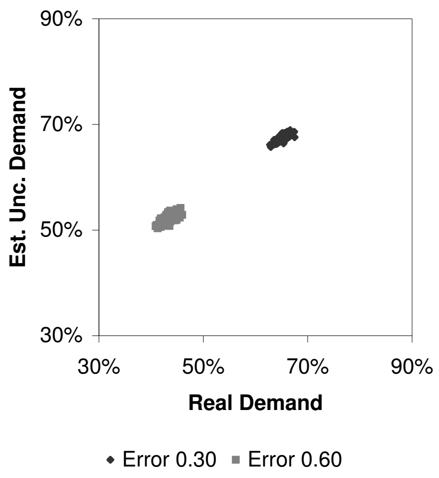

Figure 4.7.: Effect of Biased Underestimation of Forecasted Demand on PARO

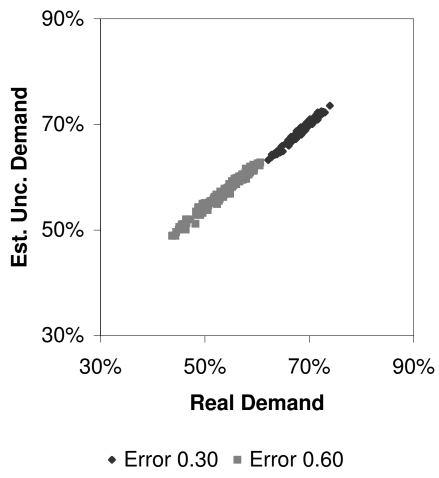

Figure 4.8.: Effect of Biased Overestimation of Forecasted Demand on PARO

the average PAROs confirm that the quality of the RM control decreased with increasing adjustment level. This was the assumption underlying the scenarios.

The last scenarios we conducted were adjusting the underlying seasonality of the booking requests. On the one hand we increased and decreased the amplitude of the underlying seasonality and on the other hand we applied a saw tooth curve to the request generator. Within five runs we change the demand level from 130% down to 70% or from 120% down to 80% and after these five runs we jump back to the starting value. We expect the error measures to decrease if we decrease the seasonality and to increase in the opposite case. The results of the scenarios are also presented in Table 4.6 and we show the scatter plot of the saw tooth curve scenarios in Figure 4.10. As expected, the overall unconstraining errors slightly decreases from 0.56 to 0.54 for the $\overline{MAE}^D$ and from 9.3% to 8.8% for the $\overline{PMAE}^D$ if we decrease the amplitude of the seasonality. If we increase the amplitude, the error measures increase to 0.60 and to 9.9%. The similarity measures remain the same, with a slightly increased r^{PARO} of 0.96 for the higher amplitude. The saw tooth curve only leads to a minor increase in the unconstraining error. However, the correlation coefficient increases significantly to nearly one, because the dispersion of the PARO values is significantly higher. We conclude that demand deviations help to increase the value of r^{PARO}, while $\overline{MAE}^{PARO}$ remains moderate.

	Base Case	Bid price decrease		Bid price increase		Adjust seasonality		Apply saw tooth curve	
Adj. level	-	25%	50%	25%	50%	-50%	+50%	130%-70%	120%-80%
$\overline{PARO}^R$ (%)	74.7	62.5	36.7	66.3	59.6	75.1	74.2	69.5	72.7
$\overline{PARO}^D$ (%)	74.7	62.9	36.7	66.4	59.5	75.1	74.3	70.8	73.2
$\overline{MAE}^{PARO}$ (%)	0.3	0.5	0.5	0.3	0.4	0.2	0.3	1.2	0.6
r^{PARO}	0.94	0.90	0.94	0.98	0.98	0.94	0.96	0.99	0.99
$\overline{R}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.4	87.8	87.2	87.2
$\overline{D}$ (thousand)	87.2	87.5	88.0	86.8	86.6	87.3	86.9	83.8	85.6
$\overline{MAE}^D$	0.56	0.61	0.66	0.58	0.60	0.53	0.60	0.67	0.59
$\overline{PMAE}^D$ (%)	9.3	10.1	11.0	9.6	10.0	8.8	9.9	10.7	9.6

Table 4.6.: Effect of Adjusted RM Control and Seasonality on PARO

4.4. Summary

In this chapter we described the network-based ROM with independent demand in detail. We highlighted some of the main properties of the ROM in this RM context and investigated the magnitude of model- and data-related errors on the validity of the ROM. After having analyzed the effect of a wrong booking order assumption in comparison to various unconstraining errors, we conclude that model-related errors do not play a major role for the validity of the ROM. As a consequence, we focus on analyzing the effect of data-related errors on the ROM in the remainder of the thesis. In this chapter we therefore also analyzed the robustness of the ROM in detail not only considering different kinds of unconstraining errors, but also further scenarios including forecast errors, applying adjusted RM controls and different sorts of seasonality. In all scenarios applied the values of the similarity measures showed results above our minimum level of similarity defined in Section 3.2. As we tested all scenarios with error levels up to the expected worst case and even beyond, we consider the network-based ROM with independent demand robust against errors in the input data for all error rates we would expect in real life. In addition, the effect of the other scenarios on the ROM was as expected, which also supports our conclusion to consider the ROM robust to deliver valid information about the RM success on a network level.

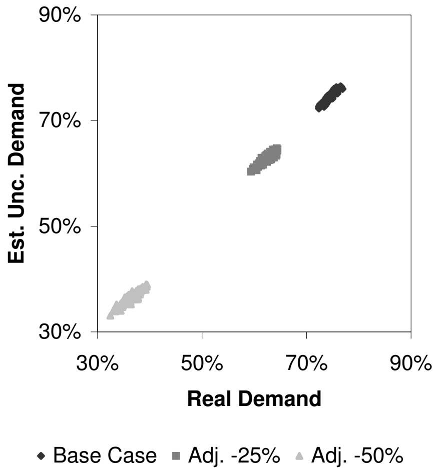

Figure 4.9.: Effect of Open RM Controls on PARO

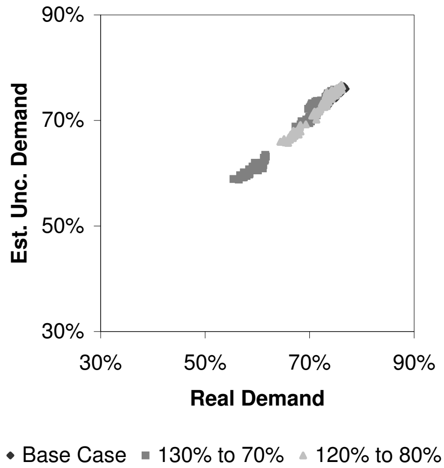

Figure 4.10.: Effect of High Deviation in Customer Demand on PARO

5. The Network-based ROM with Dependent Demand

Considering dependent demand structures in practical RM applications becomes increasingly important and common (see e.g. Weatherford and Ratliff, 2010). In this chapter we therefore introduce an enhancement of the network-based ROM with independent demand to a ROM, which considers dependent demand structures. We describe in detail how the estimations of the potential and no RM revenue are adjusted. Furthermore we discuss main properties of the network-based ROM with dependent demand. In the remainder of the chapter, we present computational results on the properties of the previously defined ROM with a special focus on the robustness on unconstraining errors. Additionally we investigate the effect of further scenarios on the ROM.

5.1. Extensions to the Network-based ROM with Independent Demand

In this section we explain the enhancement of the network-based ROM with independent demand to dependent demand structures in detail. Modifications have to be made to the estimations of the potential and the no RM revenue, because the demand model changes. The actual revenue as the result of the actual RM control is derived as explained in Chapter 4.

First, we introduce the enhancement of the potential revenue estimation introduced for independent demand. Therefore we start with the definition of the LP used for the network-based ROM with independent demand, which is shown again in Equations 5.1 to 5.3.

$$Max \sum_{i \in I} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,t} * x^+_{i,j,t} \tag{5.1}$$

$$\sum_{i \in I_l} \sum_{j \in J_{i,l,m}} \sum_{t \in T} x^+_{i,j,t} \leq cap_{l,m} \qquad \forall l \in L, \forall m \in M_l, \forall t \in T \tag{5.2}$$

$$0 \leq x^+_{i,j,t} \leq d_{i,j,t} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{5.3}$$

To estimate the potential revenue with dependent demand we still want to maximize the bookings multiplied with the given fare as shown in the objective function 5.1. All booking decisions made by the LP are also still bound to Constraint 5.2 considering the capacity of the compartments in the legs. However, we assume that the demand structure has changed from the independent demand model to a dependent demand model. In contrast to independent demand the realized demand depends on the availability of booking classes in a dependent demand context. Accordingly, Constraint 5.3 has to be adjusted to consider dependent demand. We will use the definition of dependent demand introduced in Chapter 3 in Section 3.1.1. The main idea of the enhancement is to let the LP for the potential revenue estimation also optimize the availability of booking classes. Therefore we introduce a variable $y_{i,j,t}$ to indicate, whether a booking class j for itinerary i in a given time period t is open or not. If the booking class is open $y_{i,j,t}$ takes the value 1, otherwise $y_{i,j,t}$ takes the value 0. Using this new $y_{i,j,t}$ variable Constraint 5.3 changes to 5.4. In addition we add Constraint 5.5 to ensure that $y_{i,j,t} \in \{0,1\}$.

$$0 \leq x^{+}_{i,j,t} \leq y_{i,j,t} * d^{td}_{i,j,t} - \sum_{j' \in J_{i,j}} y_{i,j',t} * d^{bd}_{i,j,j',t} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{5.4}$$

$$y_{i,j,t} \in \{0,1\} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{5.5}$$

We illustrate the adjusted demand constraint in the following examples. Using the buy-down graph introduced in Section 3.1.1 the demand constraint translates for a given itinerary i for booking classes one, two, three, four, and five in a given time period t to the following equations.

$$\begin{aligned} 0 \leq x_{i,1,t} &\leq y_{i,1,t} * 10 - y_{i,2,t} * 5 - y_{i,3,t} * 3 \\ 0 \leq x_{i,2,t} &\leq y_{i,2,t} * 16 - y_{i,4,t} * 10 \\ 0 \leq x_{i,3,t} &\leq y_{i,3,t} * 15 - y_{i,5,t} * 10 \\ 0 \leq x_{i,4,t} &\leq y_{i,4,t} * 12 - y_{i,5,t} * 8 \\ 0 \leq x_{i,5,t} &\leq y_{i,5,t} * 30 \\ y_{i,j,t} \in \{0,1\}&, \quad \forall j \in \{1,2,3,4,5\} \end{aligned}$$

The values of each x-variable are limited to the total demand of the respective booking class minus the buy-down, which is realized according to the given availability constellation. $x_{i,1,t}$ for example has an upper bound of ten minus five if booking class two is open and additionally minus three if booking class three is open, which leads to an upper bound of two in this case. The following example illustrates the resulting bounds of the demand constraints, if the first three booking classes are open and the other two booking classes are closed (i.e. $y_{i,1,t}, y_{i,2,t}, y_{i,3,t} = 1$ and $y_{i,4,t}, y_{i,5,t} = 0$).

$$\begin{aligned}
0 \leq x_{i,1,t} &\leq 1 * 10 – 1 * 5 – 1 * 3 = 2 \\
0 \leq x_{i,2,t} &\leq 1 * 16 – 0 * 10 \qquad = 16 \\
0 \leq x_{i,3,t} &\leq 1 * 15 – 0 * 10 \qquad = 15 \\
0 \leq x_{i,4,t} &\leq 0 * 12 – 0 * 8 \qquad = 0 \\
0 \leq x_{i,5,t} &\leq 0 * 30 \qquad\qquad = 0
\end{aligned}$$

Besides adjusting the demand constraint, an additional constraint to model the feasible actions has to be included in the model. According to the definition in Section 3.1.1 the opening order of the booking classes is sequentially ordered. In the previous examples we have implicitly considered this requirement, but not enforced it formally. The feasible actions can easily be modeled using the newly introduced $y_{i,j,t}$ variables.

$$y_{i,(j+1),t} \leq y_{i,j,t} \qquad \forall i \in I, \forall m \in M_i, \quad \forall j \in J_{i,m} \setminus \{j^-_{i,m}\}, \forall t \in T \tag{5.6}$$

For each booking class j Constraint 5.6 ensures that the next lower booking class $j+1$ is closed, if booking class j is closed. The feasible action constraint is applied to all booking classes j in a compartment m. The booking classes are taken from the set of all booking classes j in itinerary i that are related to compartment m $J_{i,m}$ except the lowest booking class $j^-_{i,m}$. We illustrate the constraint using a simple example. If booking classes one and two belong to the same compartment, then the feasibility constraint $y_{i,2,t} \leq y_{i,1,t}$ has to be fulfilled. If for example booking class one is closed (i.e. $y_{i,1,t} = 0$), it follows that also $y_{i,2,t} = 0$.

Up until now we only discussed the case in which $y_{i,j,t}$ was either one or zero. This means that a given booking class was either opened or closed during the entire time period. However, for the ROM with dependent demand we assume that a booking class can be closed in the course of a given time period t, as it is the case in reality. As a result $y_{i,j,t}$ can take all (fractional) values $\in [0,1]$. In Figure 5.1 we illustrate the basic assumption of closing a booking class. At the beginning of the time period all booking classes are open. After the completion of 30% of the time period booking class five is closed. All other booking classes remain open at that point in time. After 50% of the time period has been completed booking

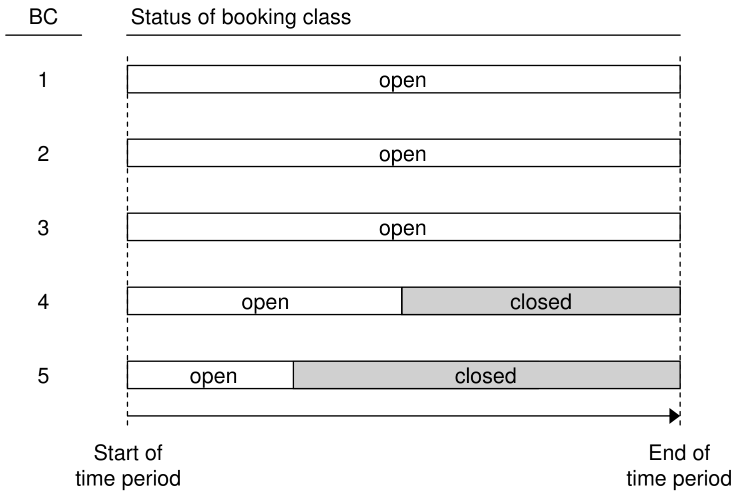

Figure 5.1.: Linear Opening Constraint During a Time Period

class four is also closed. Until the end of the time period the first three booking classes remain open. This closing assumption is reflected in the following values of y. $y_{i,1,t}, y_{i,2,t}, y_{i,3,t} = 1$, $y_{i,4,t} = 0.5$ and $y_{i,5,t} = 0.3$. If we include these fractional values of y into the demand constraint we implicitly assume that the demand is uniformly distributed in the DCP intervals. This assumption is also made by Boyd and Kallesen (2004), Walczak et al. (2010) and Fiig et al. (2010) during the demand transformation process. We illustrate the example from Figure 5.1 by calculating the upper bounds for the demand constraint.

$$\begin{aligned}
0 \leq x_{i,1,t} &\leq 1 * 10 – 1 * 5 – 1 * 3 = 2 \\
0 \leq x_{i,2,t} &\leq 1 * 16 – 0.5 * 10 \quad = 11 \\
0 \leq x_{i,3,t} &\leq 1 * 15 – 0.3 * 10 \quad = 12 \\
0 \leq x_{i,4,t} &\leq 0.5 * 12 – 0.3 * 8 \quad = 3.6 \\
0 \leq x_{i,5,t} &\leq 0.3 * 30 \qquad\qquad = 9
\end{aligned}$$

In this example the upper bound of $x_{i,2,t}$ is set to eleven. The total demand of 16 is only decreased by five, because booking class four was only open half of the time period. The realized demand for booking class four consists of 50% of the total demand and is decreased by 30% of the buy-down into booking class five. It is to be noted that it generally holds that the upper bound for the adjusted demand constraint is always greater or equal to zero. This directly follows from $d^{td}_{i,j,t} \geq \sum_{j' \in J_{i,j}} d^{bd}_{i,j,j',t}$ and the fact that the respective $y_{i,j,t}$ values adhere to Constraint 5.6.

The complete LP formulation of the network-based ROM with dependent demand is listed in Equations 5.7 to 5.11.

$$Max \sum_{i \in I} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,t} * x^{+}_{i,j,t} \tag{5.7}$$

$$\sum_{i \in I_l} \sum_{j \in J_{i,l,m}} \sum_{t \in T} x^{+}_{i,j,t} \leq cap_{l,m} \qquad \forall l \in L, \forall m \in M_l, \forall t \in T \tag{5.8}$$

$$0 \leq x^{+}_{i,j,t} \leq y_{i,j,t} * d^{td}_{i,j,t} - \sum_{j' \in J_{i,j}} y_{i,j',t} * d^{bd}_{i,j,j',t} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{5.9}$$

$$y_{i,(j+1),t} \leq y_{i,j,t} \qquad \forall i \in I, \forall m \in M_i, \forall j \in J_{i,m} \setminus \{j^{-}_{i,m}\}, \forall t \in T \tag{5.10}$$

$$y_{i,j,t} \in [0,1] \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{5.11}$$

For the no RM revenue estimation we apply a simulation of a FCFS strategy again. Algorithm 4.1 introduced in Section 4.1 can be applied again. During the simulation of a FCFS strategy we assume that all booking classes are open. The effect on the demand used in the algorithm is that all buy-down into lower booking classes is realized. The demand that correlates to this is the yieldable demand $d^{yd}_{i,j,t}$.

The result of the estimations of the potential and the no RM revenue $x^{+}_{i,j,t}$ and $x^{-}_{i,j,t}$ and the actual results of the booking period $b_{i,j,t}$ are applied to Equations 4.4 to 4.5. The derived ROM measures are determined in the same way as presented in Chapter 4 in Equations 4.7, 4.8 and 4.9.

5.2. Properties of the Network-based ROM with Dependent Demand

In Section 4.2 we discussed main properties of the network-based ROM with independent demand. The properties regarding the isolation of the RM contribution from the overall success and the probability of special cases for the RO, the ARO and the PARO are the same for the network-based ROM with dependent demand.

As a main model-related error we described the assumption on the booking order in the FCFS simulation to determine the no RM revenue for the independent demand case. With dependent demand the booking order not only plays a role in the no RM revenue estimation, but also in the estimation of the potential revenue. As described in the previous section we assume that booking classes can be closed at some point within a given time period and the realized demand in the demand constraint is distributed uniformly according to the availability of the booking classes defined by the y-variables. The following example shows that even with perfect aggregated data input, the calculation of the potential revenue with the LP defined in Equations 5.7 to 5.11 might lead to results that are below the actual revenue (for reasons of readability we omit the indices for the itinerary and the time period).

$$
\begin{array}{lclcl}
max & & 300 * x_1 + 150 * x_2 + 100 * x_3 & & \\
0 & \leq & x_1 & \leq & y_1 * 4 - y_2 * 2 \\
0 & \leq & x_2 & \leq & y_2 * 4 - y_3 * 2 \\
0 & \leq & x_3 & \leq & y_3 * 4 \\
0 & \leq & x_1 + x_2 + x_3 & \leq & 6 \\
\multicolumn{5}{l}{0 \leq y_3 \leq y_2 \leq y_1 \leq 1}
\end{array}
$$

We consider one flight leg with a capacity of six seats in this example. Three booking classes one, two and three are available to the customers. On an aggregated level the demand is described by the three demand constraints. The fourth constraint ensures the feasible actions and the value range of the y-variables. If we solve this example using an LP-solver, the optimal solution is 1,250 with $x_1 = 3, x_2 = 1$ and $x_3 = 2$. The y values are $y_1 = 1, y_2 = 0.5$ and $y_3 = 0.5$. Given our current definition of the potential revenue, this would be the respective estimate. However it is possible, that the RMS and the revenue managers were able to anticipate the customer requests in a better way leading to an actual revenue that is larger than the estimate for the potential revenue. The example in Table 5.1 gives an illustration. The column with heading 'Req.' describes the single requests. The listed booking classes describe the set of booking classes the given passenger is willing to purchase. Request '2,1' for example describes a passenger who starts looking for a ticket in booking class two and then looks for a ticket in booking class one if the former is not available. In column 'Avail.' all booking classes that are available at that point in time are listed. The availability '1,2' for example represents the situation in which booking classes one and two are open. The column 'Dec.' lists the results of the accept/deny-decision, which is based on the given request and the current availability of the booking classes. The result could either be the booking class the customer is booked into or 'rej.', if the request was rejected. In column 'Rev.' the resulting revenue is presented.

In the given example the revenue manager made booking classes one and two available at the beginning. This leads to the rejection of the first two booking

Req.	Avail.	Dec.	Rev.
3	1,2	rej.	-
3	1,2	rej.	-
3,2	1,2	2	150
3,2	1,2	2	150
2,1	1	1	300
2,1	1	1	300
1	1	1	300
1	1	1	300
		Sum	1,500

Table 5.1.: Actual Revenue with Restrictive Control and Low-before-high Booking Order

requests. The next two requests are accepted in booking class two leading two a revenue of 150 for each booking. After these two bookings the revenue manager decides to close booking class two and to only leave booking class one open. As a result four bookings in booking class one will be made based on the requests. In total this leads to a revenue of 1,500. In this case the actual revenue eventually was larger than the potential revenue estimated with the LP. However, the effect that the actual revenue might become larger than the potential revenue decreases strongly with increasing number of DCPs considered in the ROM. We expect the effect of data-related errors again to be larger and of higher importance than the model-related errors. Moreover, the assumption made within the ROM - particularly for the potential revenue - reflects the modeling decisions that had to be taken for the RM methodology applied in practice and we expect this definition in general to be a very good estimation of the potential revenue.

5.3. Computational Results

In this section we investigate the properties and in particular the robustness of the network-based ROM with dependent demand. We start with a detailed inspection of the main data-related error, i.e. errors in the estimated unconstrained demand. With dependent demand, we have to consider errors in the yieldable demand and errors in the buy-down as well. As in Chapter 4 the results of each scenario are based on the evaluation of 150 simulation runs. We conclude this section by assessing the effect of other relevant scenarios on the validity and the results of the ROM.

5.3.1. Base Case and Unconstraining Error Scenarios

In this section we investigate the effect of different unconstraining errors on the validity of the ROM. According to Section 4.3.2 in Chapter 4 we start with analyzing the effect on the absolute ROM measures. Afterwards we examine the PARO in detail and in particular assess its robustness against errors in the input data.

The first analysis we conduct is comparing the estimations of the potential and the no RM revenue of the different error scenarios for the estimated unconstrained demand. As already described in Section 3.3.2 we are able to apply errors for the yieldable demand, but also for the buy-down. Figures 5.2 and 5.3 compare the potential and no RM revenue estimates for the base case and the nine unconstraining error scenarios. The scenarios are the same as in the pre-

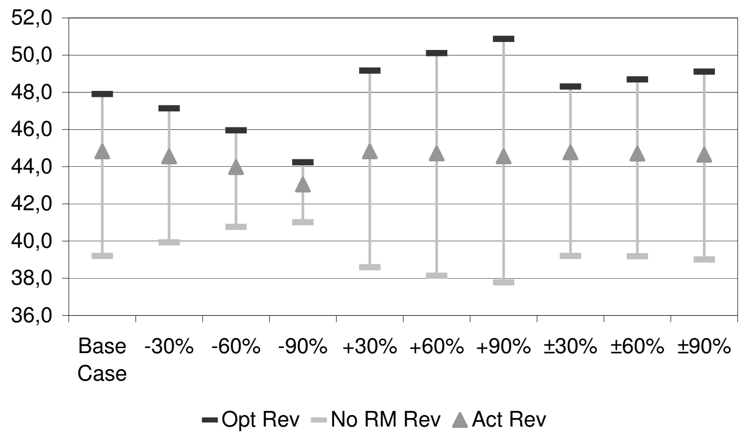

Figure 5.2.: Effect of Errors in the Unconstrained Yieldable Demand on the Potential and No RM Revenue

vious chapter. Again the error scenarios of a biased underestimation are marked with a minus (e.g. -30%), the error scenarios of a biased overestimation with a plus (e.g. $+30\%$) and the unbiased unconstraining error scenarios are marked with a plus/minus sign (e.g. $\pm 30\%$). If we apply an unconstraining error on the yieldable demand we observe results similar to the ROM with independent demand. We again observe that for an unbiased error the effect on the revenue estimates is minor. Both the estimates of the potential and the no RM revenue remain more or less constant. An overestimation of the unconstrained yieldable demand leads to an increase of the potential revenue and a decrease of the no RM revenue. An underestimation of the unconstrained yieldable demand leads

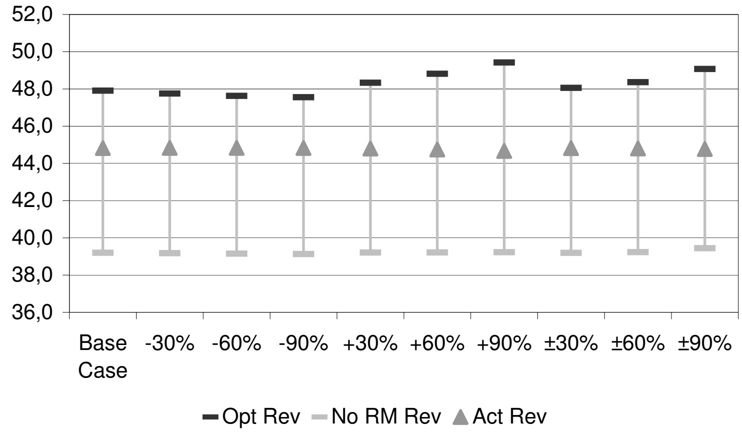

Figure 5.3.: Effect of Errors in the Unconstrained Buy-down on the Potential and No RM Revenue

to contrary results. The potential revenue estimate decreases and the no RM revenue estimate increases. If an error in the estimated unconstrained buy-down is applied, the effects on the potential and no RM revenue are lower. The potential revenue slightly increases if the buy-down is underestimated. The estimates for the no RM revenue remain very stable for all error scenarios. These observations are supported by Tables 5.2 and 5.3. The subsequent effects on the RO and ARO are very similar to the ROM with independent demand if we apply errors to the unconstrained yieldable demand. However, the absolute amount of the RO is higher on average. As already indicated in Figure 5.2, the average RO remains constant with an unbiased unconstraining error. It increases with a biased overestimation and strongly decreases with a biased underestimation. In addition, we observe that the ARO mainly shows the same characteristics as the RO. Applying errors to the unconstrained buy-down leads to significantly lower effects. In particular the ARO is very stable if errors are applied to the unconstrained buy-down, because the no RM revenue is very stable in this case. We again conclude that the ARO can be applied to quantify the contribution of the RMS in use.

In the following, we focus on the effects of the described unconstraining error scenarios on the PARO. We start with a comparison of the base case simulated with independent demand and the base case simulated with dependent demand. The scatter plots are presented in Figures 5.4 and 5.5. They show that the ROM with dependent demand is also robust for the base case. The detailed results are

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{Rev}^{+,R}$ (million)	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6
$\overline{Rev}^{+,D}$ (million)	47.9	47.1	46.0	44.2	49.2	50.1	50.9	48.3	48.7	49.1
Diff. (million)	0.7	1.5	2.6	4.4	-0.6	-1.5	-2.3	0.3	-0.1	-0.5
$\overline{Rev}$ (million)	44.8	44.6	44.0	43.0	44.8	44.7	44.6	44.8	44.7	44.6
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.2	39.9	40.8	41.0	38.6	38.1	37.8	39.2	39.2	39.0
Diff. (million)	-0.2	-0.9	-1.8	-2.0	0.4	0.9	1.2	-0.2	-0.2	0.0
$\overline{ARO}^{R}$ (million)	5.8	5.5	5.0	4.0	5.8	5.7	5.5	5.8	5.7	5.6
$\overline{ARO}^{D}$ (million)	5.6	4.6	3.2	2.0	6.2	6.6	6.8	5.6	5.5	5.6
Diff. (million)	0.2	0.9	1.8	2.0	-0.4	-0.9	-1.3	0.2	0.2	0.0
$\overline{RO}^{R}$ (million)	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6
$\overline{RO}^{D}$ (million)	8.7	7.2	5.2	3.2	10.6	12.0	13.1	9.1	9.5	10.1
Diff. (million)	0.9	2.4	4.4	6.4	-1.0	-2.4	-3.5	0.5	0.1	-0.5

Table 5.2.: Effect of Errors in the Unconstrained Yieldable Demand on ROM Measures

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{Rev}^{+,R}$ (million)	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6
$\overline{Rev}^{+,D}$ (million)	47.9	47.8	47.6	47.6	48.3	48.8	49.4	48.1	48.4	49.1
Diff. (million)	0.7	0.8	1.0	1.0	0.3	-0.2	-0.8	0.5	0.2	-0.5
$\overline{Rev}$ (million)	44.8	44.8	44.8	44.8	44.8	44.7	44.7	44.8	44.8	44.8
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.2	39.2	39.2	39.1	39.2	39.2	39.2	39.2	39.2	39.4
Diff. (million)	-0.2	-0.2	-0.2	-0.1	-0.2	-0.2	-0.2	-0.2	-0.2	-0.4
$\overline{ARO}^{R}$ (million)	5.8	5.8	5.8	5.8	5.8	5.7	5.7	5.8	5.8	5.8
$\overline{ARO}^{D}$ (million)	5.6	5.7	5.7	5.7	5.6	5.5	5.4	5.6	5.6	5.3
Diff. (million)	0.2	0.1	0.1	0.1	0.2	0.2	0.3	0.2	0.2	0.5
$\overline{RO}^{R}$ (million)	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6
$\overline{RO}^{D}$ (million)	8.7	8.6	8.5	8.4	9.1	9.6	10.2	8.9	9.1	9.6
Diff. (million)	0.9	1.0	1.1	1.2	0.5	0.0	-0.6	0.7	0.5	0.0

Table 5.3.: Effect of Errors in the Unconstrained Buy-down on ROM Measures

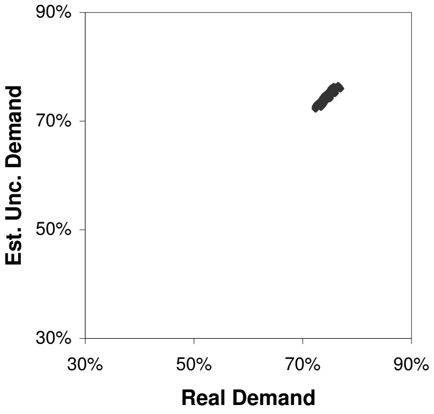

Figure 5.4.: Base Case with Independent Demand

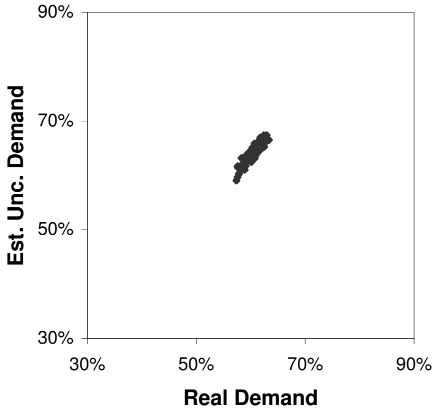

Figure 5.5.: Base Case with Dependent Demand

presented in Table 5.4. They include another column listing the values of the base case obtained from the independent demand scenarios. The values belonging to this scenario are listed in the rows of the total demand ($\overline{D}^{td}$ etc.). The tables are also enhanced by data rows to list the average real yieldable demand ($\overline{R}^{yd}$) and the average real buy-down ($\overline{R}^{bd}$). The values for the estimated unconstrained demand are also added to the table ($\overline{D}^{yd}$ and $\overline{D}^{bd}$). The error measures on the estimated unconstrained demand are complemented accordingly with the respective values ($\overline{MAE}^{D^{yd}}$, $\overline{MAE}^{D^{bd}}$, $\overline{PMAE}^{D^{yd}}$ and $\overline{PMAE}^{D^{bd}}$). The similarity measures for the ROM with dependent demand indicate a high similarity with $r^{PARO} = 0.91$. The $\overline{MAE}^{PARO}$ increases to 3.8%, which is mainly due to an underestimation of the potential revenue for all scenarios with dependent demand. However, the ROM proves itself robust against errors in the unconstrained demand also with dependent demand for the base case scenario.

In the following we analyze main results obtained by the error scenarios in the unconstrained demand for both yieldable demand and buy-down. The numerical results are listed completely, whereas we focus on some main scatter plots. The scatter plots for all error scenarios are included in the appendix. As it has been observed before, adjusting the estimated unconstrained yieldable demand leads to larger effects. In Figures 5.6 and 5.7 we present the effect of a biased underestimation and a biased overestimation of the unconstrained yieldable demand. A biased underestimation of the unconstrained yieldable demand has a significant effect on the robustness of the ROM measures. The values for r^{PARO} decrease from 0.91 to 0.42 for the case with 90% error. We also observe a strong

	Base case ind.	Base case dep.	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^{R}$ (%)	74.7	60.8	57.9	51.9	42.1	60.7	59.6	57.9	60.2	59.5	58.9
$\overline{PARO}^{D}$ (%)	74.7	64.6	64.1	61.9	63.0	58.9	54.9	51.7	61.1	58.0	55.7
$\overline{MAE}^{PARO}$ (%)	0.3	3.8	6.2	10.0	20.9	1.8	4.7	6.2	1.0	1.5	3.1
r^{PARO}	0.94	0.91	0.84	0.69	0.42	0.97	0.98	0.98	0.92	0.91	0.92
$\overline{R}^{td}$ (thousand)	87.6	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5
$\overline{R}^{yd}$ (thousand)	-	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	-	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9
$\overline{D}^{td}$ (thousand)	87.2	120.4	111.6	103.6	97.9	134.2	147.8	161.3	122.8	125.4	129.3
$\overline{D}^{yd}$ (thousand)	-	88.7	79.5	71.1	65.3	102.3	115.9	129.4	90.8	93.1	96.6
$\overline{D}^{bd}$ (thousand)	-	31.7	32.1	32.5	32.6	31.8	31.9	31.9	32.0	32.3	32.7
$\overline{MAE}^{D^{td}}$	0.56	1.37	1.47	1.77	2.02	1.87	2.65	3.51	1.67	2.22	2.80
$\overline{MAE}^{D^{yd}}$	-	0.76	0.91	1.30	1.64	1.26	2.06	2.95	1.08	1.69	2.32
$\overline{MAE}^{D^{bd}}$	-	0.87	0.88	0.89	0.90	0.87	0.87	0.87	0.87	0.88	0.90
$\overline{PMAE}^{D^{td}}$ (%)	9.3	16.9	18.1	21.8	24.8	23.0	32.6	43.3	20.6	27.3	34.4
$\overline{PMAE}^{D^{yd}}$ (%)	-	12.5	14.9	21.4	26.9	20.8	34.0	48.6	17.8	27.8	38.3
$\overline{PMAE}^{D^{bd}}$ (%)	-	42.0	42.5	43.2	43.3	42.0	42.0	42.0	42.3	42.8	43.4

Table 5.4.: Effect of Errors in the Unconstrained Yieldable Demand on PARO

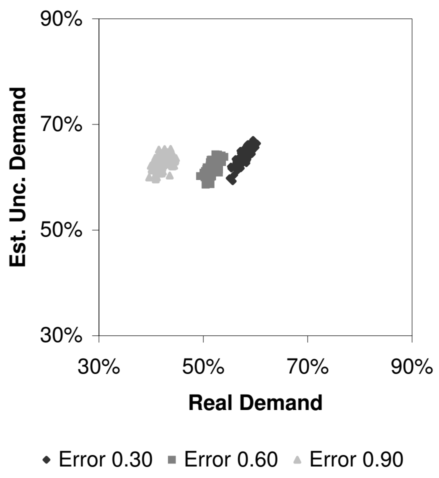

Figure 5.6.: Effect of Biased Underestimation of Unconstrained Yieldable Demand on PARO

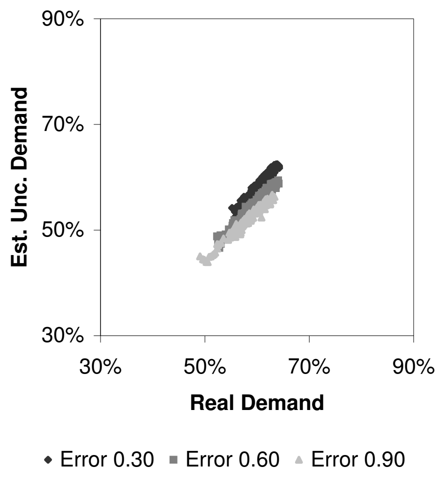

Figure 5.7.: Effect of Biased Overestimation of Unconstrained Yieldable Demand on PARO

increase in $\overline{MAE}^{PARO}$ from 3.8% to 20.9%. However, up to error level 60%, the similarity measures for the ROM still indicate a high similarity. Because an error level of 90% is unlikely in practice, we consider the ROM robust even for a biased underestimation of the unconstrained demand. In comparison to a biased underestimation, the ROM proves itself to be much more robust against a biased overestimation of unconstrained yieldable demand for all error levels. The values for r^{PARO} actually increase from 0.94 for the base case to 0.98 for the 90% error scenario. The values for $\overline{MAE}^{PARO}$ increase to 6.2%, which is still a very low value for the 90% error case. An unbiased unconstraining error leads to similar results.

Errors in the estimated unconstrained buy-down have a lower effect on the ROM. The numerical results for the buy-down scenarios are listed in Table 5.5. We focus on presenting the scatter plot for the unbiased error scenario in this section. It is presented in Figure 5.8. The effect of an unbiased error in the estimated unconstrained buy-down is minor. It is also minor for a biased over- and underestimation of the unconstrained buy-down. The values for r^{PARO} are above 0.90 in all cases. The values for $\overline{MAE}^{PARO}$ are also very promising. The maximum value measured is 6.8% given a biased underestimation with 90% error. We conclude that the ROM is also robust with unconstraining errors in the

	Base Case ind.	Base Case dep.	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^{R}$ (%)	74.7	60.8	60.9	60.9	60.8	60.5	60.0	59.1	60.7	60.5	60.2
$\overline{PARO}^{D}$ (%)	74.7	64.6	65.9	67.0	67.6	61.2	57.6	53.4	63.4	61.0	55.3
$\overline{MAE}^{PARO}$ (%)	0.3	3.8	5.1	6.1	6.8	0.8	2.4	5.8	2.7	0.6	4.9
r^{PARO}	0.94	0.91	0.91	0.90	0.90	0.94	0.95	0.96	0.93	0.93	0.94
$\overline{R}^{td}$ (thousand)	87.6	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5
$\overline{R}^{yd}$ (thousand)	-	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	-	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9
$\overline{D}^{td}$ (thousand)	87.2	120.4	111.6	102.9	94.2	130.1	140.0	150.1	120.9	121.7	123.6
$\overline{D}^{yd}$ (thousand)	-	88.7	89.3	89.8	90.5	88.9	89.1	89.6	89.1	89.7	91.2
$\overline{D}^{bd}$ (thousand)	-	31.7	22.4	13.1	3.8	41.3	50.8	60.5	31.8	32.0	32.5
$\overline{MAE}^{D^{td}}$	0.56	1.37	1.41	1.67	2.08	1.62	2.07	2.64	1.51	1.85	2.26
$\overline{MAE}^{D^{yd}}$	-	0.76	0.77	0.78	0.80	0.77	0.77	0.79	0.77	0.79	0.86
$\overline{MAE}^{D^{bd}}$	-	0.87	0.95	1.32	1.85	1.13	1.62	2.21	1.04	1.46	1.99
$\overline{PMAE}^{D^{td}}$ (%)	9.3	16.9	17.3	20.6	25.5	20.0	25.5	32.5	18.6	22.8	27.8
$\overline{PMAE}^{D^{yd}}$ (%)	-	12.5	12.7	12.9	13.2	12.6	12.8	13.0	12.7	13.0	14.2
$\overline{PMAE}^{D^{bd}}$ (%)	-	42.0	45.8	63.9	89.3	54.8	78.2	106.9	50.2	70.7	96.5

Table 5.5.: Effect of Errors in the Unconstrained Buy-down on PARO

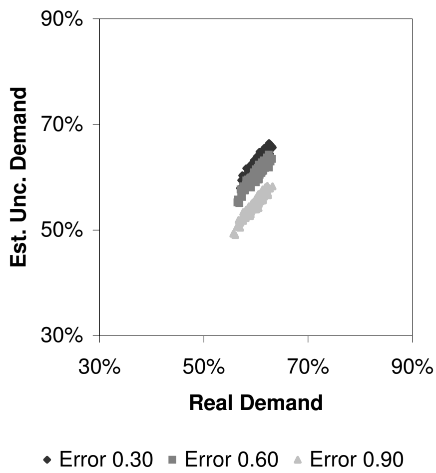

Figure 5.8.: Effect of an Unbiased Error in the Unconstrained Buy-down on PARO

estimated unconstrained buy-down.

5.3.2. Analyzing the Effect of Further Scenarios

In this section we investigate the effect of further scenarios on the ROM with dependent demand. We make use of the set of standard scenarios which have already been applied to the ROM with independent demand. We assess the effect of forecast errors, adjusted RM control and adjusted seasonality.

Effect of Forecast Errors on ROM

We start by analyzing the effect of an additional forecast error on the ROM. The results for an error in the forecasted yieldable demand are listed in Table 5.6. We also show the scatter plots for the biased under- and overestimation of the forecasted yieldable demand in Figures 5.9 and 5.10. Please note that we left out the 90% error scenario because the values are not within the 30% to 90% range. Scatter plots with a range from 0% to 100% showing the 90% error scenarios can be found in the appendix.

If an additional error in the forecast is applied, the $\overline{PARO}^R$ decreases significantly in comparison to the scenarios with an error in the estimated unconstrained demand. The similarity measures of the PARO, however, show similar tendencies. Except for a biased underestimation with 90% error they are above our

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	60.8	56.9	48.6	16.8	56.0	44.9	31.0	59.4	56.7	52.8
$\overline{PARO}^D$ (%)	64.6	62.7	56.0	47.5	53.4	39.4	25.7	59.0	53.1	46.9
$\overline{MAE}^{PARO}$ (%)	3.8	5.8	7.4	30.7	2.6	5.4	5.3	0.6	3.6	5.8
r^{PARO}	0.91	0.70	0.52	0.86	0.98	0.98	0.96	0.94	0.95	0.95
$\overline{R}^{td}$ (thousand)	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9
$\overline{D}^{td}$ (thousand)	120.4	111.7	104.7	93.2	134.6	149.7	166.5	123.0	125.7	129.6
$\overline{D}^{yd}$ (thousand)	88.7	79.6	70.6	54.7	102.8	117.8	134.5	91.0	93.3	96.8
$\overline{D}^{bd}$ (thousand)	31.7	32.1	34.1	38.6	31.9	31.9	32.0	32.1	32.4	32.8
$\overline{F}^{td}$ (thousand)	120.4	107.5	100.1	90.0	147.7	174.7	201.6	127.5	136.8	147.8
$\overline{F}^{yd}$ (thousand)	88.7	73.2	61.0	45.8	115.8	142.8	169.7	94.4	101.7	110.6
$\overline{F}^{bd}$ (thousand)	31.7	34.3	39.1	44.2	31.8	31.9	32.0	33.1	35.1	37.2
$\overline{MAE}^{D^{td}}$	1.37	1.47	1.86	2.50	1.89	2.75	3.79	1.68	2.26	2.88
$\overline{MAE}^{D^{yd}}$	0.76	0.91	1.41	2.47	1.29	2.20	3.31	1.09	1.72	2.41
$\overline{MAE}^{D^{bd}}$	0.87	0.88	0.93	1.08	0.87	0.87	0.88	0.88	0.89	0.90
$\overline{PMAE}^{D^{td}}$ (%)	16.9	18.1	22.9	30.7	23.3	33.8	46.7	20.7	27.8	35.4
$\overline{PMAE}^{D^{yd}}$ (%)	12.5	15.0	23.2	40.7	21.3	36.4	54.6	18.0	28.4	39.7
$\overline{PMAE}^{D^{bd}}$ (%)	42.0	42.6	45.0	52.1	42.1	42.2	42.5	42.4	42.9	43.6
$\overline{MAE}^{F^{td}}$	2.27	2.41	2.75	3.17	3.01	4.41	6.08	2.41	2.73	3.21
$\overline{MAE}^{F^{yd}}$	1.86	2.09	2.59	3.32	2.63	4.11	5.82	1.98	2.25	2.65
$\overline{MAE}^{F^{bd}}$	0.99	1.03	1.19	1.40	0.99	0.99	0.99	1.01	1.05	1.12
$\overline{PMAE}^{F^{td}}$ (%)	28.0	29.7	33.8	39.0	37.2	54.5	75.1	29.7	33.7	39.6
$\overline{PMAE}^{F^{yd}}$ (%)	30.8	34.5	42.7	54.7	43.6	68.0	96.3	32.7	37.2	43.8
$\overline{PMAE}^{F^{bd}}$ (%)	47.7	50.2	57.5	67.9	47.8	47.8	47.8	48.9	51.1	54.4

Table 5.6.: Effect of Errors in the Forecasted Yieldable Demand on PARO

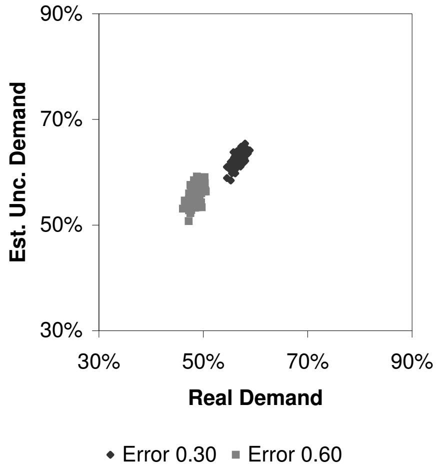

Figure 5.9.: Effect of Biased Underestimation of Forecasted Yieldable Demand on PARO

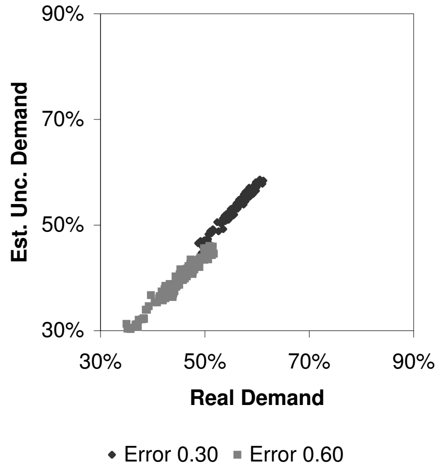

Figure 5.10.: Effect of Biased Overestimation of Forecasted Yieldable Demand on PARO

minimum level of similarity we defined before. We conclude that the ROM remains robust even if we apply a strong forecast error. As expected the quality of the RM control decreases with increasing error level. A biased underestimation of the forecasted yieldable demand, for example, leads to a decrease in RM success from 60.8% to 16.8%.

Applying an additional forecast error is comparable to the scenarios with an error in the estimated unconstrained buy-down. This is in particular due to the fact that the unconstraining error on the buy-down is applied for all booking classes no matter if they are open or not - consequently the results are approximately the same. Details are presented in the appendix.

Effect of Adjusted RM Control and Seasonality on ROM

We also applied scenarios in which we investigated the effect of an adjusted RM control and seasonality on the ROM. The results are principally identical to those obtained from the same scenarios applied to the ROM with independent demand. Detailed results are listed in Table 5.7. If the bid prices are adjusted, we observe lower average values for $\overline{PARO}^R$. The similarity measures still indicate a high similarity. $\overline{MAE}^{PARO}$ remains moderate with a maximum value of 5.8%. The correlation coefficient r^{PARO} is also very high ranging from 0.69 to 0.96. The error

	Base Case	Bid price decrease		Bid price increase		Adjust seasonality		Apply saw tooth curve	
Adj. level	-	25%	50%	25%	50%	-50%	+50%	130% - 70%	120% - 80%
$\overline{PARO}^{R}$ (%)	60.8	55.3	33.2	55.0	49.9	61.0	60.5	55.3	58.4
$\overline{PARO}^{D}$ (%)	64.6	60.9	39.1	58.2	52.4	65.1	64.3	59.8	62.6
$\overline{MAE}^{PARO}$ (%)	3.8	5.6	5.8	3.3	2.5	4.0	3.8	4.7	4.2
r^{PARO}	0.91	0.69	0.87	0.95	0.96	0.82	0.94	1.00	1.00
$\overline{R}^{td}$ (thousand)	117.5	117.5	117.5	117.5	117.5	117.2	117.7	117.0	117.0
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.4	87.8	87.3	87.3
$\overline{R}^{bd}$ (thousand)	29.9	29.9	29.9	29.9	29.9	29.8	29.9	29.8	29.8
$\overline{D}^{td}$ (thousand)	120.4	120.1	118.7	119.2	118.4	120.6	119.9	115.6	118.3
$\overline{D}^{yd}$ (thousand)	88.7	88.6	87.8	87.8	87.3	88.8	88.3	85.2	87.2
$\overline{D}^{bd}$ (thousand)	31.7	31.6	30.9	31.4	31.1	31.8	31.6	30.5	31.2
$\overline{MAE}^{D^{td}}$	1.37	1.34	1.30	1.34	1.32	1.33	1.41	1.49	1.40
$\overline{MAE}^{D^{yd}}$	0.76	0.75	0.73	0.75	0.75	0.72	0.80	0.87	0.78
$\overline{MAE}^{D^{bd}}$	0.87	0.86	0.85	0.86	0.85	0.86	0.87	0.87	0.86
$\overline{PMAE}^{D^{td}}$ (%)	16.9	16.5	16.0	16.5	16.3	16.4	17.4	18.6	17.4
$\overline{PMAE}^{D^{yd}}$ (%)	12.5	12.4	12.1	12.4	12.4	12.0	13.2	14.1	12.9
$\overline{PMAE}^{D^{bd}}$ (%)	42.0	41.6	41.1	41.5	41.3	41.8	42.2	43.3	42.4

Table 5.7.: Effect of Adjusted RM Control and Seasonality on PARO

measures are influenced on a minor level by the bid price adjustment. Compared to the base case the average values for the MAE and PMAE remain constant. The scatter plot of the restrictive RM control case is presented in Figure 5.11. The scatter plot open of the RM control case can be found in the appendix.

If we adjust the amplitude of the seasonality we observe the expected effects. If the amplitude of the seasonality is decreased the error measures decrease and $\overline{MAE}^{PARO}$ decreases. The contrary result occurs, if we increase the magnitude of the amplitude of seasonality. For both scenario the values of r^{PARO} remain above 0.84. The saw tooth curve applied to the overall demand level leads to slightly increased error measures. The $\overline{MAE}^{PARO}$ also increases a bit, whereas the correlation coefficient r^{PARO} again goes up to 1. This is in particular due to the wide range of realized PARO results along the 150 simulation runs. In Figure 5.12 the saw tooth curve scenarios are shown.

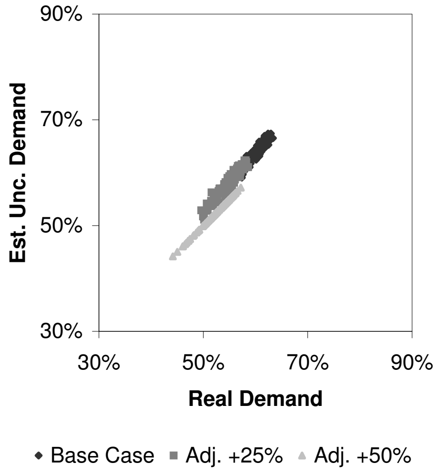

Figure 5.11.: Effect of Restrictive RM Controls on PARO

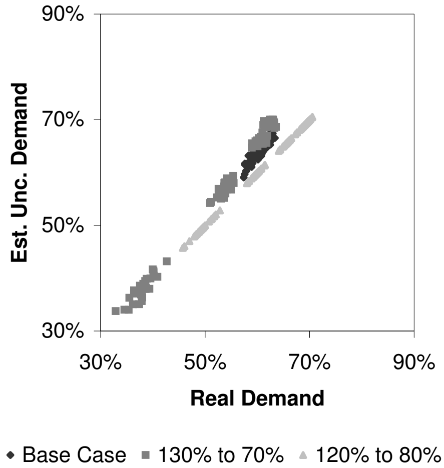

Figure 5.12.: Effect of High Deviation in Customer Demand on PARO

5.3.3. Analyzing the Effect of Different Sell-up Rates

In Chapter 3 we defined an average sell-up rate of 30% to be our base case. The real sell-up rate however might be higher or lower. Thus, we also assessed scenarios with sell-up rates of 10% and 50%. The complete set of result tables and figures can be found in the appendix. We focus on the unconstraining errors on the estimated yieldable demand to compare the behavior of the ROM according to the sell-up rate in the flight network. Table 5.8 shows the detailed results. One main result of our investigation is that no matter which sell-up rate is applied, the ROM proves itself to be robust against the basic error scenarios. The values of r^{PARO} again show high values, with a decrease for the biased underestimation of the yieldable demand. In accordance to this observation the $\overline{MAE}^{PARO}$ obtains values below our defined threshold except for the biased underestimation of the estimated unconstrained yieldable demand. For the base case it we observe that the lower the sell-up rate is, the better the values of $\overline{MAE}^{PARO}$ get. It increases from 1.3% with 10% sell-up rate to 8.6% with 50% sell-up rate. However, this is not a general trend. For the error scenarios the values of $\overline{MAE}^{PARO}$ are always higher with a sell-up rate of 10%. We illustrate the unbiased unconstraining error on the yieldable demand in Figures 5.13 and 5.14. Detailed results can be found in the appendix.

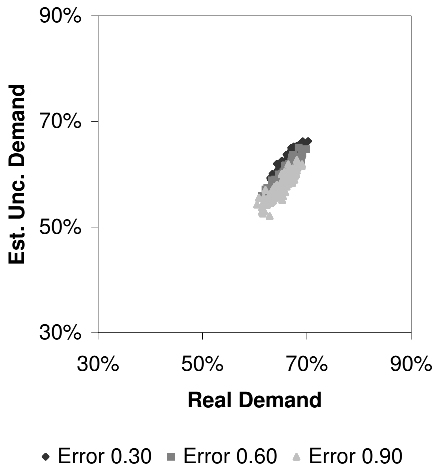

Figure 5.13.: Sell-up Rate 10%: Effect of an Unbiased Error in Unconstrained Yieldable Demand on PARO

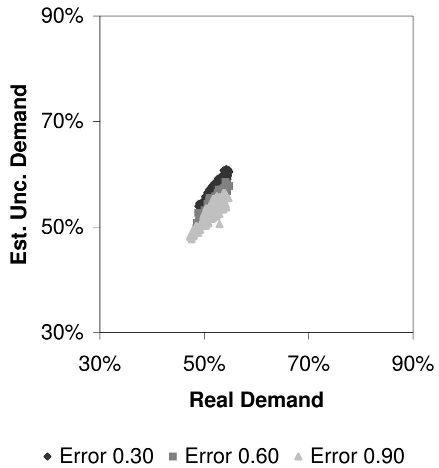

Figure 5.14.: Sell-up Rate 50%: Effect of an Unbiased Error in Unconstrained Yieldable Demand on PARO

5.4. Summary

In this chapter we introduced the network-based ROM with dependent demand in detail. We made use of a common way of modeling dependent demand structures

Sell-up rate 10%

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	67.9	64.8	57.8	43.5	67.6	66.0	64.0	67.2	66.4	65.5
$\overline{PARO}^D$ (%)	66.5	66.2	64.6	68.2	61.2	57.2	53.9	63.4	60.6	58.1
$\overline{MAE}^{PARO}$ (%)	1.3	1.5	6.8	24.7	6.4	8.8	10.1	3.9	5.8	7.3
r^{PARO}	0.89	0.75	0.57	0.39	0.96	0.97	0.97	0.90	0.91	0.89
$\overline{R}^{td}$ (thousand)	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{D}^{td}$ (thousand)	97.6	89.4	81.7	74.8	110.7	123.6	136.7	100.0	102.5	105.4
$\overline{D}^{yd}$ (thousand)	88.4	79.6	71.5	64.4	101.4	114.4	127.4	90.5	92.7	95.3
$\overline{D}^{bd}$ (thousand)	9.2	9.7	10.2	10.3	9.3	9.3	9.3	9.5	9.8	10.2
$\overline{MAE}^{D^{td}}$	1.00	1.10	1.41	1.77	1.50	2.27	3.12	1.30	1.85	2.46
$\overline{MAE}^{D^{yd}}$	0.70	0.84	1.23	1.66	1.18	1.95	2.80	1.01	1.59	2.25
$\overline{MAE}^{D^{bd}}$	0.47	0.49	0.51	0.52	0.47	0.47	0.47	0.48	0.49	0.51
$\overline{PMAE}^{D^{td}}$ (%)	15.1	16.7	21.3	26.7	22.7	34.4	47.2	19.7	27.9	37.2
$\overline{PMAE}^{D^{yd}}$ (%)	11.5	13.9	20.3	27.3	19.4	32.2	46.3	16.6	26.2	37.1
$\overline{PMAE}^{D^{bd}}$ (%)	85.1	88.8	92.7	93.7	85.1	84.9	84.8	87.0	89.5	92.5

Sell-up rate 50%

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	53.1	50.3	45.1	38.2	53.2	52.7	51.7	52.6	52.1	51.6
$\overline{PARO}^D$ (%)	61.7	60.3	57.6	56.1	55.8	52.0	49.0	58.0	54.9	52.8
$\overline{MAE}^{PARO}$ (%)	8.6	10.1	12.5	17.9	2.7	0.7	2.7	5.4	2.7	1.3
r^{PARO}	0.92	0.86	0.74	0.64	0.95	0.96	0.96	0.92	0.92	0.87
$\overline{R}^{td}$ (thousand)	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3
$\overline{D}^{td}$ (thousand)	157.1	147.8	139.7	134.6	171.4	185.8	200.1	159.5	162.7	167.4
$\overline{D}^{yd}$ (thousand)	89.1	79.4	71.3	66.4	103.4	117.6	131.9	91.3	94.2	98.4
$\overline{D}^{bd}$ (thousand)	67.9	68.4	68.4	68.2	68.0	68.2	68.3	68.2	68.5	69.0
$\overline{MAE}^{D^{td}}$	1.77	1.89	2.13	2.30	2.25	3.03	3.91	2.07	2.60	3.14
$\overline{MAE}^{D^{yd}}$	0.85	1.01	1.36	1.64	1.36	2.20	3.12	1.19	1.79	2.41
$\overline{MAE}^{D^{bd}}$	1.26	1.27	1.27	1.26	1.26	1.26	1.26	1.26	1.27	1.28
$\overline{PMAE}^{D^{td}}$ (%)	16.8	17.8	20.1	21.7	21.3	28.6	37.0	19.6	24.5	29.7
$\overline{PMAE}^{D^{yd}}$ (%)	14.1	16.6	22.4	27.0	22.5	36.2	51.5	19.6	29.5	39.8
$\overline{PMAE}^{D^{bd}}$ (%)	27.8	28.0	28.0	27.8	27.8	27.9	27.9	27.9	28.1	28.3

Table 5.8.: Applying Sell-up Rates of 10% and 50% to Flight Network

in reality to enhance the network-based ROM with independent demand. After discussing main properties of the ROM, we analyzed the robustness of the ROM, particularly against unconstraining errors in the yieldable demand and the buy-down. In all scenarios applied, the values of the similarity measures showed results above our minimum level of similarity defined in Section 3.2. Because we tested all scenarios with error levels up to the expected worst case and even beyond, we consider the network-based ROM with dependent demand robust against errors in the input data for all error levels we would expect in real life. Moreover, the effects of applying different sell-up rates in the flight network basically do not change the results. The ROM proved itself robust for all scenarios applied.

However, in comparison to the independent demand case, the magnitude of unconstraining errors is significantly higher with dependent demand. This applies in particular to the estimated unconstrained buy-down, but also for the estimated unconstrained yieldable demand. The higher average unconstraining error leads to a decrease of the similarity measures.

6. Disaggregation of ROM Measures to Single Legs

In this chapter, we build on the previously defined ROMs with independent and dependent demand and assess their potential to be used in practical applications. One important dimension is the disaggregation of the aggregated ROM measures to subparts of the total flight network and in particular to single legs.

Although the overall RM control is network-based, there are several reasons why a leg-based perspective in RM departments is important. One reason is that RM control is historically leg-based. Revenue managers were historically responsible to control several legs because network structures did not exist. This situation has significantly changed: Many airlines operate complex flight networks. However, even today many RM departments all over the world are organized according to legs or markets. Furthermore many RM controls are on a leg base, e.g. overbooking or upgrading. These decisions are leg-based because they require direct adjustments to the available capacity of a single leg. A very popular way of controlling bookings in a network-based RM environment makes use of bid-price models. These models define bid prices for using single resources, which are again the legs in the flight network. Adjustments to a more open or restrictive RM control are usually done by increasing the bid price on a specific leg. Because many RM decisions have to be taken on a leg level, there is huge interest in obtaining performance measures for a single leg. One important example is the SLF, which not necessarily indicates the RM performance, but primarily the utilization of the resource. Another reason to disaggregate the aggregated ROM measure to subparts of the network is simply having not only one aggregated measure for the entire network, but several measures suitable to the organizational structure of the revenue managers.

However, a disaggregation to a single leg usually incurs errors. The revenue optimization is performed on a network level. As with all network problems, a local optimum not necessarily corresponds to the network optimum. Thus, performance measures on a leg level can always only be a supplemental indicator. Simply maximizing the performance on one leg must not necessarily lead to the desired results for the entire flight network.

In the first section of this chapter we investigate the relationship between leg-based and network-based ROMs. In a second step we introduce several prorating methods to distribute the fares of an itinerary to single legs. After formally defining the leg-based ROM measures obtained in a network-based RM context we assess their potential applicability on a leg level. We present computational results on the robustness of the ROM disaggregated to leg level and investigate further properties.

6.1. Relation between Network and Leg Level

In this section we discuss the basic relation between the network and leg level and introduce some new definitions. In a network-based RM context passengers book itineraries containing one or more resources, i.e. legs. As a result a booking on an itinerary might lead to the use of multiple legs. This holds particularly true for airlines using hub and spoke network structures. Often these airlines try to increase the number of bookings on intercontinental flights departing from a hub with passengers from other spoke locations using feeder flights. As already described in Chapter 1 network airlines significantly use network-based controls to handle these overlapping network traffic flows.

One typical differentiation for network airlines is to differentiate between connecting and local traffic. Local traffic describes bookings on itineraries that only contain one leg, whereas connecting traffic describes itineraries in which the passenger takes at least two flights. Airlines usually measure the degree of connecting traffic within their flight network. This can be accomplished by simply calculating the share of bookings on connecting itineraries in comparison to the total number of bookings. For a common network carrier the share of bookings on connecting itineraries out of their total bookings is around 30% - 50%[1].

The share of connecting traffic can also be determined on a leg level. To quantify the degree of connecting traffic on a leg level, we start with some formal definitions. We recall the fact that L_i denotes the set of all legs l that are contained by itinerary i. In contrast to this, I_l denotes all itineraries that use leg l and I_l^γ denotes the set of all itineraries that contain more than one leg l (i.e. $|L_i| > 1$) and which are considered connecting traffic. Given these notations we define the number of cumulated bookings on a given leg l as B_l. The number of cumulated connecting traffic bookings for a given leg l is accordingly denoted

[1]Based on information discussed in personal communication with Dr. Pölt - Lufthansa German Airlines

with B_l^γ. The definitions are shown in Equations 6.1 and 6.2.

$$B_l = \sum_{i \in I_l} \sum_{j \in J_i} \sum_{t \in T} b_{i,j,t} \qquad \forall l \in L \tag{6.1}$$

$$B_l^\gamma = \sum_{i \in I_l^\gamma} \sum_{j \in J_i} \sum_{t \in T} b_{i,j,t} \qquad \forall l \in L \tag{6.2}$$

Using these definitions we introduce γ_l to measure the share of connecting traffic on a leg l. A definition of γ_l can be found in Equation 6.3.

$$\gamma_l = \frac{B_l^\gamma}{B_l} \qquad \forall l \in L \tag{6.3}$$

γ_l describes the ratio of all cumulated connecting traffic bookings B_l^γ to all cumulated bookings B_l on a leg l. The average share of connecting traffic passengers for a network airline is usually between 45% and 65%. This rate is higher than the rate based on itineraries because each connecting itinerary is counted multiple times. For each leg in an itinerary we count a booking on the respective leg.

In case we do not have any connecting traffic in the flight network, i.e. $|L_i| = 1, \forall i \in I$ we observe a special case. The estimation of the bookings for each itinerary i derived from the LP-model and the FCFS simulation algorithm do not contain any network effects. This leads to the observation that the solution for the network-based ROM is equivalent to the solution of multiple independent leg-based ROMs. The network-based ROMs defined in Chapters 4 and 5 presents a complicated way to maximize revenues on one leg in comparison to the approaches usually used for leg-based ROMs. But this special case also has some advantages for our analyses. The ROM measures on a leg level do not contain any errors due to network effects, which allows us to examine the influence of network effects on the measures. In the remainder of this chapter we use this property to describe and quantify the network effects on the ROM, if disaggregated to leg level.

6.2. Prorating Fares to Single Legs

For the calculation of the different revenue estimates (i.e. potential and no RM revenue) on a leg base we utilize the bookings on the itineraries and combine them to the respective legs. For all itineraries i that only contain one leg the assignment of the fare to the respective leg is simple. The fares of the leg l $p_{i,j,l,t}$ correspond to the fares of the itinerary $p_{i,j,t}$. If an itinerary i contains more than one leg, this assignment does not work. The fare of the itinerary has to be distributed to the respective legs. This procedure is called prorating and several ways to perform this procedure are described in detail in this section. The basic idea is to split the fares $p_{i,j,t}$ for each itinerary i to the flight legs it contains using prorate factors $\rho_{i,j,l}$ obtained for each leg l in the respective itinerary i and booking class j. A formal definition is given in Equations 6.4 - 6.6.

$$p_{i,j,l,t} = p_{i,j,t} * \rho_{i,j,l} \qquad \forall i \in I, \forall j \in J_i, \forall l \in L_i, \forall t \in T \tag{6.4}$$

$$\sum_{l \in L_i} p_{i,j,l,t} = p_{i,j,t} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{6.5}$$

$$0 \leq p_{i,j,l,t} \leq p_{i,j,t} \qquad \forall i \in I, \forall j \in J_i, \forall l \in L_i, \forall t \in T \tag{6.6}$$

The prorated fare $p_{i,j,l,t}$ for a leg l is defined in Equation 6.4. It is a share of the total fare $p_{i,j,t}$ of an itinerary i. The share is defined by $\rho_{i,j,l}$. Equations 6.5 and 6.6 ensure that the fare of an itinerary i is fully distributed to the legs and that no leg obtains a higher prorated fare than the fare of the itinerary.

A very important question is how to obtain the prorating factors $\rho_{i,j,l}$. In literature some ways to determine $\rho_{i,j,l}$ have been proposed. For example Talluri and van Ryzin (2004b) and Williamson (1992) describe some common ways to prorate fares to legs and comment on the applicability of the different methods. Among others the following methods are commonly used in practice:

- Prorating by mileage
- Prorating by fares
- Prorating by bid prices

The prorating by mileage is basically static because it uses the length of the flight legs as an input which is known beforehand and does not change over time. The prorating based on fares is a semi-static approach. Fares might change over the course of a booking period. In contrast to this the prorating by bid prices is dynamic and basically changes with every single flight departure. We concentrate on the prorating by mileage and the prorating by bid prices for the remainder of this thesis in order to analyze effects both for dynamic and static approaches.

6.2.1. Mileage

One simple proposal to prorate the fares of an itinerary between its flight legs is to use the distance of the flight legs. Equation 6.7 gives a formal definition:

$$\rho_{i,j,l} = \frac{\upsilon_l}{\sum_{l' \in L_i} \upsilon_{l'}} \qquad \forall i \in I, \forall j \in J_i, \forall l \in L_i \tag{6.7}$$

With υ_l we denote the distance of a flight leg l. The prorate factor $\rho_{i,j,l}$ is derived as the share of the distance of a leg to the total flight distance of all legs of the itinerary. Because the distance of a leg is always greater than zero, a division by zero cannot occur. This method usually privileges legs with a long distance, in particular if the other legs in the itinerary are very short. This is often the case for combinations of continental feeder flights to intercontinental flights departing from hubs.

6.2.2. Bid Prices

Another way of prorating fares is using bid prices. This method incorporates information on the importance of a single leg into the distribution of fares. The basic idea is to increase the fare ratio for those legs that have a high bid price and thus are a very important and constrained resource in the flight network. In Equation 6.8 we define the method formally.

$$\rho_{i,j,l} = \frac{max(\pi_{l,m_{l,j}}, p^{min}_{l,m_{l,j}})}{\sum_{l' \in L_i} max(\pi_{l',m_{l',j}}, p^{min}_{l',m_{l',j}})} \qquad \forall i \in I, \forall j \in J_i, \quad \forall l \in L_i \tag{6.8}$$

First, the bid prices $\pi_{l,m}$ for each compartment m on leg l have to be determined (please recall that $m_{l,j}$ corresponds to the compartment on leg l which is related to booking class j). They can e.g. be the shadow prices from the capacity constraint of the LP model solved for the potential revenue estimation (see e.g. Equations 4.2 and 5.8). It is also possible to use the bid prices of the respective booking period for each compartment. Vinod (2006), for example, proposes to store the bid prices after the departure of a plane to use them for ex-post PM. Bid prices have the disadvantage that in some cases $\pi_{l,m}$ might be zero and could potentially lead to a division by zero. This usually happens in low demand situations. To prevent this, we propose to use the maximum of the given bid price $\pi_{l,m}$ and the minimum fare for the compartment $p^{min}_{l,m}$. For example the minimum fare for the local itinerary containing that leg can be used. This procedure ensures that a value greater than zero is used for each leg in the calculation of the prorating factors. However, this procedure leads to the effect that the distribution of the fares is stronger aligned to the distribution of local fares, because low bid prices are increased to the minimum local fare $p^{min}_{l,m}$.

If we do not want to discard any bid prices with a value of zero, we propose a slightly more aggressive distribution of the fares. It is defined in Equation 6.9

$$\rho_{i,j,l} = \begin{cases} \frac{\pi_{l,m_{l,j}}}{\sum_{l' \in L_i} \pi_{l',m_{l',j}}} & \sum_{l' \in L_i} \pi_{l',m_{l',j}} > 0 \\ \frac{p^{min}_{l,m_{l,j}}}{\sum_{l' \in L_i} p^{min}_{l',m_{l',j}}} & otherwise \end{cases} \quad \forall i \in I, \forall j \in J_i, \forall l \in L_i \tag{6.9}$$

In this case the bid prices of a compartment are used unless all bid prices of the itinerary are zero. Only in this case we make use of the minimum revenue of the compartments. This leads to a much more aggressive split of the fares, because all legs with a zero bid price do not get any revenue share. This only changes if all bid prices for the itinerary are zero.

6.3. Model Definition on a Leg Base

The ROM measures on a leg base are calculated with the results of the estimations described in Chapters 4 and 5. Basic input is the number of estimated bookings for the potential and no RM revenue $x^+_{i,j,t}$ and $x^-_{i,j,t}$, but also the number of actual bookings $b_{i,j,t}$. As described in the previous sections the bookings on an itinerary are applied to all related legs together with the prorated fares $p_{i,j,l,t}$. Based on this information the potential revenue Rev^+_l, the actual revenue Rev_l and the no RM revenue Rev^-_l are calculated as described in Equations 6.10, 6.11 and 6.12.

$$Rev^+_l = \sum_{i \in I_l} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,l,t} * x^+_{i,j,t} \qquad \forall l \in L \tag{6.10}$$

$$Rev_l = \sum_{i \in I_l} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,l,t} * b_{i,j,t} \qquad \forall l \in L \tag{6.11}$$

$$Rev^-_l = \sum_{i \in I_l} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,l,t} * x^-_{i,j,t} \qquad \forall l \in L \tag{6.12}$$

The values for Rev^+_l, Rev_l and Rev^-_l are used as the input for calculating the ROM measures on a leg base. A formal definition is given in Equations 6.13, 6.14 and 6.15. The ROM measures on a leg base enable to compare the performance of single legs. As mentioned earlier these measures incur errors because of network effects, if there is connecting traffic in the flight network. In the remainder of this thesis we analyze the extent of these effect.

$$RO_l = Rev_l^+ - Rev_l^- \qquad \forall l \in L \tag{6.13}$$

$$ARO_l = Rev_l - Rev_l^- \qquad \forall l \in L \tag{6.14}$$

$$PARO_l = \frac{ARO_l}{RO_l} \qquad \forall l \in L \tag{6.15}$$

The definitions for RO_l, ARO_l and $PARO_l$ are basically the same as for the network level, but in contrast to the network level, we obtain ROM measures for each leg l. However, this also leads to a potential problem, that was not very likely on the aggregated network level. For some legs it might be the case that the RO is zero. This happens if the potential and the no RM revenue are the same. Mainly this constellation occurs, if there is low demand on a flight and the RM control is not able to increase revenues. To handle these situations we extend the definition for the PARO in Equation 6.16.

$$PARO_l \quad = \quad \begin{cases} \frac{ARO_l}{RO_l} & RO_l > 0 \\ 1 & otherwise \end{cases} \qquad \forall l \in L \tag{6.16}$$

We define the PARO to be 100%, if the RO is zero or below zero. Values below zero may occur in particular in network-based environments, if for example the simulated FCFS strategy accepts many bookings of itineraries using a leg, but the LP, which estimated the potential revenue bookings, only allocates a few bookings to this leg.

We have not yet discussed the case in which the PARO becomes greater than 100% or smaller than 0%, i.e. turns negative. This happens when the ARO gets larger than the RO or the ARO turns negative. Especially the case of a negative ARO is quite common. It usually describes situations in which the RM control was very restrictive, most likely due to a demand forecast that was too high. In the following we propose to use only PARO values between 0% and 100%. Very poor RM control leading to PARO values below zero will be set to 0% and PARO values above 100% indicating very good RM control will be set to 100%. We base this proposal on the fact, that values out of this range sometimes take arbitrary high or low values. We show some examples in the next section. In the remainder of this thesis we call this adjustment *capping*. Equation 6.17 defines capping formally.

$$PARO_l \quad = \quad \begin{cases} PARO_l & 0 \leq PARO_l \leq 1 \\ 0 & PARO_l < 0 \\ 1 & PARO_l > 1 \end{cases} \qquad \forall l \in L \tag{6.17}$$

$$\tag{6.18}$$

After we have obtained ROM measures for each leg and adjusted them in the described manner, we suggest to filter out some flight departures for further analysis. As it has been defined before, all cases in which the RO is less or equal to zero the PARO has an arbitrary value. We defined the value to be 100%. However, these 100% are not comparable to the 100% obtained in case of perfect RM controls. It is difficult to make an interpretation of those cases possible in which the RO for a flight departure is zero or below zero. We propose to filter out these flight departures and examine them separately. We refer to this approach as *filtering* in the following.

All the definitions made in this section are based on the consideration of one flight departure. In RM practice it is common to observe performance measures for a longer time period. Forecast errors, for example, are measured on a monthly base. Thus, we propose to examine ROM measures that are based on multiple flight departures. As the input for the ROM measures we therefore use average values of the actual and the estimated potential and no RM revenue over a time period of two weeks (14 days) or one month (30 days). With the use of averaging we aspire to decrease the negative effect of unconstraining errors and network effects on the leg-based measures. This concept is denoted with *averaging*.

6.4. Computational Results

In this section we present computational results of the disaggregation of the ROM measures to single legs. We focus on the PARO and in particular on the influences of network effects and errors in the estimated unconstrained demand on the robustness of the PARO.

6.4.1. No-connecting-traffic Flight Network: Network Level

We start off with an investigation of a flight network with no connecting traffic. The flight network consists of the same 728 flights as the realistic flight network. As described earlier, there are no negative network effects on the validity of the ROM measures with flight networks that do not contain any connecting traffic. First, we analyze the aggregated PAROs over all flight legs as conducted in Chapters 4 and 5. For this analysis and the rest of this section we focus on the base case and the unbiased unconstraining error scenarios with error level of 30%, 60% and 90% for both independent and dependent demand. The scatter plots of the base cases are presented in Figures 6.1 and 6.2. Please note that the scatter plots range from 40% to 100% (instead of from 30% to 90%). Detailed results of all scenarios are presented in Table 6.1. The structure of the table is similar to the

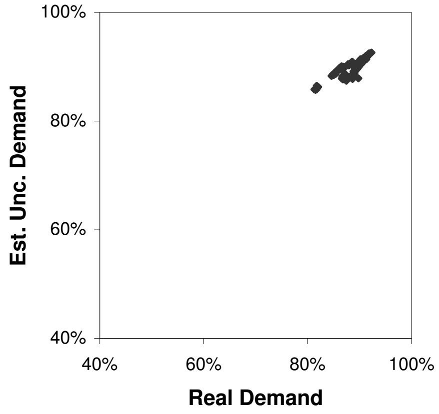

Figure 6.1.: No-connecting-traffic Flight Network with Independent Demand Aggregated to Network Level

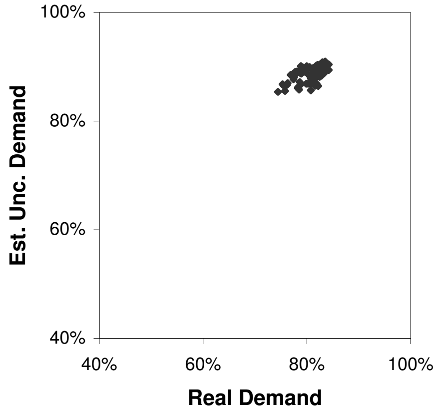

Figure 6.2.: No-connecting-traffic Flight Network with Dependent Demand Aggregated to Network Level

one used in the previous chapters. The scenarios presented in the columns are the base case and the three unbiased unconstraining error scenarios for independent demand. The base case and the three unbiased unconstraining error scenarios of the yieldable demand and the three unbiased unconstraining error scenarios of the buy-down for dependent demand are also included. For both independent and dependent demand the PAROs show good results. The values of $\overline{MAE}^{PARO}$ are comparable to our realistic flight network scenarios. The scatter plot also shows a high linear relation for both base cases. The correlation coefficient r^{PARO} decreases slightly compared to the realistic flight network. However, with values

	Independent demand				Dependent demand						
	Base	Error level			Base	Error level YD			Error level BD		
	Case	30%	60%	90%	Case	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	89.2	89.3	89.3	89.3	81.2	81.7	82.1	82.3	81.4	81.6	81.9
$\overline{PARO}^D$ (%)	90.3	89.8	89.2	88.7	88.9	84.1	80.2	77.1	87.8	85.6	79.8
$\overline{MAE}^{PARO}$ (%)	1.2	0.8	0.9	1.2	7.7	2.4	2.1	5.2	6.4	4.0	2.2
r^{PARO}	0.88	0.88	0.88	0.84	0.62	0.73	0.76	0.83	0.68	0.75	0.80

Table 6.1.: Results for No-connecting-traffic Flight Network Aggregated over All Flight Legs

over 0.62 for all error scenarios the aggregated PAROs are also considered robust against unconstraining errors.

6.4.2. No-connecting-traffic Flight Network: Leg Level

Using the same flight network with no connecting traffic we now analyze the ROM measures on a leg level. We again performed 150 simulation runs and make use of five (averaged) flight departures. In our analysis we obtain PARO values with real and estimated unconstrained demand for each simulation run and flight leg and present them in Figure 6.3. The scatter plot shows some extreme cases, in which the PARO values are significantly below 0% or above 100%. These extreme cases were already predicted in the previous section. They are usually not observed on an aggregated network level, which is illustrated in the scatter plots in Chapters 4 and 5. We do not measure the correlation coefficient and the MAE in this case, because we expect the outliers to disturb the similarity measures significantly. However, we analyze the number of cases in which the PARO values are below 0% or above 100% and also the cases in which the RO is equal to or below zero. The results are shown in Table 6.2. In the first three result rows we list the share of cases in which the condition

	Independent demand				Dependent demand						
	Base	Error level			Base	Error level YD			Error level BD		
	Case	30%	60%	90%	Case	30%	60%	90%	30%	60%	90%
Cases for est. unc. dmd, in which condition holds (%)											
$PARO_l < 0$ (%)	0.7	1.0	1.2	1.3	1.0	2.0	3.5	3.8	1.1	1.5	2.3
$PARO_l > 1$ (%)	0.0	0.0	0.0	0.0	1.0	1.1	3.2	4.4	0.6	0.3	0.1
$RO_l \leq 0$ (%)	45.4	45.1	45.3	45.9	44.4	43.2	40.9	39.6	44.3	44.1	43.8
Cases, in which fulfillment of condition matches between real and est. unc. dmd. (%)											
$PARO_l < 0$ (%)	99.3	99.1	98.9	98.3	98.1	97.2	95.9	96.5	98.2	97.8	97.0
$PARO_l > 1$ (%)	100.0	100.0	100.0	100.0	99.0	98.9	96.8	95.6	99.4	99.7	99.9
$RO_l \leq 0$ (%)	99.1	99.1	98.6	97.7	56.1	57.3	59.5	60.8	56.2	56.4	56.7

Table 6.2.: Analyzing Special Cases for No-connecting-traffic Flight Network

denoted in the first column holds for the ROM measures that were obtained with estimated unconstrained demand. In the last three rows we analyze the share of cases in which the fulfillment of the given condition matches between real and estimated unconstrained demand. It can be observed that there is only a small percentage of cases in which the PARO actually becomes less than 0% or greater than 100%. The share of matches of the fulfillment of the condition between the results obtained with real demand are very high with above 95% for both independent and dependent demand. Using the estimated unconstrained demand the RO is estimated to be smaller or equal to zero in about 40% to 45% of the cases for both independent and dependent demand. However, the number of matches between real and estimated unconstrained demand is very high for independent demand at around 97% and significantly smaller at around 55% for dependent demand. We conclude that if we cap the PAROs calculated with real

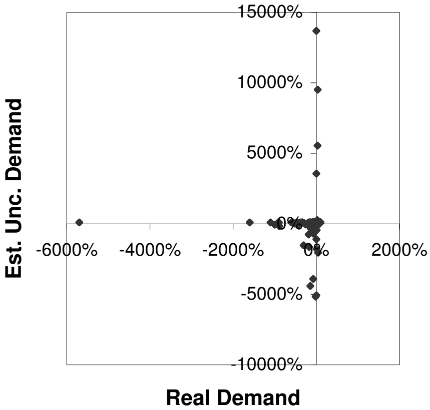

Figure 6.3.: No-connecting-traffic Flight Network with Dependent Demand - No Capping and Filtering

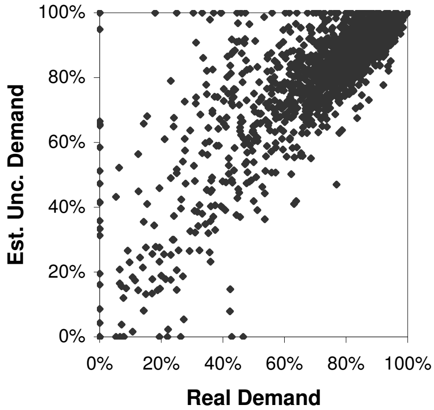

Figure 6.4.: No-connecting-traffic Flight Network with Dependent Demand

demand to 0% or to 100% the PAROs calculated with estimated unconstrained demand would be capped the same way. The same is true for filtering out the flight departures with the independent demand scenario. For dependent demand the congruence of the filter is smaller. This means that filtering out a flight departure due to the RO obtained with the estimated unconstrained demand is not necessary, because the RO for real demand is greater than zero. Thus, the results of the similarity measures might incur an error due to filtering. This effect has to be kept in mind while analyzing scenarios with a filter being applied.

Detailed results, in which we capped and filtered the PAROs are presented in Table 6.3. The first results describe the scenario in which we capped the PAROs. For independent demand this already leads to good values for r^{PARO}. For dependent demand there is still no linear relation observable. If we also apply the filter mentioned above the values for r^{PARO} are high for both independent and dependent demand. r^{PARO} is above 0.56 even for a very high unconstraining error. The $\overline{MAE}^{PARO}$ also indicates strong similarity with better values for independent

	Independent demand				Dependent demand						
	Base	Error level			Base	Error level YD			Error level BD		
	Case	30%	60%	90%	Case	30%	60%	90%	30%	60%	90%
Capping											
$\overline{MAE}^{PARO}$ (%)	2.9	3.4	4.5	6.8	48.6	48.3	48.1	48.1	48.1	47.4	47.0
r^{PARO}	0.83	0.82	0.76	0.62	-0.15	-0.15	-0.10	-0.10	-0.16	-0.18	-0.20
Filtering											
flight dep. incl. (%)	54.6	54.9	54.7	54.1	55.6	56.8	59.1	60.4	55.7	55.9	56.2
$\overline{MAE}^{PARO}$ (%)	5.1	6.1	8.0	11.6	8.5	10.0	13.0	14.8	7.8	6.8	6.6
r^{PARO}	0.81	0.77	0.71	0.56	0.85	0.75	0.69	0.64	0.85	0.87	0.89
Averaging over two weeks											
flight dep. incl. (%)	67.3	67.7	67.6	67.7	67.4	68.9	71.6	73.6	67.4	67.7	68.2
$\overline{MAE}^{PARO}$ (%)	3.4	4.0	4.9	5.9	11.9	7.3	6.5	6.9	10.6	5.6	5.7
r^{PARO}	0.89	0.85	0.82	0.80	0.85	0.93	0.93	0.93	0.87	0.97	0.96
Averaging over one month											
flight dep. incl. (%)	69.9	70.2	70.2	70.1	70.2	71.5	74.2	76.3	70.1	70.3	70.8
$\overline{MAE}^{PARO}$ (%)	3.1	3.5	4.2	5.0	12.9	6.8	5.7	5.9	11.6	5.5	5.6
r^{PARO}	0.91	0.88	0.86	0.84	0.85	0.96	0.96	0.95	0.87	0.97	0.97

Table 6.3.: Similarity Measures for the No-connecting-traffic Flight Network

demand. This result can also be observed in the scatter plot depicted in Figure 6.4. In our analysis we also observe that the decrease in similarity observed on a network level for dependent demand is also strongly reflected on a leg level. The results for independent demand are significantly better.

In practical applications it is common to use average values of certain figures over a given time period. In the following we investigate two weeks and one month as common time periods for averaging. In Figures 6.5 and 6.6 we present the corresponding results. The detailed results can also be found in Table 6.3. The results show that the correlation coefficient r^{PARO} significantly increases for both independent and dependent demand and also $\overline{MAE}^{PARO}$ decreases. Averaging over two weeks leads to values of r^{PARO} above 0.80 and they further increase to 0.84 if we use averaging over one month. The values of $\overline{MAE}^{PARO}$ on average decrease over all error scenarios.

We conclude that the similarity measures obtained for the main error scenarios indicate that the PAROs can be used to track performance on a leg level if no connecting traffic is applied in the flight network. Capping the PAROs to 0% and 100% is a very useful concept to allow the application of the ROM. Filtering out flight departures is another powerful method to increase the robustness of the ROM. We also conclude that using an average over a certain time period further increases robustness. We propose to apply a monthly averaging, because

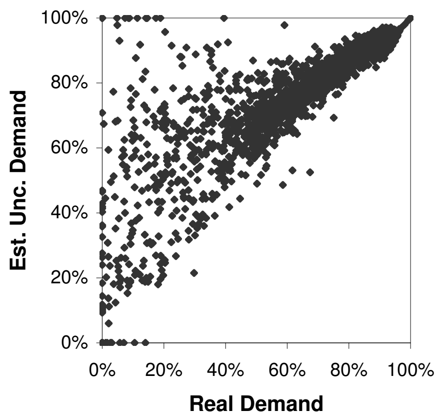

Figure 6.5.: No-connecting-traffic Flight Network with Dependent Demand - Averaged over 2 Weeks

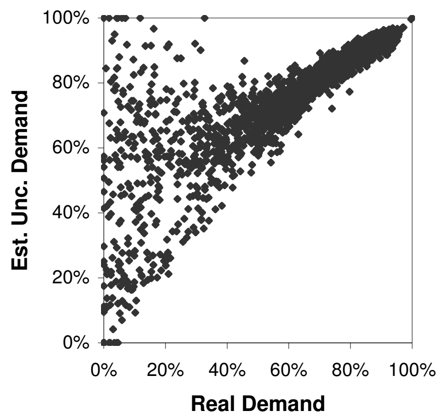

Figure 6.6.: No-connecting-traffic Flight Network with Dependent Demand - Averaged over One Month

it shows good results and this time period is already known from tracking forecast errors in operational RMS. However, even if we do not have any errors induced by network effects, the use of PAROs on a leg level needs specific treatment. In Figures 6.5 and 6.6 we observe some outliers, in particular for lower PARO values. If the ROM is intended to be applied in a real life system, it might be worth analyzing which common characteristic these outliers share to filter them out later on.

6.4.3. Realistic Flight Network: Leg Level

The assumption of a flight network without connecting traffic is not applicable for a network carrier in reality. In this section we analyze the potential to disaggregate the ROM measures to leg level if connecting traffic is applied. We base our analyses on the realistic flight network that we already used in the previous chapters. The fares are prorated by mileage to the legs per default. Although it is likely that some model-related errors occur while disaggregating the network results to leg level, we still consider the values obtained with the real demand to be the best estimates for the correct values. Thus, we continue to compare the ROM measures calculated with real demand to those measures that were calculated with the estimated unconstrained demand. We begin by analyzing the number of special cases. The results are presented in Table 6.4. The analysis of

	Independent demand				Dependent demand						
	Base	Error level			Base	Error level YD			Error level BD		
	Case	30%	60%	90%	Case	30%	60%	90%	30%	60%	90%
Cases for est. unc. Dmd, in which condition holds (%)											
$PARO_l < 0$ (%)	5.7	5.3	4.8	5.9	9.1	10.8	14.1	14.8	9.5	10.1	14.1
$PARO_l > 1$ (%)	3.7	3.9	4.2	4.5	2.1	2.0	3.3	3.6	2.4	2.0	1.0
$RO_l \leq 0$ (%)	39.9	39.9	39.9	40.5	37.8	37.5	35.4	34.2	37.7	38.0	37.5
Cases, in which fulfillment of condition matches between real and est. unc. dmd. (%)											
$PARO_l < 0$ (%)	95.6	95.5	94.9	94.0	91.3	89.9	87.6	85.6	91.0	90.6	88.0
$PARO_l > 1$ (%)	97.5	97.0	95.7	95.0	97.4	97.4	96.1	95.9	97.2	97.6	98.5
$RO_l \leq 0$ (%)	96.3	95.6	95.1	93.8	64.0	64.2	66.1	67.4	64.3	63.8	64.1

Table 6.4.: Analyzing Special Cases for Realistic Flight Network

special cases of the realistic flight network shows an increased number of PAROs to be capped. Nevertheless, the share of matches between real and estimated unconstrained demand remains high. The number of cases in which the RO is smaller than or equal to zero is very similar to the no-connecting-traffic flight network. However, for dependent demand the number of matches between real and estimated unconstrained demand increases to approximately 65%.

If we cap the PAROs, filter out the flight departures with RO being smaller than or equal to zero and take the average over one month we obtain the results presented in Table 6.5. If we only cap the PAROs, the results of the similarity

	Independent demand				Dependent demand						
	Base	Error level			Base	Error level YD			Error level BD		
	Case	30%	60%	90%	Case	30%	60%	90%	30%	60%	90%
Capping											
flight dep. incl. (%)	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
$\overline{MAE}^{PARO}$ (%)	7.2	7.8	9.4	11.3	43.8	44.1	44.0	44.6	43.2	43.0	43.1
r^{PARO}	0.76	0.74	0.68	0.62	-0.01	-0.02	-0.01	-0.01	0.00	-0.02	-0.06
Filtering											
flight dep. incl. (%)	60.1	60.1	60.1	59.5	62.2	62.5	64.6	65.8	62.3	62.0	62.5
$\overline{MAE}^{PARO}$ (%)	10.4	11.1	13.6	16.4	13.5	14.4	17.2	19.5	12.9	12.1	12.6
r^{PARO}	0.74	0.72	0.64	0.57	0.76	0.75	0.67	0.61	0.78	0.79	0.80
Averaging over one month											
flight dep. incl. (%)	70.0	70.0	70.2	70.2	71.8	72.5	74.2	75.5	71.6	72.0	72.5
$\overline{MAE}^{PARO}$ (%)	4.3	4.2	5.2	6.0	11.7	8.8	9.9	11.2	11.1	7.7	9.3
r^{PARO}	0.91	0.92	0.89	0.87	0.83	0.90	0.87	0.84	0.84	0.92	0.92

Table 6.5.: Similarity Measures for the Realistic Flight Network

measures are similar to the no-connecting-traffic flight network. With independent demand the values of r^{PARO} indicate a high similarity. With dependent demand we again measure no correlation. The $\overline{MAE}^{PARO}$ with dependent demand for any given error scenario is also very high with around 45%. This changes if we apply the filter to the RO, too. The scatter plots in Figures 6.7 and 6.8 confirm the results shown in the result table. The $\overline{MAE}^{PARO}$ decreases significantly to

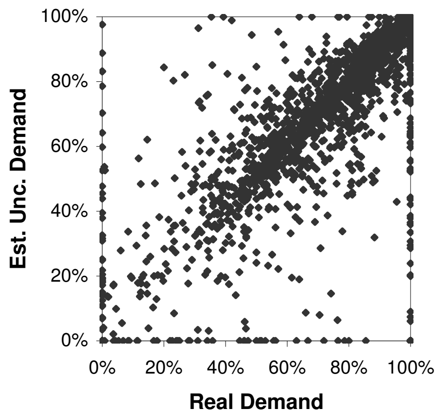

Figure 6.7.: Realistic Flight Network with Independent Demand

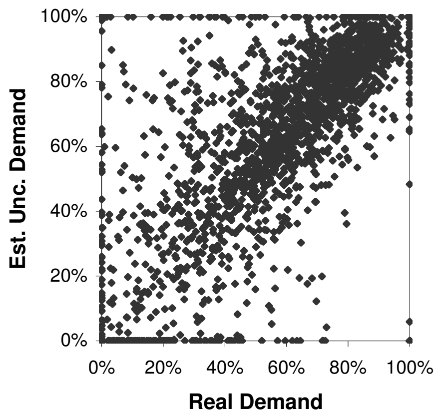

Figure 6.8.: Realistic Flight Network with Dependent Demand

values between 10% and 20% and the correlation coefficient is above 0.61 for all error scenarios. However, in particular with dependent demand the scatter plot reveals some outliers that disturb the robustness. The detailed results and the scatter plots lead to the conclusion that the similarity and thus the robustness for independent demand is significantly higher than for dependent demand.

The robustness of the ROM can further be increased by using an average over one month. The scatter plots of the base cases both for independent and dependent demand support these findings. They are presented in Figures 6.9 and 6.10. The correlation coefficients r^{PARO} are above 0.84 for all scenarios and the values for $\overline{MAE}^{PARO}$ also show a significant decrease. In addition, the number of flight departures included in the evaluation increased on average by 10% to values of around 70%. Moreover it can be observed that the application of a realistic flight network - and that means including network effects into the ROM calculation - leads to worse results compared to the no-connecting-traffic flight network scenario. However, in particular the correlation coefficient r^{PARO} indicates a high similarity and shows comparable results. The values of $\overline{MAE}^{PARO}$

are much higher with the realistic flight network.

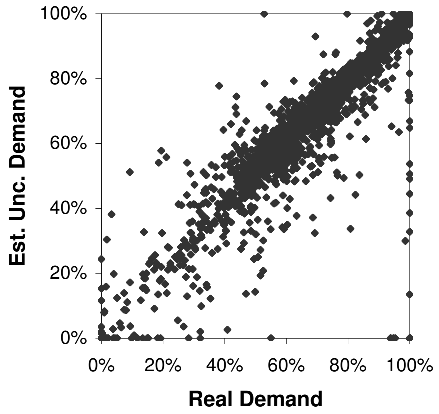

Figure 6.9.: Realistic Flight Network with Independent Demand - Averaged over One Month

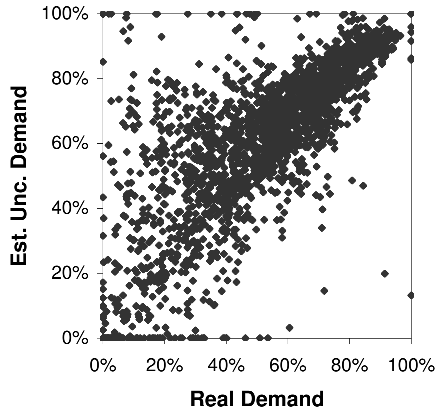

Figure 6.10.: Realistic Flight Network with Dependent Demand - Averaged over One Month

In Figure 6.11 we present a scatter plot of an unbiased error in the yieldable demand with an error level of 30%. As we already observed in Chapter 5 the unbiased unconstraining error in the yieldable demand increases robustness in our simulation environment. This also holds true for the results on a leg level. The correlation coefficient r^{PARO} is higher for error levels 30% and 60% than for the base case and also the values of $\overline{MAE}^{PARO}$ are smaller. These findings are supported by the scatter plot in which we see less outliers and a better linear relation.

Prorating of fares was not necessary with a no-connecting-traffic flight network. All itineraries contain only one flight leg and the fares of the itineraries can be applied to the legs without splitting them. In the analyses performed so far, we prorated the fares based on the distance of the contained flight legs. In the following we investigate the effect of using prorating methods based on bid prices. We used the moderate bid-price prorating and the aggressive bid-price prorating introduced in Section 6.2. The results are listed in Table 6.6 and shown in Figures 6.12 and 6.13. They show that the robustness of the ROM increases if the moderate bid-price method is applied. For all error scenarios the correlation coefficient r^{PARO} increased. The minimum value of r^{PARO} is 0.87, which is already a very high value. The values of $\overline{MAE}^{PARO}$ also decrease in all assessed cases. The scatter plot shows a decreased number of outliers and a stronger linear

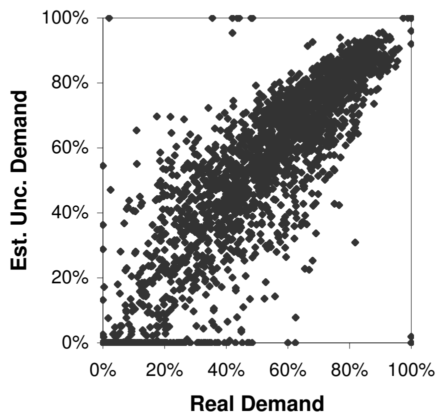

Figure 6.11.: Realistic Flight Network with Dependent Demand with 30% Unbiased Error on Unconstrained Yieldable Demand - Averaged over One Month

relation. The increase in similarity especially relates to the dependent demand scenarios. In contrast, the aggressive bid-price prorating method does not lead to better results. For some scenarios an improvement in similarity can be observed and in some cases the similarity decreases compared to the prorating by mileage. We conclude that it might be worth to further explore the moderate bid-price prorating method. One main challenge in practice will be to convince the revenue managers to accept this way of prorating, because usually a static mileage- or semi static fare-based prorating approach is applied.

Another main differentiation is usually taken between continental and intercontinental flights. We also analyze the robustness of the ROM for both continental and intercontinental flights in our flight network. We use a miles-based prorating method and apply capping, filtering and averaging. The detailed results are presented in Table 6.7 and Figures 6.14 and 6.15. The results for continental flights are comparable to the results of all flight legs. The values of r^{PARO} and $\overline{MAE}^{PARO}$ do not differ much. The scatter plot supports these findings. It looks similar to the scatter plot obtained for the entire flight network. In contrast to this, we observe very good results for intercontinental flights, in particular with independent demand. Values of r^{PARO} and $\overline{MAE}^{PARO}$ are very good. The very high linear relation can be observed in the respective scatter plot. Additionally, the number of flight departures included is almost 100% for intercontinental flights. From the given results we conclude that intercontinental flights are more robust against errors in the estimated unconstrained demand than continental

	Independent demand				Dependent demand						
	Base	Error level			Base	Error level YD			Error level BD		
	Case	30%	60%	90%	Case	30%	60%	90%	30%	60%	90%
Moderate bid-price prorating											
flight dep. incl. (%)	70.6	70.6	70.9	70.9	72.3	73.1	74.8	76.0	72.2	72.6	73.0
$\overline{MAE}^{PARO}$ (%)	4.0	4.0	4.8	5.5	10.8	7.5	8.4	9.5	10.1	6.4	7.8
r^{PARO}	0.91	0.92	0.90	0.89	0.87	0.93	0.90	0.87	0.88	0.95	0.94
Aggressive bid-price prorating											
flight dep. incl. (%)	56.3	56.5	57.1	57.7	60.6	61.7	69.2	71.4	60.1	60.5	61.1
$\overline{MAE}^{PARO}$ (%)	4.4	4.7	5.1	5.8	13.2	7.9	7.3	7.8	12.1	6.8	7.8
r^{PARO}	0.88	0.85	0.85	0.83	0.79	0.92	0.93	0.91	0.81	0.94	0.94

Table 6.6.: Similarity Measures for the Realistic Flight Network - Focus on Bid-price Prorating

	Independent demand				Dependent demand						
	Base	Error level			Base	Error level YD			Error level BD		
	Case	30%	60%	90%	Case	30%	60%	90%	30%	60%	90%
Continental flights											
flight dep. incl. (%)	57.2	57.2	57.4	57.4	59.0	59.8	61.4	62.7	58.9	59.3	59.7
$\overline{MAE}^{PARO}$ (%)	4.9	4.8	5.9	6.8	13.1	9.4	10.3	11.5	12.4	8.4	9.9
r^{PARO}	0.91	0.92	0.88	0.86	0.83	0.90	0.87	0.84	0.84	0.92	0.92
Intercontinental flights											
flight dep. incl. (%)	97.9	97.9	97.9	97.9	97.9	97.9	97.9	97.9	97.9	97.9	97.7
$\overline{MAE}^{PARO}$ (%)	1.4	1.5	1.9	2.6	5.3	5.8	8.0	9.3	5.1	4.6	6.3
r^{PARO}	0.98	0.98	0.97	0.95	0.94	0.90	0.82	0.77	0.94	0.94	0.94

Table 6.7.: Similarity Measures for the Realistic Flight Network - Separating Continental and Intercontinental Flights

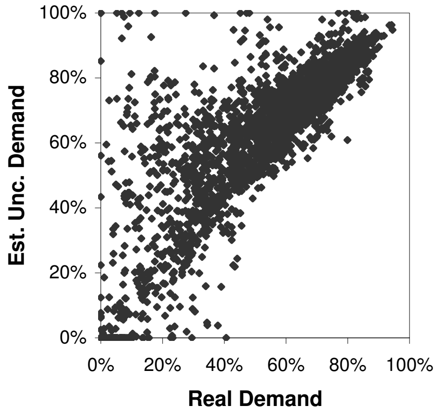

Figure 6.12.: Realistic Flight Network with Dependent Demand - Bid Price Moderate and Averaged over One Month

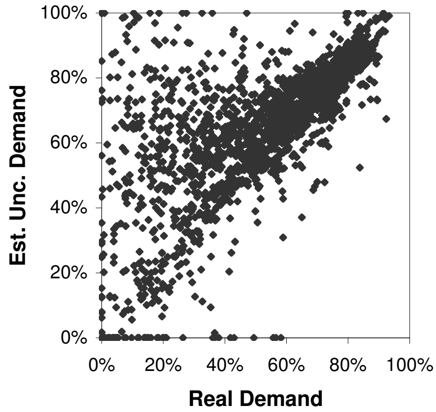

Figure 6.13.: Realistic Flight Network with Dependent Demand - Bid Price Aggressive and Averaged over One Month

flights. We observe less outliers that have to be examined further. The results for continental flights also indicate sufficient similarity. The scatter plot indicates that the outliers for the entire flight network can mainly be found within continental flights.

6.5. Summary

As a general conclusion of the investigation of the ROM measures in a realistic flight network with connecting traffic we consider the ROM on a leg level robust against errors in the estimated unconstrained demand for the base cases and the most important unconstraining error scenarios. We consider both the ROM with independent and dependent demand to be robust. We observed a decrease in the quality of the ROM measures due to network effects, however the decrease is minor compared to the effect of the transition from independent to dependent demand. The capping of the PAROs to values between 0% and 100%, the filtering out of flight departures with a RO of less or equal zero and the averaging of the flight departures over one month are important, in particular with regard to dependent demand. The robustness of the ROM in our scenarios was significantly higher with independent demand. For dependent demand the errors already observed on an aggregated network level lead to subsequent errors on a leg level.

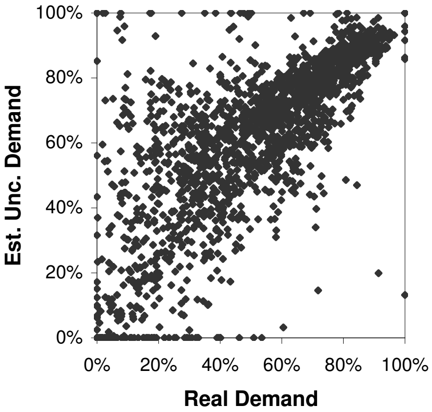

Figure 6.14.: Realistic Flight Network with Dependent Demand - Continental Flights and Averaged over One Month

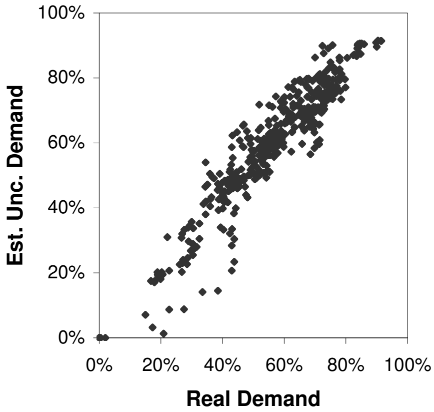

Figure 6.15.: Realistic Flight Network with Dependent Demand - Intercontinental Flights and Averaged over One Month

The analysis of the outliers will be a main task in making the ROM applicable in a real life situation. As the analysis between intercontinental and continental flights proved, most of the outliers might be found within the continental flights. It might also be worth looking at other common characteristics of these outliers to filter out these flight departures. This could lead to less flight departures that are part of the performance evaluation done by the ROM. However, it would lead to an increased acceptance by the revenue managers, due to its higher robustness and validity.

7. Disaggregation of ROM Measures to Single Components

So far we have neither considered no-shows and cancelations nor overbooking and upgrading in the ROM. In practice overbooking and upgrading are commonly used to further improve revenues. For practical applicability of the ROM it is crucial that it reflects these main approaches to increase revenues with RM. Therefore we first extend the network-based ROM in general to consider overbooking and upgrading and introduce the necessary enhancements in this section. In the second part we introduce ways to isolate the contribution of these RM components from the overall success and provide computational results.

7.1. Extending the Network-based ROM to Overbooking and Upgrading

As described in Chapter 1, airlines often face the challenge that passengers with a valid ticket do not show up at the time of flight departure. The reasons are flexible tickets or simply delays in connecting flights. With $q_{i,j}$ we denote the show-up rate of passengers booked on itinerary i in booking class j, i.e. the share of passengers showing up at the departure of a plane. The show-up rate is usually determined by the ratio of cumulated bookings for an itinerary after no-shows and the total number of cumulated bookings. Usually the show-up rates can be derived from the operational systems of an airline. In the remainder we use the terms no-shows and show-ups simultaneously. Cancelations might already occur during the booking period. A cancelation occurs, if a passenger cancels and returns his ticket before the departure of the plane. After a cancelation the seat is available for sale again. In the following we denote the cancelation rate $k_{i,j,t}$ to describe the share of bookings on itinerary i and booking class j that are canceled in this time period. $k_{i,j,t}$ applies to all bookings that have been booked until the end of time period t.

In order to incorporate overbooking and upgrading into the ROM the calculations of the potential, the actual and the no RM revenue have to be adjusted.

The necessary adjustments are described in the following subsections.

7.1.1. Potential Revenue with Upgrading

The first enhancement we apply is the consideration of upgrading in the potential revenue estimation. If upgrading is applied in the RM control, empty seats in a higher valued compartment are made available for passengers who are willing to book into a lower valued compartment. This is usually done by virtually increasing the capacity of the lower valued compartment if excess demand for this compartment is forecasted and for the higher valued compartment on that flight the forecast indicates empty seats at the end of the booking period. The LP presented in Chapter 5 can simply be enhanced to allow upgrading. We show the model again in Equations 7.1 to 7.4.

$$Max \sum_{i \in I} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,t} * x^+_{i,j,t} \tag{7.1}$$

$$\sum_{i \in I_l} \sum_{j \in J_{i,l,m}} \sum_{t \in T} x^+_{i,j,t} \leq cap_{l,m} \qquad \forall l \in L, \forall m \in M_l, \forall t \in T \tag{7.2}$$

$$0 \leq x^+_{i,j,t} \leq y_{i,j,t} * d^{td}_{i,j,t} - \sum_{j' \in J_{i,j}} y_{i,j',t} * d^{bd}_{i,j,j',t} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{7.3}$$

$$y_{i,j',t} \leq y_{i,j,t} \qquad \forall i \in I, \forall j \in J_i, \forall j' \in J_{i,j}, \forall t \in T \tag{7.4}$$

For example, a plane with an economy compartment with 100 seats and a business compartment with 30 seats could have the virtual extended capacity of 130 seats for the economy compartment. If we exchange the capacity constraint as presented in Equation 7.5 we allow the LP to increase the potential number of bookings into a given compartment by the capacity of all higher valued compartments. In our example the potential number of economy bookings would be increased to 130. The capacity of the highest valued compartment - in this case the business compartment - would not be changed, because upgrading is not possible for this compartment. This leads to the necessity to introduce another capacity constraint shown in Equation 7.6 to ensure that the LP does not distribute more bookings on a leg than seats are available. In the given constraint we introduced the set $J_{i,l}$ which contains all booking classes that are booked on leg l in itinerary i.

$$\sum_{i \in I_l} \sum_{j \in J_{i,l,m}} \sum_{t \in T} x^{+,U}_{i,j,t} \leq \sum_{m' \in M_l : m' \leq m} cap_{l,m'} \qquad \forall l \in L, \forall m \in M_l, \forall t \in T \quad (7.5)$$

$$\sum_{i \in I_l} \sum_{j \in J_{i,l}} \sum_{t \in T} x^{+,U}_{i,j,t} \leq cap_l \qquad \forall l \in L, \forall t \in T \quad (7.6)$$

With the use of $x^{+,U}_{i,j,t}$ the potential revenue with consideration of upgrading $Rev^{+,U}$ can be calculated using the basic formula 4.4 known from Chapter 4.

7.1.2. Potential Revenue with Overbooking

The other important enhancement is calculating the potential revenue with overbooking: We assume that we know the no-show and cancelation rates and are able to apply perfect overbooking controls and to compensate for cancelations in the LP model. In order to integrate this assumption the estimated unconstrained demand has to be adjusted to the show-up rates and the cancelation rates.

In the independent demand case, the adjustment is simple as illustrated in Equation 7.7. We apply the cancelation rate to the demand for each time period in the future t' starting with the current time period t. This set of time periods is denoted with T_t. Afterwards we apply the show-up rate to the demand that was already adjusted to the expected cancelations. We denote the resulting value with $\hat{d}_{i,j,t}$.

$$\hat{d}_{i,j,t} = d_{i,j,t} * \prod_{t' \in T_t} (1 - k_{i,j,t'}) * q_{i,j} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \quad (7.7)$$

If we assume dependent demand structures, the adjustment is more complicated, because we have to adjust the estimates for total demand and buy-down simultaneously to ensure consistency. The necessary steps are presented in Algorithm 7.1. The basic idea is again to apply the cancelation rates $k_{i,j,t}$ and show-up rate $q_{i,j}$ for a booking class j to the demand of this booking class. However, the buy-down $d^{bd}_{i,j,j',t}$ is by definition part of the total demand $d^{td}_{i,j,t}$ in booking class j, but also of total demand $d^{td}_{i,j',t}$ in booking class j'. Thus, it is not possible to simply apply the cancelation and show-up rate of a booking class to both total demand and buy-down. It is solely possible to apply the cancelation and show-up rates to the total demand of the lowest booking class because there is no buy-down into lower booking classes (Line 5). To ensure consistency in all other booking classes, the buy-down $d^{bd}_{i,j,j',t}$ from a booking class j into another booking class j' is changed using the average resulting cancelation and show-up rate of the total demand of booking class j' (Line 10). Afterwards the cancelation

Algorithm 7.1: Estimation of Dependent Demand after No-shows and Cancelations

1 **foreach** $t \in T$ **do**
2   **foreach** $i \in I$ **do**
3   **for** $j = 1$ **to** $|J_i|$ **do**
4   **if** $j = |J_i|$ **then**
5                 $\hat{d}^{td}_{i,j,t} = d^{td}_{i,j,t} * \prod_{t' \in T_t}(1 - k_{i,j,t'}) * q_{i,j}$
6   **foreach** $j' \in J_{i,j}$ **do**
7                     $\hat{d}^{bd}_{i,j,j',t} = 0$
8   **else**
9   **foreach** $j' \in J_{i,j}$ **do**
10                     $\hat{d}^{bd}_{i,j,j',t} = d^{bd}_{i,j,j',t} * \frac{\hat{d}^{td}_{i,(j+1),t}}{d^{td}_{i,(j+1),t}}$
11                 $\hat{d}^{td}_{i,j,t} = (d^{td}_{i,j,t} - \sum_{j' \in J_{i,j}} d^{bd}_{i,j,j',t}) * \prod_{t' \in T_t}(1 - k_{i,j,t'}) * q_{i,j} + \sum_{j' \in J_{i,j}} \hat{d}^{bd}_{i,j,j',t}$
12             $\hat{d}^{yd}_{i,j,t} = \hat{d}^{td}_{i,j,t} - \sum_{j' \in J_{i,j}} \hat{d}^{bd}_{i,j,j',t}$

and show-up rates are applied to the yieldable demand, which is the difference between total demand and all buy-downs into lower booking classes (Line 11) to determine the adjusted total demand $\hat{d}^{td}_{i,j,t}$. The application of the cancelation and no-show rates is performed in the same way as introduced in Equation 7.7. Lastly, the adjusted yieldable demand $\hat{d}^{yd}_{i,j,t}$ is derived based on the adjusted total demand and buy-down.

In a second step we modify Constraint 7.3 in the LP to determine the potential revenue under consideration of no-shows and cancelations. Constraint 7.8 shows the adjustment. The estimates for the unconstrained demand $d^{td}_{i,j,t}$ and $d^{bd}_{i,j,j',t}$ are replaced by the estimates considering no-shows and cancelations $\hat{d}^{td}_{i,j,t}$ and $\hat{d}^{bd}_{i,j,j',t}$. The Equation 4.3 is modified to use $\hat{d}_{i,j,t}$ instead of $d_{i,j,t}$ in the independent demand case in a similar way.

$$0 \leq x^{+,O}_{i,j,t} \leq y_{i,j,t} * \hat{d}^{td}_{i,j,t} - \sum_{j' \in J_{i,j}} y_{i,j',t} * \hat{d}^{bd}_{i,j,j',t} \qquad \forall i \in I, \forall j \in J_i, \; \forall t \in T \qquad (7.8)$$

The y-constraint defined in Equation 7.4 ensuring the feasible actions remains unchanged. The estimated bookings for the potential revenue with overbooking are denoted with $x_{i,j,t}^{+,O}$ in the remainder of the thesis. The potential revenue with overbooking $Rev^{+,O}$ is calculated like the other potential revenues.

The described enhancement can be applied no matter if upgrading is also considered or not. However, in practical applications usually both overbooking and upgrading play an important role and are applied in the RM controls. In this case we extend the potential revenue with overbooking to also allow upgrading and denote the estimated bookings with $x_{i,j,t}^{+,O,U}$. The potential revenue with overbooking and upgrading $Rev^{+,O,U}$ is defined according to the other definitions.

7.1.3. Actual Revenue after No-shows and Cancelations

The actual revenue as one important input of the ROM has to also be adjusted for no-shows and cancelations. We denote the bookings after consideration of no-shows and cancelations with $\hat{b}_{i,j,t}$ and define them formally in Equation 7.9. This formula draws back on the same way of deducting cancelations as in Equation 7.7.

$$\hat{b}_{i,j,t} = b_{i,j,t} * \prod_{t' \in T_t} (1 - k_{i,j,t'}) * q_{i,j} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \tag{7.9}$$

If overbooking is applied it is possible that even after consideration of no-shows there are more passengers for a flight than seats available in the plane. Before explaining how airlines usually deal with this situation, we define the cumulated bookings after no-shows and cancelations $\hat{B}_{l,m}$, the excess bookings $B_{l,m}^{ex}$ and the free capacity of a compartment m in Equations 7.10, 7.11 and 7.12.

$$\hat{B}_{l,m} = \sum_{i \in I_l} \sum_{j \in J_{i,l,m}} \sum_{t \in T} \hat{b}_{i,j,t} \qquad \forall l \in L, \forall m \in M_l \tag{7.10}$$

$$B_{l,m}^{ex} = max(\hat{B}_{l,m} - cap_{l,m}, 0) \qquad \forall l \in L, \forall m \in M_l \tag{7.11}$$

$$cap_{l,m}^{f} = max(cap_{l,m} - \hat{B}_{l,m}, 0) \qquad \forall l \in L, \forall m \in M_l \tag{7.12}$$

For all compartments with excess bookings we decide whether these oversold seats lead to upgrading, downgrading or denied boarding. If there are excess bookings on a compartment an airline's priority is to prevent denied boardings. This can be done via upgrading or downgrading. An airline would of course prefer upgrading instead of downgrading because a customer would always be willing to take a seat in a higher valued compartment but would expect a compensatory payment if placed into a lower valued compartment. An airline would start with the highest valued compartment trying to upgrade excess passengers. If this is not possible, it would try to downgrade them. If not all passengers could be upgraded or downgraded, the residual passengers are denied boarding, which also incurs another compensatory payment. In Algorithm 7.2 we describe the general case for an unspecified number of compartments per leg to determine the number of upgraded, downgraded and denied boarded passengers per compartment. Starting with the highest valued compartment the algorithm tries to upgrade excess passengers first, then tries to downgrade them and finally marks them as denied boardings.

After passengers that are upgraded, downgraded and denied boarded have been determined the actual revenue after no-shows and cancelations Rev^N is adjusted according to Equation 7.13. In this formula we observe one interaction between network and leg level in network-based RM. The general revenue figures are a result of bookings on network-based itineraries. The compensation payments, i.e. the denied boarding costs $p^{db}_{l,m}$ and downgrading costs $p^{dg}_{l,m}$, are determined on a leg level, because they depend on the availability and capacity of the resources of the flight network, the single flight legs.

$$Rev^N = \sum_{i \in I} \sum_{j \in J_i} \sum_{t \in T} p_{i,j,t} * \hat{b}_{i,j,t} - \sum_{l \in L, m \in M_l} B^{db}_{l,m} * p^{db}_{l,m} - \sum_{l \in L, m \in M_l} B^{dg}_{l,m} * p^{dg}_{l,m} \quad (7.13)$$

7.1.4. No RM Revenue after No-shows and Cancelations

The adjustment of the no RM revenue to consider no-shows and cancelations requires only minor modifications, too. Because we assume a no RM situation and thus simulate the FCFS strategy, we do not consider any upgrading or overbooking in the estimation of the no RM revenue. We estimate values for $x^-_{i,j,t}$ using an extended version of Algorithm 4.1 introduced in Chapter 4. Cancelations already occur during the course of a booking period and thus the handling of cancelations has to be included into our algorithm to simulate a FCFS revenue estimation. The algorithm remains the same except for the fact that at the end of each time period the cancelations are deducted from the number of bookings and the capacity is increased accordingly. The enhancement is shown in Algorithm 7.3 in Lines 12 to 18 in detail. In the algorithm we use the unadjusted unconstrained demand $d_{i,j,t}$ in the independent demand case or the unadjusted unconstrained yieldable demand $d^{yd}_{i,j,t}$ in the dependent demand case. After having accomplished Algorithm 7.3 we have to apply the show-up rate to the estimates to obtain the estimated bookings after no-shows $x^{-,N}_{i,j,t}$ as described in Equation 7.14.

$$x^{-,N}_{i,j,t} = x^-_{i,j,t} * q_{i,j} \qquad \forall i \in I, \forall j \in J_i, \forall t \in T \qquad (7.14)$$

Algorithm 7.2: Determine Number of Upgraded, Downgraded and Denied Boarded Passengers

foreach $l \in L$ **do**
    Initialize values
    foreach $m \in M_l$ **do**
        $B^{ex}_{l,m} = max(\hat{B}_{l,m} - cap_{l,m}, 0)$
        $cap^{f}_{l,m} = max(cap_{l,m} - \hat{B}_{l,m}, 0)$
        $B^{dg}_{l,m} = 0$
        $B^{up}_{l,m} = 0$
    for $m \leftarrow |M_l|$ **downto** 1 **do**
        $ex = B^{ex}_{l,m}$
        Determine upgrades
        $m' = m + 1$
        while $(ex > 0 \wedge m' \leq |M_l|)$ **do**
            $up = min(ex, cap^{f}_{l,m'})$
            $B^{up}_{l,m} = B^{up}_{l,m} + up$
            $cap^{f}_{l,m'} = cap^{f}_{l,m'} - up$
            $ex = ex - up$
            $m' = m' + 1$
        Determine downgrades
        $m' = m - 1$
        while $(ex > 0 \wedge m' \geq 1)$ **do**
            $dg = min(ex, cap^{f}_{l,m'})$
            $B^{dg}_{l,m} = B^{dg}_{l,m} + dg$
            $cap^{f}_{l,m'} = cap^{f}_{l,m'} - dg$
            $ex = ex - dg$
            $m' = m' - 1$
        Determine denied boardings
        $B^{db}_{l,m} = B^{ex}_{l,m} - B^{dg}_{l,m} - B^{up}_{l,m}$

Algorithm 7.3: Estimation of No RM Revenue after No-shows and Cancelations

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Input: $\mathbb{P}_t$, $\forall t \in T$

foreach $l \in L$ **do**
    foreach $m \in M_l$ **do**
        $cap^f_{l,m} = cap_{l,m}$

for $t = 1$ **to** $|T|$ **do**
    foreach $(i, j) \in \mathbb{P}_t$ **do**
        $sl = \infty$
        foreach $l \in L_i$ **do**
            $sl = min(sl, cap^f_{l,m_{l,j}})$
        $x^-_{i,j,t} = x^-_{i,j,t} + min(sl, d_{i,j,t})$
        foreach $l \in L_i$ **do**
            $cap^f_{l,m_{l,j}} = cap^f_{l,m_{l,j}} - min(sl, d_{i,j,t})$
    foreach $(i, j) \in \mathbb{P}_t$ **do**
        $canc = 0$
        for $t' = 1$ **to** t **do**
            $canc = canc + x^-_{i,j,t'} * (1 - k_{i,j,t})$
            $x^-_{i,j,t'} = x^-_{i,j,t'} * (1 - k_{i,j,t})$
        foreach $l \in L_i$ **do**
            $cap^f_{l,m_{l,j}} = cap^f_{l,m_{l,j}} + canc$

After the show-up rates have been applied, the actual revenue after no-shows and cancelations Rev^N has to be calculated using the basic formula 4.5 introduced in Chapter 4.

The calculation of the derived ROM measures has to be adjusted to the new estimates for the potential, the actual and the no RM revenue. Depending on the scenario and the applied RM methodology one single adjusted revenue estimate has to be chosen. In practical applications usually both upgrading and overbooking are applied. Thus, we only present the normal case in which $Rev^{+,O,U}$ serves as the potential revenue, Rev^N as the actual revenue and $Rev^{-,N}$ as the no RM revenue. This changes the definitions of RO, ARO and PARO according to Equations 7.15 to 7.17.

$$RO = Rev^{+,O,U} - Rev^{-,N} \tag{7.15}$$

$$ARO = Rev^N - Rev^{-,N} \tag{7.16}$$

$$PARO = \frac{ARO}{RO} \tag{7.17}$$

7.2. Measuring Overbooking and Upgrading Success

In the previous section we enhanced the ROM to incorporate cancelations, no-shows, overbooking and upgrading. However, we did not introduce new measures that are able to indicate the performance of the RM methods mentioned above. In Chapter 2 we discussed several ways to measure the success of RM components. Because overbooking and upgrading are important components of common RM systems we follow the suggestion by Pölt (2001) and introduce methods to split the success into overbooking, upgrading and fare-mix success.

The basic idea is to split the overall RO and ARO into three subparts, namely one for overbooking, one for upgrading and one residual part for the fare-mix. However, the success of a component cannot be exactly isolated. All RM components are interdependent and influence each other. Smith et al. (1992) and Pölt (2001) describe the interdependence of different sub-measures as an important challenge. Thus, for all proposed methods of disaggregation we assume a certain interdependency.

In the following we assume that overbooking and upgrading increased the number of bookings relative to the case in which none of the above components were applied. The main idea is to estimate the number of potential additional bookings and to compare them to the number that has been estimated as a contribution by overbooking and upgrading. The ARO and the RO depend on the average incremental revenue we apply to the additional bookings.

If both overbooking and upgrading are applied, the separation of the number of additional bookings into overbooking and upgrading gets more complicated. In the following sections we therefore first introduce the estimation of additional bookings for overbooking and upgrading separately and describe the common case with both overbooking and upgrading applied afterwards. We start with defining the incremental average revenue.

7.2.1. Incremental Revenue due to Overbooking and Upgrading

A crucial point is the definition of the incremental revenue that is applied to the number of bookings that are considered to be the outcome of overbooking and upgrading. One way is taking the yield or the average revenue of the respective compartment. We define the average revenue $p^{avg}_{l,m}$ for a compartment m on leg l in Equation 7.18.

$$p^{avg}_{l,m} = \frac{\sum_{i \in I_l} \sum_{j \in J_{i,l,m}} \sum_{t \in T} p_{i,j,l,t} * b_{i,j,t}}{B_{l,m}} \qquad \forall l \in L, \forall m \in M_l \qquad (7.18)$$

The formula sums up all bookings multiplied with the respective prorated fare and divides it by the total number of bookings for the compartment $B_{l,m}$. If the incremental revenue applied to the additional bookings is calculated through this formula, then it can be assumed that the fare-mix remains constant for all additional bookings due to overbooking and upgrading. A more realistic assumption is that the bookings with the highest fares will be accepted no matter if overbooking was applied or not. This is due to the following assumptions: First, that the RM control has protected seats for the higher fare classes and second, that overbooking and upgrading only have allowed additional bookings with low fares.

We present our approach to obtain the incremental revenue due to low fare bookings in Algorithm 7.4. The algorithm calculates the average incremental revenue for a given number of additional bookings $B^{add}_{l,m}$. Another input of the algorithm is an ordered set $\mathbb{P}_{l,m}$. It stores all valid booking combinations (i, j, t) $\in I_l \times J_{i,l,m} \times T$ and these are sorted by their fare $p_{i,j,l,t}$ in an ascending order.

Starting with the booking combination (i,j,t) with the lowest fare associated to it, the algorithm determines the total incremental revenue rev that is achieved with additional bookings. bl denotes the number of additional bookings left that still have to be included into the total revenue. Finally the average incremental

Algorithm 7.4: Determination of Incremental Revenue per Compartment

Input: $B^{add}_{l,m}$ and $\mathbb{P}_{l,m}$, $\forall l \in L, \forall m \in M_l$

1 **foreach** $l \in L$ **do**
2   **foreach** $m \in M_l$ **do**
3   **if** $B^{add}_{l,m} > 0$ **then**
4       $bl = B^{add}_{l,m}$
5   **while** $bl > 0$ **do**
6   get next $(i, j, t) \in \mathbb{P}_{l,m}$
7         $rev = rev + (p_{i,j,l,t} * min(bl, b_{i,j,t}))$
8         $bl = bl - min(bl, b_{i,j,t})$
9       $p^{inc}_{l,m} = rev/B^{add}_{l,m}$
10   **else**
11       $p^{inc}_{l,m} = 0$

revenue $p^{inc}_{l,m}$ is calculated (see Line 9). In the following we primarily focus on the incremental revenue $p^{inc}_{l,m}$ due to its more realistic assumptions.

7.2.2. ROM with Upgrading

We first separate the ROM measures into upgrading and fare-mix success. In this section we therefore assume that the RM control does not apply overbooking, each customer is showing up at the departure of the flight and no customer cancels a booking. The main number to be estimated is the number of additional bookings that we consider a result of upgrading. In our current scenario the estimation is simple. Because the RM control has not applied overbooking we neither observe denied boardings nor downgrades. Thus, the number of excess bookings in a compartment can be clearly related to upgrading. The number of additional bookings $B^U_{l,m}$ is simply the number of all passengers exceeding the capacity (see Equation 7.19).

$$B^U_{l,m} = \begin{cases} 0 & m = m^+_l \\ B^{ex}_{l,m} & otherwise \end{cases} \qquad \forall l \in L, \forall m \in M_l \tag{7.19}$$

Figure 7.1 illustrates this. In the highest valued compartment m^+_l the RM control has not increased the capacity. Thus there are no passengers exceeding the capacity. The value for $B^U_{l,m}$ is zero in this compartment.

The ARO for upgrading ARO^U_l is the number of additional bookings $B^U_{l,m}$ multiplied by the incremental revenue $p^{inc}_{l,m}$ (see Equation 7.20). As described

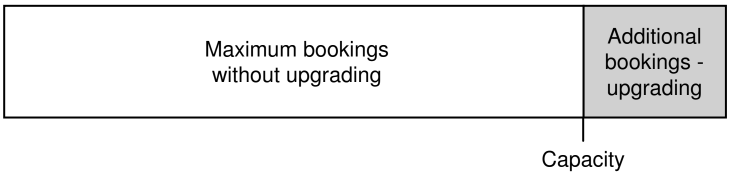

Figure 7.1.: Additional Bookings Related to Upgrading

earlier the ARO for the fare-mix ARO_l^F is the residual part of ARO_l (see Equation 7.21).

$$ARO_l^U = \sum_{m \in M_l} B_{l,m}^U * p_{l,m}^{inc} \qquad \forall l \in L \tag{7.20}$$

$$ARO_l^F = ARO_l - ARO_l^U \qquad \forall l \in L \tag{7.21}$$

The definition of the RO for upgrading RO_l^U is similar to the definition of the ARO. First, a theoretical number of additional bookings that can be related to upgrading $X_{l,m}^U$ is determined and then multiplied by the incremental revenue $p_{l,m}^{inc}$. In analogy to $B_{l,m}^U$, $X_{l,m}^U$ is the difference between the cumulated potential bookings on the compartment $X_{l,m}^{+,U}$ and the capacity of the compartment $cap_{l,m}$.

$$X_{l,m}^U = max(X_{l,m}^{+,U} - cap_{l,m}, 0) \qquad \forall l \in L, \forall m \in M_l \tag{7.22}$$

RO_l^U is determined in analogy to ARO_l^U and the RO of the fare-mix is defined as the residual RO after deducting RO_l^U (see Equations 7.23 and 7.24).

$$RO_l^U = \sum_{m \in M_l} X_{l,m}^U * p_{l,m}^{inc} \qquad \forall l \in L \tag{7.23}$$

$$RO_l^F = RO_l - RO_l^U \qquad \forall l \in L \tag{7.24}$$

7.2.3. ROM with Overbooking

In this section we focus on the separation of the ROM measures into overbooking and fare-mix-success. To estimate the number of additional bookings that are applicable to overbooking we make another important assumption. We assume that without applying overbooking RM controls the maximum number of bookings $B_{l,m}$ is the capacity of the compartment $cap_{l,m}$. At the end of the booking period passengers showed up with the average show-up rate $q_{l,m}$. We furthermore assume that as a result the maximum number of bookings for the given compartment after no-shows is $cap_{l,m} * q_{l,m}$. The overbooking control virtually increases the capacity to prevent too many empty seats because of no-shows. Taking all of these assumptions together we define the difference between the bookings after no-shows and cancelations $\hat{B}_{l,m}$ and the adjusted capacity $cap_{l,m} * q_{l,m}$ as those additional bookings that can be applied to overbooking $B^O_{l,m}$ (see Equation 7.25).

$$B^O_{l,m} = max(\hat{B}_{l,m} - cap_{l,m} * q_{l,m}, 0) \qquad \forall l \in L, \forall m \in M_l \qquad (7.25)$$

Figure 7.2 illustrates the definition.

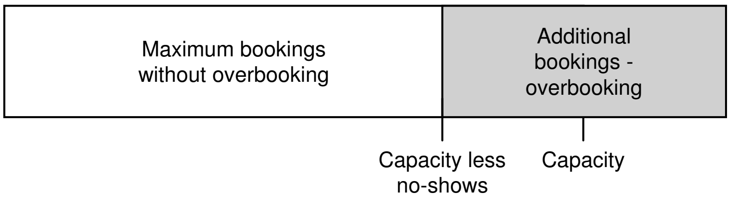

Figure 7.2.: Additional Bookings Related to Overbooking

However, it is possible that passenger bookings exceed the capacity of the compartments. In this case we have to apply Algorithm 7.2 to find out how many passengers can be upgraded and which ones have to be downgraded or denied boarding. We assume that the costs for denied boarding and downgrading decrease the ARO of overbooking ARO^O_l (see Equations 7.26 and 7.27).

$$ARO^O_l = \sum_{m \in M_l} (B^O_{l,m} * p^{inc}_{l,m} - B^{db}_{l,m} * p^{db}_{l,m} - B^{dg}_{l,m} * p^{dg}_{l,m}) \qquad \forall l \in L \quad (7.26)$$

$$ARO^F_l = ARO_l - ARO^O_l \qquad \forall l \in L \quad (7.27)$$

In general, denied boardings do not increase the ARO of overbooking. Surely excess bookings increase the number of additional bookings applied to overbooking. However, as $p^{inc}_{l,m}$ is usually smaller than $p^{db}_{l,m}$, the denied boarding costs are higher than the additional achieved revenue by the excess bookings.

The theoretical amount of additional bookings that can be obtained with overbooking $X^O_{l,m}$ are derived in accordance to $B^O_{l,m}$. We use the difference between the estimates for the potential revenue with overbooking $X^{+,O}_{l,m}$ and the adjusted capacity of the compartment m already used before.

$$X^O_{l,m} = max(X^{+,O}_{l,m} - cap_{l,m} * q_{l,m}, 0) \qquad \forall l \in L, \forall m \in M_l \qquad (7.28)$$

The theoretical RO that is achievable with overbooking RO^O_l is derived in analogy to RO^U_l. Like the RO of upgrading the RO of overbooking is always ≥ 0. The RO for the fare-mix RO^F_l is again the residual RO (see Equations 7.29

and 7.30).

$$RO_l^O = \sum_{m \in M_l} X_{l,m}^O * p_{l,m}^{inc} \qquad \forall l \in L \tag{7.29}$$

$$RO_l^F = RO_l - RO_l^O \qquad \forall l \in L \tag{7.30}$$

7.2.4. ROM with Overbooking and Upgrading

In practice, usually both overbooking and upgrading are part of the RMS. The concepts described in the two previous sections can further be used. However, adjustments have to be made because it has to be decided, whether an additional booking belongs to overbooking or upgrading. Figure 7.3 shows how we separate the additional bookings into overbooking and upgrading success.

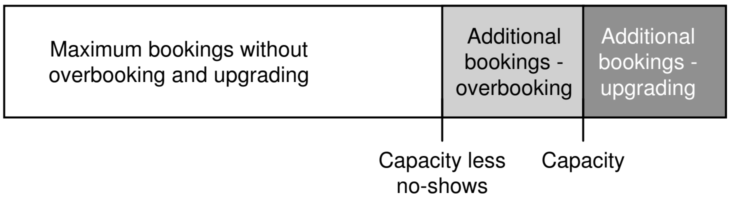

Figure 7.3.: Additional Bookings Related to Overbooking and Upgrading

We assume that all bookings exceeding the capacity belong to upgrading and the bookings exceeding the adjusted capacity belong to overbooking. The definition of $B_{l,m}^U$ stays the same. It still represents all excess bookings in a compartment, except in the highest valued compartment. By definition, upgrading is not possible here. The definition of the number of additional bookings related to overbooking $B_{l,m}^O$ is adjusted by deducting $B_{l,m}^U$. The denied boardings and downgrades are calculated using Algorithm 7.2. We assume that they are a result of overbooking and thus solely decrease ARO_l^O. The adjusted determination of $B_{l,m}^O$ is depicted in Equation 7.31.

$$B_{l,m}^O = max(B_{l,m} - cap_{l,m} * q_{l,m} - B_{l,m}^U, 0) \qquad \forall l \in L, \forall m \in M_l \tag{7.31}$$

The definition of the AROs of overbooking and upgrading remains the same. Only the ARO of fare-mix ARO_l^F has to be redefined in Equation 7.32

$$ARO_l^F = ARO_l - ARO_l^U - ARO_l^O \qquad \forall l \in L \tag{7.32}$$

The separation of $X_{l,m}^U$ and $X_{l,m}^O$ equals the split between the estimates of the achieved additional bookings related to overbooking and upgrading $B_{l,m}^O$ and

$B^U_{l,m}$. The main input is the estimated number of potential bookings $X^{+,O,U}_{l,m}$ on a compartment m under consideration of overbooking and upgrading (see Equations 7.33 and 7.34).

$$X^U_{l,m} = max(X^{+,O,U}_{l,m} - cap_{l,m}, 0) \qquad \forall l \in L, \forall m \in M_l \quad (7.33)$$

$$X^O_{l,m} = max(X^{+,O,U}_{l,m} - cap_{l,m} * q_{l,m} - X^U_{l,m}, 0) \qquad \forall l \in L, \forall m \in M_l \quad (7.34)$$

The definition of RO^F_l has also to be adjusted:

$$RO^F_l = RO_l - RO^U_l - RO^O_l \qquad \forall l \in L \qquad (7.35)$$

7.3. Computational Results

In this section we present computational results on the isolation of upgrading, overbooking and fare-mix success from the overall ROM measures. In contrast to the analyses performed so far, the RMS applies overbooking and upgrading if needed in the scenario. As a prerequisite the request generator creates requests with no-show behavior. Although we modeled cancelations in the formal definitions, we did not apply them in our RM simulations. In our simulations, we focus on the base case for dependent demand and on the realistic flight network. The results for the no-connecting-traffic flight network and for independent demand are very similar and can be found in the appendix.

In Chapters 4 and 5 we did not consider upgrading and overbooking in the analysis on the robustness of the ROM. In Table 7.1 we analyze the similarity measures and error measures, if overbooking and upgrading are applied. The

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
$\overline{PARO}^R$ (%)	63.3	63.0	59.1	60.9	60.5	63.4	59.0
$\overline{PARO}^D$ (%)	67.5	67.2	62.6	64.7	64.3	67.6	62.6
$\overline{MAE}^{PARO}$ (%)	4.2	4.2	3.5	3.8	3.7	4.3	3.6
r^{PARO}	0.90	0.90	0.90	0.92	0.91	0.89	0.90

Table 7.1.: PAROs on an Aggregated Network Level with Upgrading and Overbooking Applied

assessed scenarios can be divided into three groups: 1) both overbooking and upgrading have been applied, 2) only overbooking has been applied and 3) only upgrading has been applied. 'Reg.' in a column header denotes that overbooking or upgrading was applied with regular settings and no adjustments. If the entry in the column header is '-50%' the overbooking or upgrading levels were reduced by 50%.

Figure 7.4 shows the scatter plot for the base case, in which both overbooking and upgrading are applied with unadjusted levels. We observe that the error

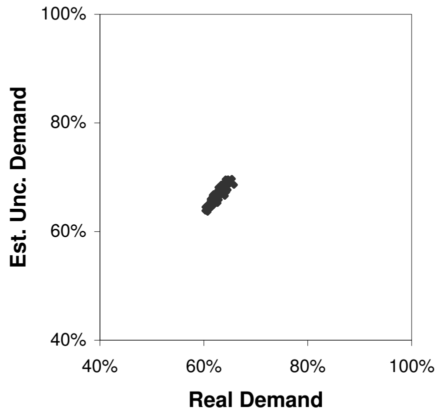

Figure 7.4.: Realistic Flight Network with Dependent Demand with Overbooking and Upgrading Aggregated to Network Level

measures remain constant. The similarity measures indicate a very high resemblance. We conclude that enhancing the ROM to overbooking and upgrading on a network level does not affect the robustness.

In a first analysis to examine the potential isolation of single RM components we focus on the ARO and assess it for both upgrading and overbooking. In practice, particularly the values of ARO_l^O are of interest because they describe the absolute success of overbooking. This is important because overbooking also incurs a risk of denied boardings and a loss in customer goodwill.

In Table 7.2 we compare the AROs calculated with the average revenue $p_{l,m}^{avg}$ and the incremental revenue $p_{l,m}^{inc}$. We observe that the AROs in all cases roughly double if we assume that the average revenue on a leg is the correct revenue to be applied on additional bookings. We also observe that the values of the ARO are quite stable and reflect the underlying overbooking and upgrading controls. If we decrease overbooking levels by 50%, the $\overline{ARO}^O$ also decreases by nearly 50%. In the second part of the table we compare the AROs for overbooking and upgrading to the actual revenue. Depending on the incremental revenue assumed, overbooking is responsible for 2.7% or 1.3% of total revenue. Upgrading is not as important as overbooking and only contributes with 0.4% or 0.2%.

Beyond using the ARO to justify the application of upgrading and overbooking

Overbooking	Reg.	Reg.	-50%	None	None	Reg.	-50%
Upgrading	Reg.	-50%	Reg.	Reg.	-50%	None	None
$\overline{ARO}^O$ based on $p_{l,m}^{avg}$ (million)	1.17	1.16	0.68	-	-	1.15	0.57
$\overline{ARO}^O$ based on $p_{l,m}^{inc}$ (million)	0.56	0.56	0.35	-	-	0.55	0.29
Diff. (million)	0.60	0.60	0.33	-	-	0.60	0.28
$\overline{ARO}^U$ based on $p_{l,m}^{avg}$ (million)	0.16	0.11	0.06	0.16	0.10	-	-
$\overline{ARO}^U$ based on $p_{l,m}^{inc}$ (million)	0.09	0.06	0.03	0.08	0.05	-	-
Diff. (million)	0.08	0.05	0.03	0.08	0.05	-	-
$\overline{Rev}$ (million)	43.3	43.2	42.8	44.9	44.9	43.2	42.7
$\overline{ARO}^D$ (million)	6.5	6.4	6.0	5.8	5.7	6.3	5.9
$\overline{ARO}^O/\overline{Rev}$ based on $p_{l,m}^{avg}$ (%)	2.7	2.7	1.6	-	-	2.7	1.3
$\overline{ARO}^O/\overline{Rev}$ based on $p_{l,m}^{inc}$ (%)	1.3	1.3	0.8	-	-	1.3	0.7
$\overline{ARO}^U/\overline{Rev}$ based on $p_{l,m}^{avg}$ (%)	0.4	0.3	0.1	0.4	0.2	-	-
$\overline{ARO}^U/\overline{Rev}$ based on $p_{l,m}^{inc}$ (%)	0.2	0.1	0.1	0.2	0.1	-	-

Table 7.2.: Comparison of RO and ARO between Incremental and Average Revenues

the question of robustness is also relevant for the PAROs calculated for overbooking, upgrading and fare-mix. The analyzed scenarios remain the same. In Table 7.3 we present the similarity measures for $PARO^O$, $PARO^U$ and $PARO^F$. In figures 7.5, 7.6 and 7.7 we show the corresponding scatter plots for the base case with dependent demand with regular overbooking and upgrading settings. We focus on the realistic flight network scenarios and refer the reader for the no-connecting-traffic flight network to the appendix. We observe that the PAROs calculated for overbooking and upgrading are very robust. The scatter plots contain only a few outliers. The scatter plot and the similarity measures for the fare-mix are comparable to the overall PARO measure. Averaging over multiple flight departures is not necessary for upgrading and overbooking and does not improve the similarity measures. The share of flight departures included grows as well as the $\overline{MAE}^{PARO^O}$ and $\overline{MAE}^{PARO^U}$. The results for fare-mix however increase with the application of averaging.

7.4. Summary

In this chapter we assessed the potential to disaggregate the ROM measures to isolate the contribution of overbooking, upgrading and fare-mix from the overall success. We conclude that an isolation of overbooking, upgrading and fare-mix

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. incl. (%)	34.3	30.9	34.3	-	-	34.2	30.0
$\overline{MAE}^{PARO^O}$ (%)	1.7	2.2	1.6	-	-	1.6	2.2
r^{PARO^O}	0.96	0.92	0.97	-	-	0.97	0.91
flight dep. incl. (%)	27.6	27.4	25.9	18.1	16.0	-	-
$\overline{MAE}^{PARO^U}$ (%)	2.5	2.6	2.5	3.1	1.5	-	-
r^{PARO^U}	0.95	0.93	0.90	0.89	0.93	-	-
flight dep. incl. (%)	62.7	62.7	62.8	62.2	62.3	62.7	62.8
$\overline{MAE}^{PARO^F}$ (%)	13.9	13.7	13.6	13.8	13.6	14.0	13.7
r^{PARO^F}	0.78	0.79	0.77	0.75	0.76	0.77	0.77

Table 7.3.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on Realistic Flight Network

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. incl. (%)	53.0	53.0	52.4	-	-	52.9	52.5
$\overline{MAE}^{PARO^O}$ (%)	2.8	2.9	3.8	-	-	2.7	3.7
r^{PARO}	0.97	0.96	0.86	-	-	0.97	0.81
flight dep. incl. (%)	38.3	38.5	37.9	33.5	32.8	-	-
$\overline{MAE}^{PARO^U}$ (%)	5.9	5.8	2.4	3.8	2.2	-	-
r^{PARO}	0.85	0.79	0.79	0.91	0.95	-	-
flight dep. incl. (%)	72.3	72.4	72.4	71.9	72.0	72.3	72.3
$\overline{MAE}^{PARO^F}$ (%)	14.2	14.0	13.0	12.0	11.9	14.1	12.9
r^{PARO}	0.76	0.77	0.78	0.82	0.83	0.76	0.78

Table 7.4.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on Realistic Flight Network Using Averaging

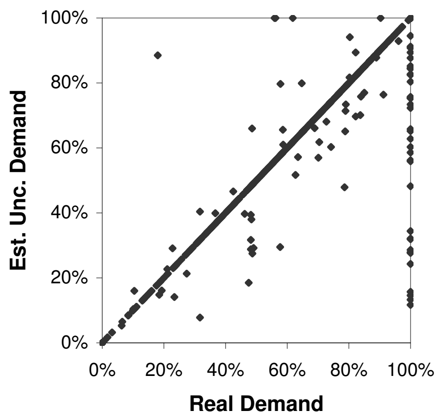

Figure 7.5.: Realistic Flight Network with Dependent Demand - Overbooking

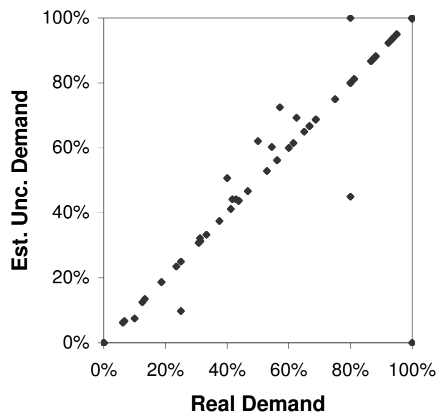

Figure 7.6.: Realistic Flight Network with Dependent Demand - Upgrading

success is reasonable and leads to good results. In particular the isolation of overbooking and upgrading success leads to promising results. The values obtained from one simulation run are robust both for independent and dependent demand. Furthermore we propose to use the incremental revenue and not the average revenue on a flight leg to value the overbooking and upgrading success: A realistic assumption of the additional bookings attributable to overbooking and upgrading suggests that these are the ones which correspond to the lowest fare. This of course leads to a significant decrease in total revenue that is attributed to overbooking and upgrading.

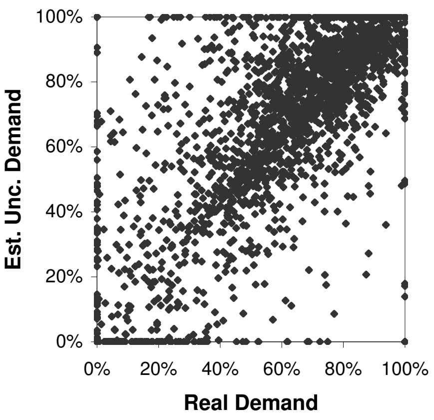

Figure 7.7.: Realistic Flight Network with Dependent Demand - Fare-mix

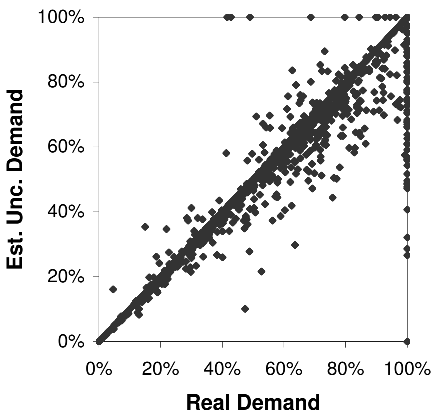

Figure 7.8.: Realistic Flight Network with Dependent Demand and Averaged over One Month - Overbooking

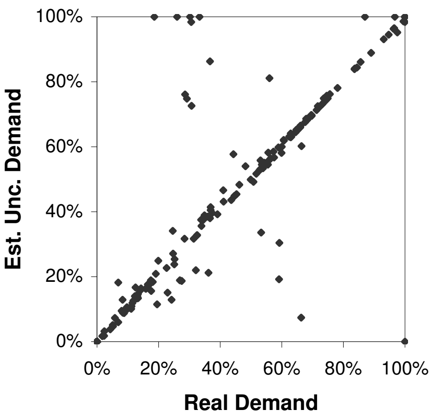

Figure 7.9.: Realistic Flight Network with Dependent Demand and Averaged over One Month - Upgrading

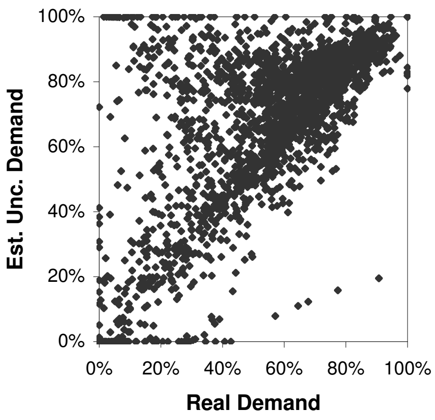

Figure 7.10.: Realistic Flight Network with Dependent Demand and Averaged over One Month - Fare-mix

8. Summary and Concluding Remarks

In this thesis we addressed the topic of performance measurement in airline RM and in particular the network-based ROM with independent and dependent demand. Performance measurement is an important part of the application of RM controls at an airline. It is employed to continuously assess the contribution of the RM techniques in use, to give the revenue managers feedback on their actions and to fine-tune the RMS. However, the major developments in airline RM science - advancing from leg-based to network-based RM controls and from independent to dependent demand structures - pose new questions and challenges to the ROM.

In the first chapter we introduced the main concepts and terminology of airline RM and in addition discussed methods to measure its performance. In particular we described the ROM as one way to measure RM performance in detail. In Chapter 2 we provided a literature review of airline RM with a specific focus on the major developments in demand modeling and optimization techniques in the last decades. We gave a thorough overview about the transition from leg-based to network-based RM controls and the advancement from independent demand models to dependent demand structures. We described state-of-the-art methods for both demand modeling and optimization techniques. After a detailed overview about current developments in performance measurement and specifically the ROM we motivated our research on network-based ROMs with independent and dependent demand.

In Chapter 3 we introduced a novel simulation-based approach to investigate ROM properties. First, it comprises a simulation environment that reflects state-of-the-art models and methods of operational RMS of large network airlines and uses input data that corresponds to reality as well as possible. Second, we presented a novel approach to measure the robustness of the ROM using the previously described simulation environment and furthermore designed several scenarios to thoroughly investigate the properties of the ROM.

A detailed assessment of the ROM with independent demand was presented in Chapter 4. After describing the network-based ROM with independent demand in detail, we discussed some of its main properties and in particular the effect of model- and data-related errors on the ROM. Computational results show that data-related errors, i.e. errors in the input data, have a higher effect on the validity of the ROM results than model-related errors. In addition, the ROM proved itself to be robust against errors in the unconstrained demand up to our previously defined worst case scenarios and even beyond. Thus, we consider the ROM applicable in practical RMS.

In Chapter 5 we enhanced the network-based ROM with independent demand to dependent demand structures. We have chosen a modeling approach for the dependent demand which is common in practical RMS that consider demand dependencies. We described the modification of the ROM in detail and discussed the main properties of the adjusted ROM. As with independent demand the network-based ROM with dependent demand proved to be robust and is considered applicable in real life applications. However, in comparison to the ROM with independent demand we observed a decrease in robustness which is due to a higher overall error level in the estimated unconstrained demand.

After having assessed the ROM for both independent and dependent demand on a network level, we investigated ways to consider practical aspects in the ROM. In Chapters 4 and 5 we focussed our research on the main properties and correlation between the ROM and different error scenarios. We did neither incorporate common RM components such as overbooking or upgrading nor intended to disaggregate the measures to sub-measures that are useful in a practical RM context. However, these are important questions in reality.

Therefore we discussed a potential disaggregation of the ROM measures to subparts of the flight network in Chapter 6. We reviewed several methods to prorate fares to single legs and techniques to increase the quality of the leg-based ROM measures such as capping, filtering and averaging. Our analysis shows that the ROM proved itself to be robust even if used on a leg level. However, the effect of unconstraining errors increases significantly in particular with dependent demand. Thus, we suggest to thoroughly analyze which flight departures should be included in the ROM evaluation and which should be evaluated differently.

The integration of single RM components into the ROM and a potential disaggregation of the ROM measures to those components is discussed in Chapter 7. First, we integrated no-shows and cancelations into the network-based ROM with independent and dependent demand. In a second step we proposed a disaggregation into upgrading, overbooking and fare-mix success. The ROM that considers no-shows and cancelations also proved to be robust and applicable in real life. The disaggregation to single RM components delivered very promising results. In particular the ROM measures for overbooking and upgrading showed a high robustness.

Overall, we assessed the ROM for a large network airline with its main facets in a very detailed manner. However, the results might be different for airlines with other network characteristics such as low cost carriers or regional airlines. Moreover, competitors and airline alliances have not explicitly been considered in our investigations, but play a very important role in today´s revenue management environments. The analysis of different network characteristics and the consideration of competitors and alliances could be one field for further research. In addition, we did not focus on customer lifetime value models, but on pure transaction-based RM models. Also the growing importance of dynamic pricing was not taken into account in this thesis. Incorporating these developments into the ROM could be another stream of future research. In this thesis we defined the estimations of the potential and the no RM revenue based on some main assumptions and practical consideration such as availability of demand data. However, it might be worth thinking about different ways of defining the reference points to compare the actual revenue with. Moreover, the research on dependent demand structures in airline RM still shows significant developments and an increasing number of airlines is going to implement methods to support these methodologies. For example a lot of research is done with general customer-choice models. We suggest to integrate new findings in this area into the ROM continuously. Moreover, we propose to investigate the interaction and combination of ROM measures with other performance measures. In the future, not only an integration of the ROM into training tools for revenue managers could be investigated, but also the potential to use the ROM as a pre-departure performance measure.

A. Detailed Test Results

In the next sections we list the detailed results of the analyses we conducted in the course of this thesis. We show additional scatter plots and tables that supplement the findings and conclusions of our thesis.

A.1. The Network-based ROM with Independent Demand

In this section we list supplemental scatter plots of our analyses of the network-based ROM with independent demand. In addition, we present extended result tables that include the similarity measures for all ROM measures.

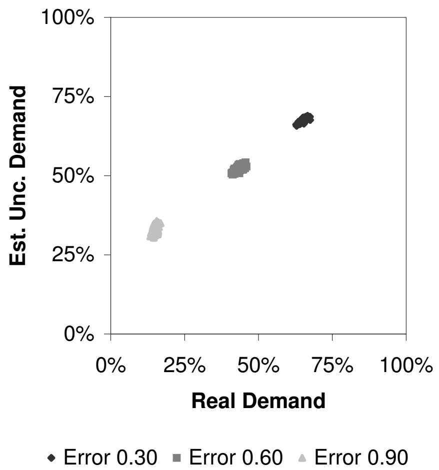

Figure A.1.: Effect of a Biased Underestimation of the Forecasted Demand on PARO

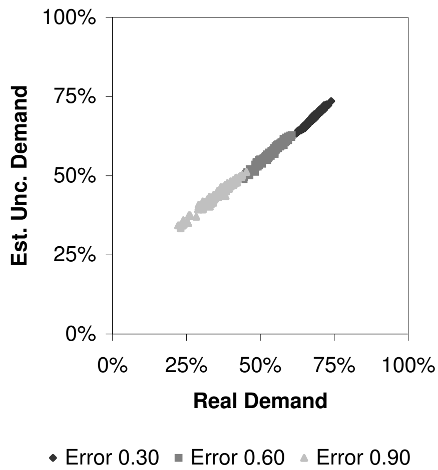

Figure A.2.: Effect of a Biased Overestimation of the Forecasted Demand on PARO

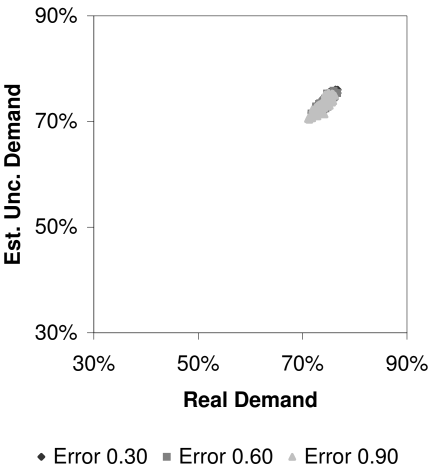

Figure A.3.: Effect of an Unbiased Error of the Forecasted Demand on PARO

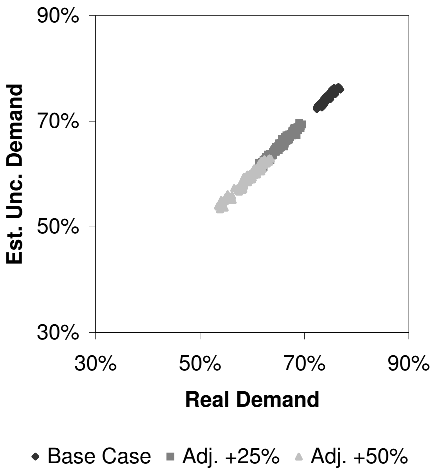

Figure A.4.: Effect of Restrictive RM Controls on PARO

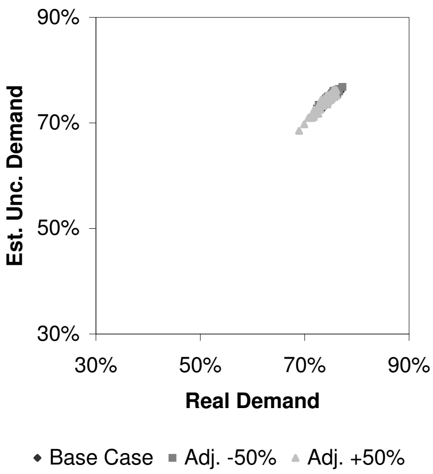

Figure A.5.: Effect of Adjusted Seasonality on PARO

Error level	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^{R}$ (%)	74.7	71.0	64.1	49.6	76.8	78.0	78.7	74.8	74.6	74.5
$\overline{PARO}^{D}$ (%)	74.7	71.6	66.9	59.4	76.3	77.4	78.2	74.4	74.0	73.9
$\overline{MAE}^{PARO}$ (%)	0.3	0.6	2.8	9.8	0.5	0.6	0.6	0.4	0.6	0.7
r^{PARO}	0.94	0.87	0.75	0.64	0.97	0.97	0.96	0.94	0.90	0.86
$\overline{ARO}^{R}$ (million)	5.6	5.3	4.8	3.7	5.8	5.8	5.9	5.6	5.6	5.6
$\overline{ARO}^{D}$ (million)	5.6	4.5	3.0	1.0	6.6	7.3	7.9	5.7	5.7	5.7
$\overline{MAE}^{ARO}$ (million)	0.1	0.8	1.8	2.7	0.8	1.4	2.0	0.1	0.1	0.1
r^{ARO}	0.98	0.97	0.94	0.73	0.98	0.98	0.98	0.97	0.95	0.90
$\overline{RO}^{R}$ (million)	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5
$\overline{RO}^{D}$ (million)	7.5	6.3	4.5	1.6	8.6	9.4	10.1	7.6	7.6	7.7
$\overline{MAE}^{RO}$ (million)	0.1	1.2	2.9	5.8	1.1	1.9	2.6	0.1	0.2	0.2
r^{RO}	0.98	0.98	0.95	0.81	0.98	0.98	0.97	0.97	0.96	0.91
$\overline{Rev}^{+,R}$ (million)	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5
$\overline{Rev}^{+,D}$ (million)	46.6	46.2	45.3	43.4	46.8	47.0	47.1	46.6	46.6	46.6
$\overline{MAE}^{Rev^+}$ (million)	0.0	0.4	1.2	3.1	0.3	0.5	0.6	0.1	0.1	0.1
r^{Rev^+}	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.6	44.4	43.8	42.8	44.8	44.9	44.9	44.6	44.6	44.6
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.0	39.8	40.8	41.8	38.2	37.6	37.1	39.0	39.0	38.9
$\overline{MAE}^{Rev^-}$ (million)	0.1	0.8	1.8	2.7	0.8	1.4	2.0	0.1	0.1	0.1
r^{Rev^-}	0.99	0.99	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.98
$\overline{R}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{D}$ (thousand)	87.2	79.8	72.6	65.4	95.1	102.9	110.7	87.5	87.8	88.2
$\overline{F}$ (thousand)	87.1	79.8	72.6	65.4	95.0	102.9	110.7	87.4	87.7	88.1
$\overline{MAE}^{D}$	0.56	0.73	1.11	1.55	0.76	1.17	1.66	0.75	1.15	1.62
$\overline{PMAE}^{D}$ (%)	9.3	12.0	18.2	25.6	12.6	19.4	27.5	12.3	18.9	26.8
$\overline{MAE}^{F}$	1.83	1.97	2.28	2.63	2.02	2.40	2.86	1.85	1.89	1.95
$\overline{PMAE}^{F}$ (%)	30.3	32.4	37.6	43.4	33.4	39.7	47.3	30.5	31.2	32.2

Table A.1.: Effect of Unconstraining Errors on ROM Measures

Error level	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	74.7	65.0	43.2	15.1	69.0	53.8	35.5	74.7	74.4	73.9
$\overline{PARO}^D$ (%)	74.7	67.4	52.1	33.4	69.3	57.3	44.0	74.3	73.8	73.2
$\overline{MAE}^{PARO}$ (%)	0.3	2.4	8.9	18.3	0.4	3.5	8.5	0.4	0.6	0.8
r^{PARO}	0.94	0.81	0.76	0.49	0.99	0.99	0.98	0.93	0.89	0.84
$\overline{ARO}^R$ (million)	5.6	4.9	3.2	1.1	5.2	4.0	2.7	5.6	5.6	5.5
$\overline{ARO}^D$ (million)	5.6	4.3	2.4	0.5	6.0	5.5	4.7	5.7	5.6	5.6
$\overline{MAE}^{ARO}$ (million)	0.1	0.5	0.8	0.6	0.8	1.5	2.1	0.1	0.1	0.1
r^{ARO}	0.98	0.95	0.91	0.72	0.99	0.99	0.98	0.97	0.94	0.89
$\overline{RO}^R$ (million)	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5	7.5
$\overline{RO}^D$ (million)	7.5	6.4	4.7	1.6	8.6	9.7	10.7	7.6	7.6	7.7
$\overline{MAE}^{RO}$ (million)	0.1	1.1	2.8	5.9	1.1	2.2	3.3	0.1	0.2	0.2
r^{RO}	0.98	0.98	0.96	0.87	0.98	0.97	0.96	0.97	0.94	0.91
$\overline{Rev}^{+,R}$ (million)	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5	46.5
$\overline{Rev}^{+,D}$ (million)	46.6	46.0	44.5	41.2	46.9	47.2	47.7	46.6	46.6	46.6
$\overline{MAE}^{Rev^+}$ (million)	0.0	0.5	2.0	5.3	0.3	0.7	1.2	0.1	0.1	0.1
r^{Rev^+}	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.6	43.9	42.3	40.2	44.2	43.1	41.7	44.6	44.6	44.6
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.0	39.6	39.9	39.7	38.2	37.5	37.0	39.0	39.0	39.0
$\overline{MAE}^{Rev^-}$ (million)	0.1	0.5	0.8	0.6	0.8	1.5	2.1	0.1	0.1	0.1
r^{Rev^-}	0.99	1.00	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.98
$\overline{R}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{D}$ (thousand)	87.2	80.0	72.7	65.2	95.1	104.6	115.6	87.5	87.8	88.2
$\overline{F}$ (thousand)	87.1	61.2	35.2	8.9	112.9	138.5	163.8	87.1	87.1	87.1
$\overline{MAE}^D$	0.56	0.75	1.13	1.57	0.78	1.31	2.02	0.75	1.15	1.63
$\overline{PMAE}^D$ (%)	9.3	12.3	18.6	25.9	12.9	21.7	33.4	12.3	19.0	26.9
$\overline{MAE}^F$	1.83	2.37	3.76	5.47	2.50	3.85	5.44	1.89	2.05	2.29
$\overline{PMAE}^F$ (%)	30.3	39.0	62.0	90.2	41.4	63.7	90.0	31.2	33.9	37.7

Table A.2.: Effect of Forecast Errors on ROM Measures

	Base Case	Bid price decrease		Bid price increase		Adjust seasonality		Apply saw tooth curve	
Adj. level	-	25%	50%	25%	50%	-50%	+50%	130% - 70%	120% - 80%
$\overline{PARO}^R$ (%)	74.7	62.5	36.7	66.3	59.6	75.1	74.2	69.5	72.7
$\overline{PARO}^D$ (%)	74.7	62.9	36.7	66.4	59.5	75.1	74.3	70.8	73.2
$\overline{MAE}^{PARO}$ (%)	0.3	0.5	0.5	0.3	0.4	0.2	0.3	1.2	0.6
r^{PARO}	0.94	0.90	0.94	0.98	0.98	0.94	0.96	0.99	0.99
$\overline{ARO}^R$ (million)	5.6	4.7	2.7	5.0	4.5	5.6	5.6	5.3	5.4
$\overline{ARO}^D$ (million)	5.6	4.8	2.9	5.0	4.4	5.6	5.6	5.1	5.4
$\overline{MAE}^{ARO}$ (million)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.5	0.3
r^{ARO}	0.98	0.96	0.96	0.98	0.98	0.95	0.99	1.00	1.00
$\overline{RO}^R$ (million)	7.5	7.5	7.5	7.5	7.5	7.4	7.6	7.4	7.4
$\overline{RO}^D$ (million)	7.5	7.6	7.8	7.5	7.4	7.5	7.6	7.1	7.3
$\overline{MAE}^{RO}$ (million)	0.1	0.2	0.3	0.1	0.1	0.1	0.1	0.8	0.5
r^{RO}	0.98	0.97	0.95	0.98	0.98	0.95	0.99	1.00	1.00
$\overline{Rev}^{+,R}$ (million)	46.5	46.5	46.5	46.5	46.5	46.6	46.5	46.0	46.3
$\overline{Rev}^{+,D}$ (million)	46.6	46.6	46.7	46.5	46.5	46.6	46.5	45.8	46.2
$\overline{MAE}^{Rev^+}$ (million)	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.3	0.2
r^{Rev^+}	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.6	43.7	41.8	44.0	43.5	44.7	44.5	43.8	44.3
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.1	38.9	38.5	38.9
$\overline{Rev}^{-,D}$ (million)	39.0	38.9	38.9	39.1	39.1	39.1	38.9	38.7	38.9
$\overline{MAE}^{Rev^-}$ (million)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.5	0.3
r^{Rev^-}	0.99	1.00	1.00	0.99	0.99	0.99	1.00	1.00	1.00
$\overline{R}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.4	87.8	87.2	87.2
$\overline{D}$ (thousand)	87.2	87.5	88.0	86.8	86.6	87.3	86.9	83.8	85.6
$\overline{F}$ (thousand)	87.1	87.4	87.9	86.8	86.6	87.3	86.8	83.8	85.6
$\overline{MAE}^D$	0.56	0.61	0.66	0.58	0.60	0.53	0.60	0.67	0.59
$\overline{PMAE}^D$ (%)	9.3	10.1	11.0	9.6	10.0	8.8	9.9	10.7	9.6
$\overline{MAE}^F$	1.83	1.83	1.83	1.83	1.83	1.77	1.92	2.11	1.91
$\overline{PMAE}^F$ (%)	30.3	30.2	30.3	30.3	30.2	29.2	31.8	36.0	32.1

Table A.3.: Effect of Adjusted RM Controls and Seasonality on ROM Measures

A.2. The Network-based ROM with Dependent Demand

In this section we list supplemental scatter plots and tables of our analyses of the network-based ROM with dependent demand. Most of the results for the base case scenario with a sell-up rate of 30% are already presented in Chapter 5. In the contrary, most of the results for the scenarios with sell-up rates of 10% and 50% are listed in the following sections. As with the previous section we present extended result tables that include the similarity measures for all ROM measures.

A.2.1. The Base Case: Sell-up Rate 30%

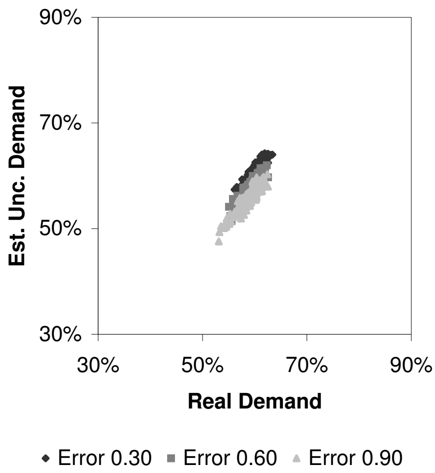

Figure A.6.: Effect of an Unbiased Error of the Unconstrained Yieldable Demand on PARO

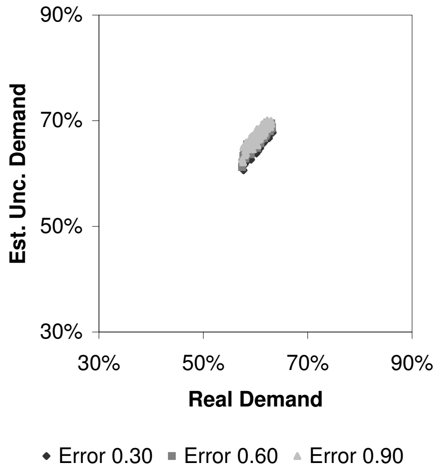

Figure A.7.: Effect of a Biased Underestimation of the Unconstrained Buy-down on PARO

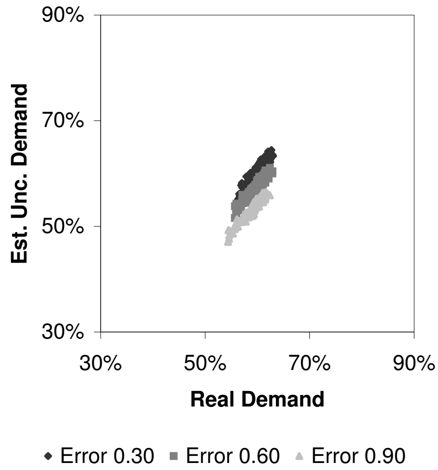

Figure A.8.: Effect of a Biased Overestimation of the Unconstrained Buy-down on PARO

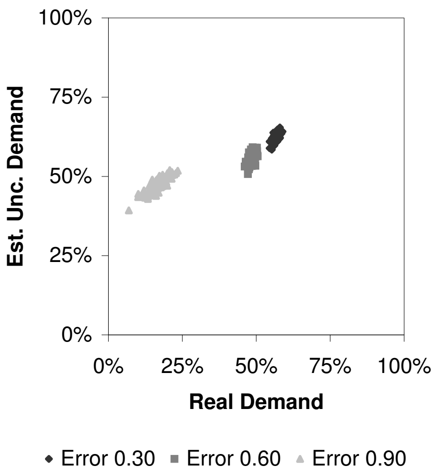

Figure A.9.: Effect of a Biased Underestimation of the Forecasted Yieldable Demand on PARO

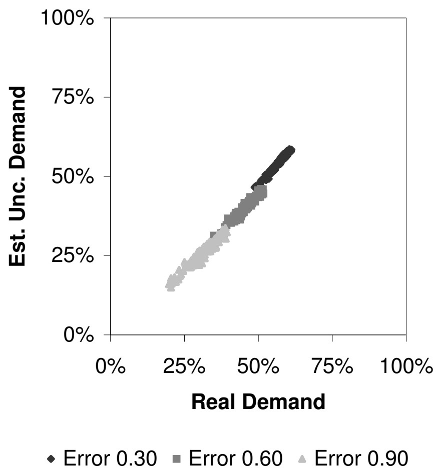

Figure A.10.: Effect of Biased Overestimation of the Forecasted Yieldable Demand on PARO

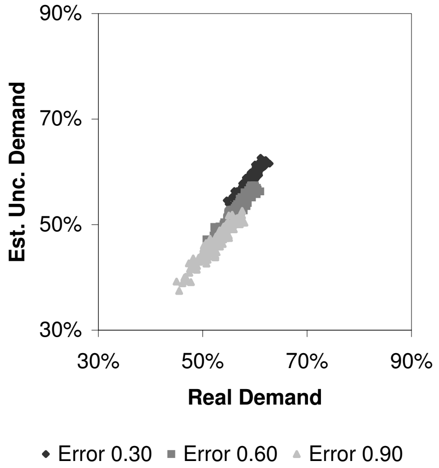

Figure A.11.: Effect of an Unbiased Error of the Forecasted Yieldable Demand on PARO

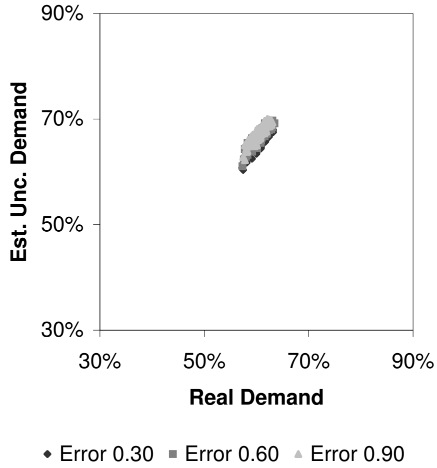

Figure A.12.: Effect of a Biased Underestimation of the Forecasted Buy-down on PARO

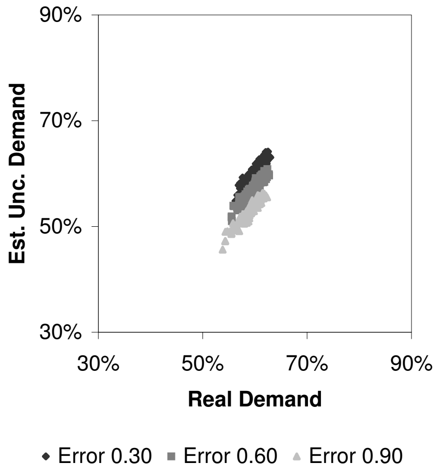

Figure A.13.: Effect of a Biased Overestimation of the Forecasted Buy-down on PARO

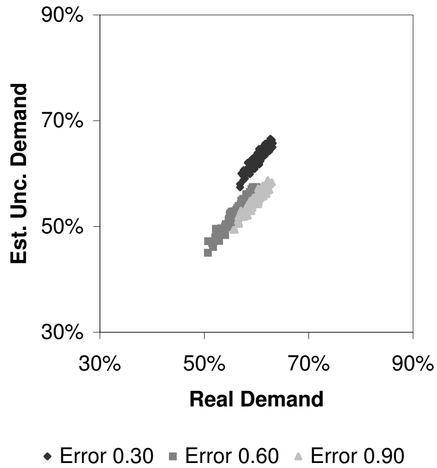

Figure A.14.: Effect of an Unbiased Error of the Forecasted Buy-down on PARO

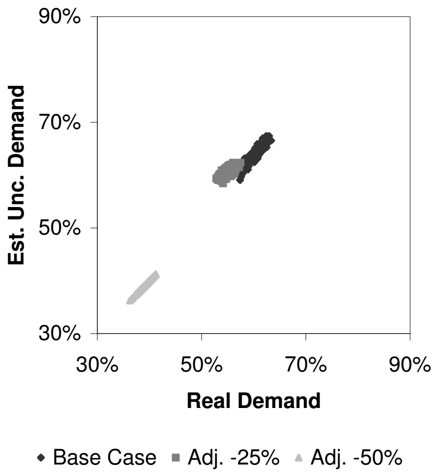

Figure A.15.: Effect of Open RM Controls on PARO

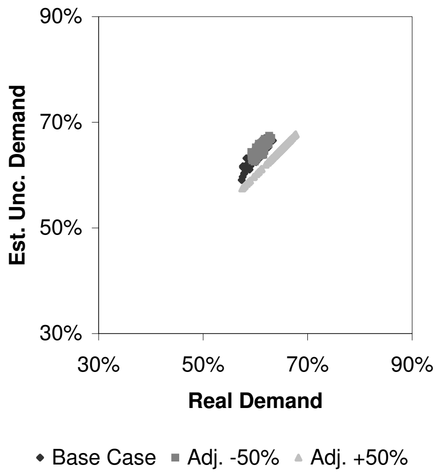

Figure A.16.: Effect of Adjusted Seasonality on PARO

Error level	Base Case -	Biased underestimation 30%	60%	90%	Biased overestimation 30%	60%	90%	Unbiased error 30%	60%	90%
$\overline{PARO}^{R}$ (%)	60.8	57.9	51.9	42.1	60.7	59.6	57.9	60.2	59.5	58.9
$\overline{PARO}^{D}$ (%)	64.6	64.1	61.9	63.0	58.9	54.9	51.7	61.1	58.0	55.7
$\overline{MAE}^{PARO}$ (%)	3.8	6.2	10.0	20.9	1.8	4.7	6.2	1.0	1.5	3.1
r^{PARO}	0.91	0.84	0.69	0.42	0.97	0.98	0.98	0.92	0.91	0.92
$\overline{ARO}^{R}$ (million)	5.8	5.5	5.0	4.0	5.8	5.7	5.5	5.8	5.7	5.6
$\overline{ARO}^{D}$ (million)	5.6	4.6	3.2	2.0	6.2	6.6	6.8	5.6	5.5	5.6
$\overline{MAE}^{ARO}$ (million)	0.2	0.9	1.7	2.0	0.4	0.9	1.2	0.2	0.2	0.1
r^{ARO}	0.97	0.95	0.88	0.77	0.98	0.98	0.98	0.97	0.95	0.93
$\overline{RO}^{R}$ (million)	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6
$\overline{RO}^{D}$ (million)	8.7	7.2	5.2	3.2	10.6	12.0	13.1	9.1	9.5	10.1
$\overline{MAE}^{RO}$ (million)	0.8	2.3	4.4	6.3	1.0	2.4	3.5	0.4	0.1	0.5
r^{RO}	0.96	0.94	0.87	0.77	0.96	0.96	0.95	0.95	0.93	0.90
$\overline{Rev}^{+,R}$ (million)	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6
$\overline{Rev}^{+,D}$ (million)	47.9	47.1	46.0	44.2	49.2	50.1	50.9	48.3	48.7	49.1
$\overline{MAE}^{Rev^{+}}$ (million)	0.7	1.4	2.6	4.3	0.6	1.5	2.3	0.3	0.1	0.5
$r^{Rev^{+}}$	1.00	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99
$\overline{Rev}$ (million)	44.8	44.6	44.0	43.0	44.8	44.7	44.6	44.8	44.7	44.6
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.2	39.9	40.8	41.0	38.6	38.1	37.8	39.2	39.2	39.0
$\overline{MAE}^{Rev^{-}}$ (million)	0.2	0.9	1.7	2.0	0.4	0.9	1.2	0.2	0.2	0.1
$r^{Rev^{-}}$	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.97
$\overline{R}^{td}$ (thousand)	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9
$\overline{D}^{td}$ (thousand)	120.4	111.6	103.6	97.9	134.2	147.8	161.3	122.8	125.4	129.3
$\overline{D}^{yd}$ (thousand)	88.7	79.5	71.1	65.3	102.3	115.9	129.4	90.8	93.1	96.6
$\overline{D}^{bd}$ (thousand)	31.7	32.1	32.5	32.6	31.8	31.9	31.9	32.0	32.3	32.7
$\overline{F}^{td}$ (thousand)	120.4	111.6	103.5	97.8	134.1	147.7	161.3	122.7	125.3	129.2
$\overline{F}^{yd}$ (thousand)	88.7	79.5	71.0	65.2	102.3	115.9	129.4	90.8	93.0	96.5
$\overline{F}^{bd}$ (thousand)	31.7	32.1	32.5	32.6	31.8	31.9	31.9	32.0	32.3	32.7
$\overline{MAE}^{D^{td}}$	1.37	1.47	1.77	2.02	1.87	2.65	3.51	1.67	2.22	2.80
$\overline{MAE}^{D^{yd}}$	0.76	0.91	1.30	1.64	1.26	2.06	2.95	1.08	1.69	2.32
$\overline{MAE}^{D^{bd}}$	0.87	0.88	0.89	0.90	0.87	0.87	0.87	0.87	0.88	0.90
$\overline{PMAE}^{D^{td}}$ (%)	16.9	18.1	21.8	24.8	23.0	32.6	43.3	20.6	27.3	34.4
$\overline{PMAE}^{D^{yd}}$ (%)	12.5	14.9	21.4	26.9	20.8	34.0	48.6	17.8	27.8	38.3
$\overline{PMAE}^{D^{bd}}$ (%)	42.0	42.5	43.2	43.3	42.0	42.0	42.0	42.3	42.8	43.4
$\overline{MAE}^{F^{td}}$	2.27	2.37	2.65	2.86	2.66	3.35	4.17	2.34	2.45	2.63
$\overline{MAE}^{F^{yd}}$	1.86	1.99	2.33	2.61	2.25	2.97	3.80	1.92	2.03	2.20
$\overline{MAE}^{F^{bd}}$	0.99	1.00	1.01	1.01	0.99	0.99	0.99	0.99	1.00	1.01
$\overline{PMAE}^{F^{td}}$ (%)	28.0	29.2	32.6	35.2	32.8	41.4	51.4	28.8	30.3	32.4
$\overline{PMAE}^{F^{yd}}$ (%)	30.8	32.9	38.5	43.1	37.2	49.1	62.8	31.7	33.6	36.3
$\overline{PMAE}^{F^{bd}}$ (%)	47.7	48.3	49.0	49.1	47.8	47.8	47.8	48.1	48.5	49.0

Table A.4.: Effect of Unconstraining Errors of the Yieldable Demand on ROM Measures

	Base	Biased			Biased					
	Case	underestimation			overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	60.8	60.9	60.9	60.8	60.5	60.0	59.1	60.7	60.5	60.2
$\overline{PARO}^D$ (%)	64.6	65.9	67.0	67.6	61.2	57.6	53.4	63.4	61.0	55.3
$\overline{MAE}^{PARO}$ (%)	3.8	5.1	6.1	6.8	0.8	2.4	5.8	2.7	0.6	4.9
r^{PARO}	0.91	0.91	0.90	0.90	0.94	0.95	0.96	0.93	0.93	0.94
$\overline{ARO}^R$ (million)	5.8	5.8	5.8	5.8	5.8	5.7	5.7	5.8	5.8	5.8
$\overline{ARO}^D$ (million)	5.6	5.7	5.7	5.7	5.6	5.5	5.4	5.6	5.6	5.3
$\overline{MAE}^{ARO}$ (million)	0.2	0.2	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.4
r^{ARO}	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
$\overline{RO}^R$ (million)	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6
$\overline{RO}^D$ (million)	8.7	8.6	8.5	8.4	9.1	9.6	10.2	8.9	9.1	9.6
$\overline{MAE}^{RO}$ (million)	0.8	1.0	1.1	1.1	0.4	0.1	0.6	0.7	0.4	0.1
r^{RO}	0.96	0.96	0.97	0.97	0.96	0.96	0.96	0.96	0.96	0.96
$\overline{Rev}^{+,R}$ (million)	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6
$\overline{Rev}^{+,D}$ (million)	47.9	47.8	47.6	47.6	48.3	48.8	49.4	48.1	48.4	49.1
$\overline{MAE}^{Rev^+}$ (million)	0.7	0.8	0.9	1.0	0.2	0.2	0.9	0.5	0.2	0.5
r^{Rev^+}	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.8	44.8	44.8	44.8	44.8	44.7	44.7	44.8	44.8	44.8
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.2	39.2	39.2	39.1	39.2	39.2	39.2	39.2	39.2	39.4
$\overline{MAE}^{Rev^-}$ (million)	0.2	0.2	0.1	0.1	0.2	0.2	0.2	0.2	0.2	0.4
r^{Rev^-}	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$\overline{R}^{td}$ (thousand)	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9
$\overline{D}^{td}$ (thousand)	120.4	111.6	102.9	94.2	130.1	140.0	150.1	120.9	121.7	123.6
$\overline{D}^{yd}$ (thousand)	88.7	89.3	89.8	90.5	88.9	89.1	89.6	89.1	89.7	91.2
$\overline{D}^{bd}$ (thousand)	31.7	22.4	13.1	3.8	41.3	50.8	60.5	31.8	32.0	32.5
$\overline{F}^{td}$ (thousand)	120.4	111.6	102.9	94.2	130.1	139.9	150.0	120.9	121.7	123.6
$\overline{F}^{yd}$ (thousand)	88.7	89.2	89.8	90.5	88.9	89.1	89.5	89.1	89.7	91.1
$\overline{F}^{bd}$ (thousand)	31.7	22.4	13.1	3.8	41.2	50.8	60.5	31.8	32.0	32.5
$\overline{MAE}^{D^{td}}$	1.37	1.41	1.67	2.08	1.62	2.07	2.64	1.51	1.85	2.26
$\overline{MAE}^{D^{yd}}$	0.76	0.77	0.78	0.80	0.77	0.77	0.79	0.77	0.79	0.86
$\overline{MAE}^{D^{bd}}$	0.87	0.95	1.32	1.85	1.13	1.62	2.21	1.04	1.46	1.99
$\overline{PMAE}^{D^{td}}$ (%)	16.9	17.3	20.6	25.5	20.0	25.5	32.5	18.6	22.8	27.8
$\overline{PMAE}^{D^{yd}}$ (%)	12.5	12.7	12.9	13.2	12.6	12.8	13.0	12.7	13.0	14.2
$\overline{PMAE}^{D^{bd}}$ (%)	42.0	45.8	63.9	89.3	54.8	78.2	106.9	50.2	70.7	96.5
$\overline{MAE}^{F^{td}}$	2.27	2.28	2.43	2.71	2.45	2.78	3.22	2.29	2.32	2.38
$\overline{MAE}^{F^{yd}}$	1.86	1.88	1.89	1.91	1.87	1.87	1.88	1.87	1.88	1.90
$\overline{MAE}^{F^{bd}}$	0.99	1.03	1.36	1.85	1.24	1.70	2.26	1.00	1.04	1.10
$\overline{PMAE}^{F^{td}}$ (%)	28.0	28.0	29.9	33.3	30.2	34.3	39.7	28.2	28.6	29.4
$\overline{PMAE}^{F^{yd}}$ (%)	30.8	31.0	31.2	31.5	30.8	30.9	31.0	30.9	31.1	31.5
$\overline{PMAE}^{F^{bd}}$ (%)	47.7	49.8	65.6	89.6	60.2	82.3	109.6	48.5	50.4	53.4

Table A.5.: Effect of Unconstraining Errors of the Buy-down on ROM Measures

Error level	Base Case -	Biased underestimation 30%	60%	90%	Biased overestimation 30%	60%	90%	Unbiased error 30%	60%	90%
$\overline{PARO}^R$ (%)	60.8	56.9	48.6	16.8	56.0	44.9	31.0	59.4	56.7	52.8
$\overline{PARO}^D$ (%)	64.6	62.7	56.0	47.5	53.4	39.4	25.7	59.0	53.1	46.9
$\overline{MAE}^{PARO}$ (%)	3.8	5.8	7.4	30.7	2.6	5.4	5.3	0.6	3.6	5.8
r^{PARO}	0.91	0.70	0.52	0.86	0.98	0.98	0.96	0.94	0.95	0.95
$\overline{ARO}^R$ (million)	5.8	5.4	4.6	1.6	5.4	4.3	3.0	5.7	5.4	5.1
$\overline{ARO}^D$ (million)	5.6	4.6	3.1	2.1	5.7	4.8	3.6	5.4	5.1	4.8
$\overline{MAE}^{ARO}$ (million)	0.2	0.9	1.6	0.5	0.3	0.5	0.6	0.3	0.3	0.3
r^{ARO}	0.97	0.95	0.88	0.86	0.98	0.98	0.97	0.97	0.96	0.95
$\overline{RO}^R$ (million)	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6
$\overline{RO}^D$ (million)	8.7	7.3	5.5	4.5	10.6	12.3	13.8	9.2	9.6	10.1
$\overline{MAE}^{RO}$ (million)	0.8	2.3	4.1	5.1	1.1	2.7	4.3	0.4	0.1	0.6
r^{RO}	0.96	0.94	0.88	0.76	0.96	0.96	0.95	0.95	0.93	0.89
$\overline{Rev}^{+,R}$ (million)	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6
$\overline{Rev}^{+,D}$ (million)	47.9	47.2	46.1	43.0	49.3	50.7	52.3	48.4	48.9	49.4
$\overline{MAE}^{Rev^+}$ (million)	0.7	1.4	2.5	5.6	0.8	2.2	3.7	0.1	0.4	0.9
r^{Rev^+}	1.00	1.00	0.99	0.99	1.00	1.00	0.99	1.00	0.99	0.99
$\overline{Rev}$ (million)	44.8	44.5	43.7	40.6	44.4	43.3	42.0	44.7	44.4	44.1
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.2	39.9	40.6	38.5	38.7	38.5	38.4	39.3	39.3	39.3
$\overline{MAE}^{Rev^-}$ (million)	0.2	0.9	1.6	0.5	0.3	0.5	0.6	0.3	0.3	0.3
r^{Rev^-}	0.99	0.99	0.99	0.97	0.99	0.99	0.98	0.99	0.99	0.98
$\overline{R}^{td}$ (thousand)	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9
$\overline{D}^{td}$ (thousand)	120.4	111.7	104.7	93.2	134.6	149.7	166.5	123.0	125.7	129.6
$\overline{D}^{yd}$ (thousand)	88.7	79.6	70.6	54.7	102.8	117.8	134.5	91.0	93.3	96.8
$\overline{D}^{bd}$ (thousand)	31.7	32.1	34.1	38.6	31.9	31.9	32.0	32.1	32.4	32.8
$\overline{F}^{td}$ (thousand)	120.4	107.5	100.1	90.0	147.7	174.7	201.6	127.5	136.8	147.8
$\overline{F}^{yd}$ (thousand)	88.7	73.2	61.0	45.8	115.8	142.8	169.7	94.4	101.7	110.6
$\overline{F}^{bd}$ (thousand)	31.7	34.3	39.1	44.2	31.8	31.9	32.0	33.1	35.1	37.2
$\overline{MAE}^{D^{td}}$	1.37	1.47	1.86	2.50	1.89	2.75	3.79	1.68	2.26	2.88
$\overline{MAE}^{D^{yd}}$	0.76	0.91	1.41	2.47	1.29	2.20	3.31	1.09	1.72	2.41
$\overline{MAE}^{D^{bd}}$	0.87	0.88	0.93	1.08	0.87	0.87	0.88	0.88	0.89	0.90
$\overline{PMAE}^{D^{td}}$ (%)	16.9	18.1	22.9	30.7	23.3	33.8	46.7	20.7	27.8	35.4
$\overline{PMAE}^{D^{yd}}$ (%)	12.5	15.0	23.2	40.7	21.3	36.4	54.6	18.0	28.4	39.7
$\overline{PMAE}^{D^{bd}}$ (%)	42.0	42.6	45.0	52.1	42.1	42.2	42.5	42.4	42.9	43.6
$\overline{MAE}^{F^{td}}$	2.27	2.41	2.75	3.17	3.01	4.41	6.08	2.41	2.73	3.21
$\overline{MAE}^{F^{yd}}$	1.86	2.09	2.59	3.32	2.63	4.11	5.82	1.98	2.25	2.65
$\overline{MAE}^{F^{bd}}$	0.99	1.03	1.19	1.40	0.99	0.99	0.99	1.01	1.05	1.12
$\overline{PMAE}^{F^{td}}$ (%)	28.0	29.7	33.8	39.0	37.2	54.5	75.1	29.7	33.7	39.6
$\overline{PMAE}^{F^{yd}}$ (%)	30.8	34.5	42.7	54.7	43.6	68.0	96.3	32.7	37.2	43.8
$\overline{PMAE}^{F^{bd}}$ (%)	47.7	50.2	57.5	67.9	47.8	47.8	47.8	48.9	51.1	54.4

Table A.6.: Effect of Forecast Errors of the Yieldable Demand on ROM Measures

Error level	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	60.8	60.8	60.9	60.8	60.4	60.0	59.0	60.6	56.7	60.2
$\overline{PARO}^D$ (%)	64.6	65.8	67.0	67.6	61.0	57.4	53.0	63.4	53.1	55.4
$\overline{MAE}^{PARO}$ (%)	3.8	5.0	6.2	6.8	0.7	2.6	6.0	2.7	3.6	4.8
r^{PARO}	0.91	0.91	0.90	0.90	0.93	0.94	0.95	0.92	0.95	0.94
$\overline{ARO}^R$ (million)	5.8	5.8	5.8	5.8	5.8	5.7	5.6	5.8	5.4	5.8
$\overline{ARO}^D$ (million)	5.6	5.7	5.7	5.7	5.6	5.5	5.4	5.6	5.1	5.3
$\overline{MAE}^{ARO}$ (million)	0.2	0.2	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.4
r^{ARO}	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.96	0.97
$\overline{RO}^R$ (million)	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6	9.6
$\overline{RO}^D$ (million)	8.7	8.6	8.5	8.4	9.1	9.6	10.2	8.9	9.6	9.6
$\overline{MAE}^{RO}$ (million)	0.8	1.0	1.1	1.1	0.4	0.1	0.6	0.7	0.1	0.1
r^{RO}	0.96	0.96	0.96	0.97	0.96	0.96	0.96	0.96	0.93	0.96
$\overline{Rev}^{+,R}$ (million)	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6	48.6
$\overline{Rev}^{+,D}$ (million)	47.9	47.8	47.6	47.6	48.4	48.8	49.5	48.1	48.9	49.1
$\overline{MAE}^{Rev^+}$ (million)	0.7	0.8	0.9	1.0	0.2	0.3	0.9	0.5	0.4	0.5
r^{Rev^+}	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00
$\overline{Rev}$ (million)	44.8	44.8	44.8	44.8	44.8	44.7	44.7	44.8	44.4	44.8
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.2	39.2	39.1	39.1	39.2	39.2	39.3	39.2	39.3	39.4
$\overline{MAE}^{Rev^-}$ (million)	0.2	0.2	0.1	0.1	0.2	0.2	0.2	0.2	0.3	0.4
r^{Rev^-}	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$\overline{R}^{td}$ (thousand)	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5	117.5
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9	29.9
$\overline{D}^{td}$ (thousand)	120.4	111.7	103.0	94.3	130.2	140.0	150.1	120.9	125.7	123.6
$\overline{D}^{yd}$ (thousand)	88.7	89.3	89.9	90.5	88.9	89.2	89.6	89.1	93.3	91.2
$\overline{D}^{bd}$ (thousand)	31.7	22.4	13.1	3.8	41.3	50.9	60.5	31.8	32.4	32.5
$\overline{F}^{td}$ (thousand)	120.4	111.6	102.9	94.2	130.1	140.0	150.1	120.9	136.8	123.6
$\overline{F}^{yd}$ (thousand)	88.7	89.3	89.9	90.5	88.9	89.1	89.6	89.1	101.7	91.2
$\overline{F}^{bd}$ (thousand)	31.7	22.4	13.1	3.8	41.3	50.8	60.5	31.8	35.1	32.4
$\overline{MAE}^{D^{td}}$	1.37	1.41	1.67	2.08	1.62	2.07	2.64	1.51	2.26	2.26
$\overline{MAE}^{D^{yd}}$	0.76	0.77	0.78	0.80	0.77	0.77	0.79	0.77	1.72	0.86
$\overline{MAE}^{D^{bd}}$	0.87	0.95	1.32	1.84	1.13	1.62	2.21	1.04	0.89	1.99
$\overline{PMAE}^{D^{td}}$ (%)	16.9	17.3	20.6	25.5	20.0	25.5	32.5	18.6	27.8	27.8
$\overline{PMAE}^{D^{yd}}$ (%)	12.5	12.7	12.9	13.3	12.7	12.8	13.0	12.7	28.4	14.2
$\overline{PMAE}^{D^{bd}}$ (%)	42.0	45.8	63.9	89.3	54.8	78.3	106.9	50.3	42.9	96.5
$\overline{MAE}^{F^{td}}$	2.27	2.28	2.43	2.71	2.45	2.78	3.22	2.29	2.73	2.38
$\overline{MAE}^{F^{yd}}$	1.86	1.88	1.89	1.91	1.87	1.87	1.88	1.87	2.25	1.90
$\overline{MAE}^{F^{bd}}$	0.99	1.03	1.36	1.85	1.24	1.70	2.26	1.00	1.05	1.10
$\overline{PMAE}^{F^{td}}$ (%)	28.0	28.0	29.9	33.3	30.3	34.3	39.7	28.2	33.7	29.4
$\overline{PMAE}^{F^{yd}}$ (%)	30.8	31.0	31.2	31.5	30.9	30.9	31.0	30.9	37.2	31.5
$\overline{PMAE}^{F^{bd}}$ (%)	47.7	49.8	65.6	89.7	60.2	82.4	109.7	48.5	51.1	53.4

Table A.7.: Effect of Forecast Errors of the Buy-down on ROM Measures

Adj. level	Base Case -	Bid price decrease 25%	50%	Bid price increase 25%	50%	Adjust seasonality -50%	+50%	Apply saw tooth curve 130% - 70%	120% - 80%
$\overline{PARO}^R$ (%)	60.8	55.3	33.2	55.0	49.9	61.0	60.5	55.3	58.4
$\overline{PARO}^D$ (%)	64.6	60.9	39.1	58.2	52.4	65.1	64.3	59.8	62.6
$\overline{MAE}^{PARO}$ (%)	3.8	5.6	5.8	3.3	2.5	4.0	3.8	4.7	4.2
r^{PARO}	0.91	0.69	0.87	0.95	0.96	0.82	0.94	1.00	1.00
$\overline{ARO}^R$ (million)	5.8	5.3	3.2	5.3	4.8	5.8	5.8	5.5	5.6
$\overline{ARO}^D$ (million)	5.6	5.3	3.2	5.0	4.4	5.6	5.6	5.1	5.4
$\overline{MAE}^{ARO}$ (million)	0.2	0.1	0.1	0.3	0.3	0.1	0.2	0.4	0.3
r^{ARO}	0.97	0.96	0.95	0.98	0.98	0.94	0.98	1.00	1.00
$\overline{RO}^R$ (million)	9.6	9.6	9.6	9.6	9.6	9.5	9.7	9.5	9.5
$\overline{RO}^D$ (million)	8.7	8.7	8.3	8.5	8.4	8.7	8.7	8.2	8.5
$\overline{MAE}^{RO}$ (million)	0.8	0.8	1.3	1.0	1.1	0.8	0.9	1.4	1.0
r^{RO}	0.96	0.95	0.92	0.94	0.94	0.86	0.98	1.00	1.00
$\overline{Rev}^{+,R}$ (million)	48.6	48.6	48.6	48.6	48.6	48.6	48.5	48.0	48.3
$\overline{Rev}^{+,D}$ (million)	47.9	47.7	47.2	47.8	47.8	47.9	47.8	47.1	47.6
$\overline{MAE}^{Rev^+}$ (million)	0.7	0.9	1.3	0.7	0.8	0.7	0.7	1.0	0.7
r^{Rev^+}	1.00	1.00	0.99	1.00	0.99	0.99	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.8	44.3	42.2	44.3	43.8	44.9	44.7	44.0	44.5
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.1	38.9	38.5	38.9
$\overline{Rev}^{-,D}$ (million)	39.2	39.0	39.0	39.3	39.4	39.3	39.1	38.9	39.1
$\overline{MAE}^{Rev^-}$ (million)	0.2	0.1	0.1	0.3	0.3	0.1	0.2	0.4	0.3
r^{Rev^-}	0.99	0.99	1.00	0.99	0.99	0.98	1.00	1.00	1.00
$\overline{R}^{td}$ (thousand)	117.5	117.5	117.5	117.5	117.5	117.2	117.7	117.0	117.0
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.4	87.8	87.3	87.3
$\overline{R}^{bd}$ (thousand)	29.9	29.9	29.9	29.9	29.9	29.8	29.9	29.8	29.8
$\overline{D}^{td}$ (thousand)	120.4	120.1	118.7	119.2	118.4	120.6	119.9	115.6	118.3
$\overline{D}^{yd}$ (thousand)	88.7	88.6	87.8	87.8	87.3	88.8	88.3	85.2	87.2
$\overline{D}^{bd}$ (thousand)	31.7	31.6	30.9	31.4	31.1	31.8	31.6	30.5	31.2
$\overline{F}^{td}$ (thousand)	120.4	120.1	118.7	119.1	118.3	120.6	119.8	115.7	118.4
$\overline{F}^{yd}$ (thousand)	88.7	88.5	87.8	87.7	87.3	88.8	88.2	85.2	87.2
$\overline{F}^{bd}$ (thousand)	31.7	31.6	30.9	31.4	31.1	31.8	31.5	30.5	31.2
$\overline{MAE}^{D^{td}}$	1.37	1.34	1.30	1.34	1.32	1.33	1.41	1.49	1.40
$\overline{MAE}^{D^{yd}}$	0.76	0.75	0.73	0.75	0.75	0.72	0.80	0.87	0.78
$\overline{MAE}^{D^{bd}}$	0.87	0.86	0.85	0.86	0.85	0.86	0.87	0.87	0.86
$\overline{PMAE}^{D^{td}}$ (%)	16.9	16.5	16.0	16.5	16.3	16.4	17.4	18.6	17.4
$\overline{PMAE}^{D^{yd}}$ (%)	12.5	12.4	12.1	12.4	12.4	12.0	13.2	14.1	12.9
$\overline{PMAE}^{D^{bd}}$ (%)	42.0	41.6	41.1	41.5	41.3	41.8	42.2	43.3	42.4
$\overline{MAE}^{F^{td}}$	2.27	2.25	2.22	2.25	2.24	2.18	2.40	2.65	2.38
$\overline{MAE}^{F^{yd}}$	1.86	1.85	1.84	1.85	1.85	1.80	1.95	2.13	1.94
$\overline{MAE}^{F^{bd}}$	0.99	0.98	0.97	0.98	0.97	0.97	1.01	1.03	1.00
$\overline{PMAE}^{F^{td}}$ (%)	28.0	27.8	27.4	27.7	27.6	26.9	29.5	34.0	29.9
$\overline{PMAE}^{F^{yd}}$ (%)	30.8	30.6	30.3	30.6	30.6	29.7	32.3	36.4	32.6
$\overline{PMAE}^{F^{bd}}$ (%)	47.7	47.4	46.8	47.3	47.1	47.0	48.7	52.2	49.2

Table A.8.: Effect of Adjusted RM Controls and Seasonality on ROM Measures

A.2.2. Sell-up Rate 10%

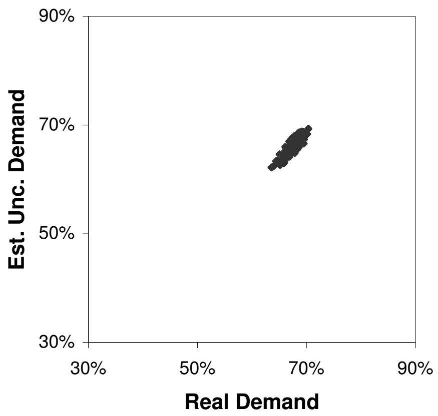

Figure A.17.: Sell-up Rate 10%: Base Case

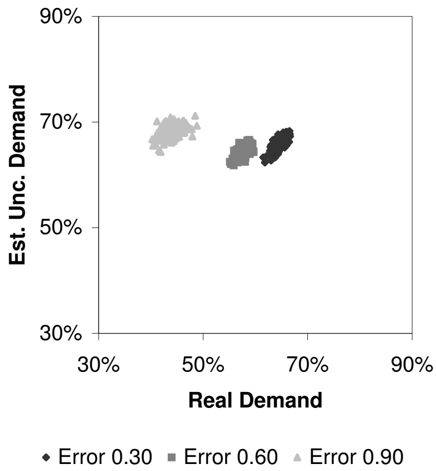

Figure A.18.: Effect of a Biased Underestimation of the Unconstrained Yieldable Demand on PARO

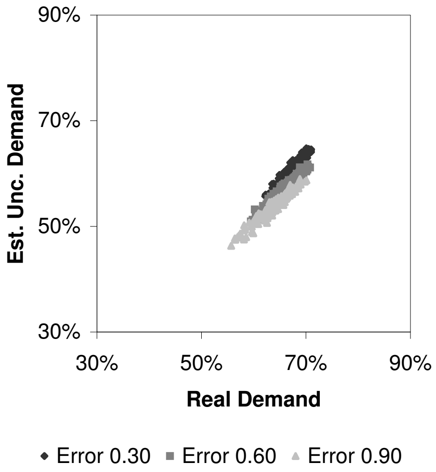

Figure A.19.: Effect of a Biased Overestimation of the Unconstrained Yieldable Demand on PARO

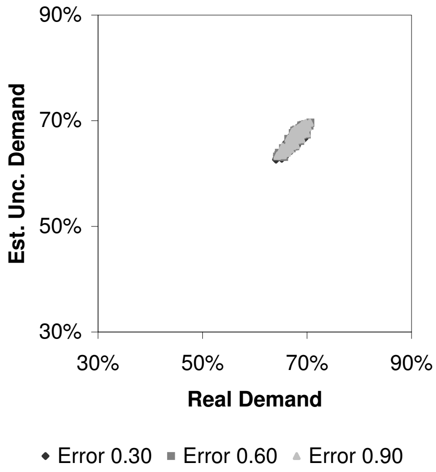

Figure A.20.: Effect of a Biased Underestimation of the Unconstrained Buy-down on PARO

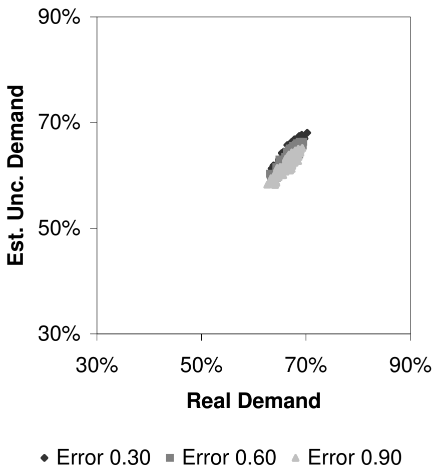

Figure A.21.: Effect of a Biased Overestimation of the Unconstrained Buy-down on PARO

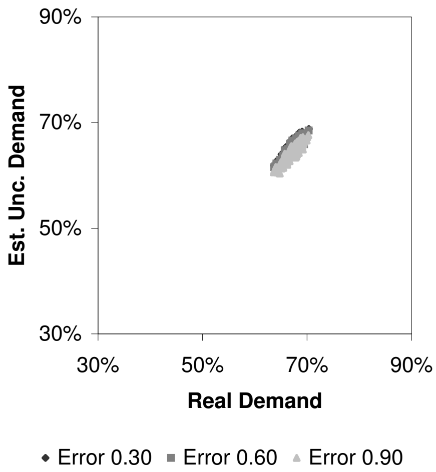

Figure A.22.: Effect of an Unbiased Error of the Unconstrained Buy-down on PARO

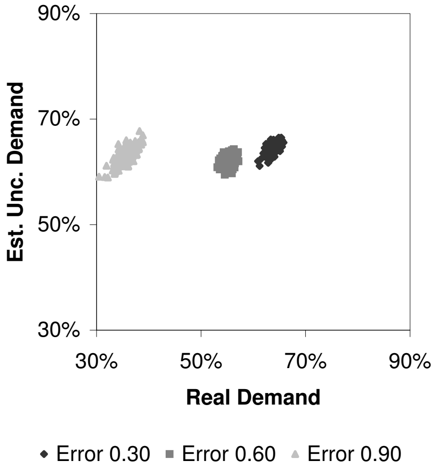

Figure A.23.: Effect of a Biased Underestimation of the Forecasted Yieldable Demand on PARO

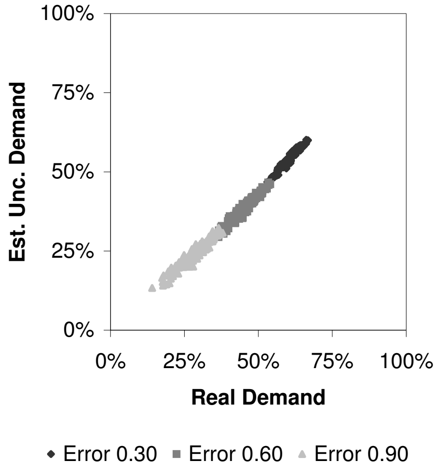

Figure A.24.: Effect of a Biased Overestimation of the Forecasted Yieldable Demand on PARO

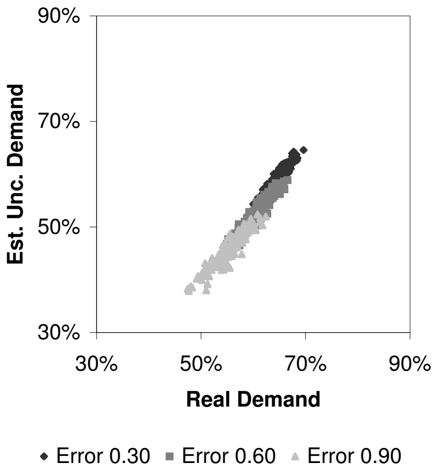

Figure A.25.: Effect of an Unbiased Error of the Forecasted Yieldable Demand on PARO

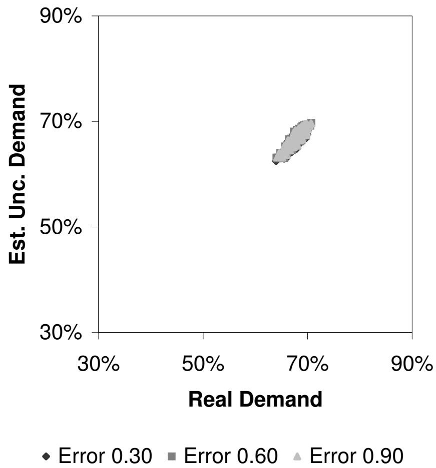

Figure A.26.: Effect of a Biased Underestimation of the Forecasted Buy-down on PARO

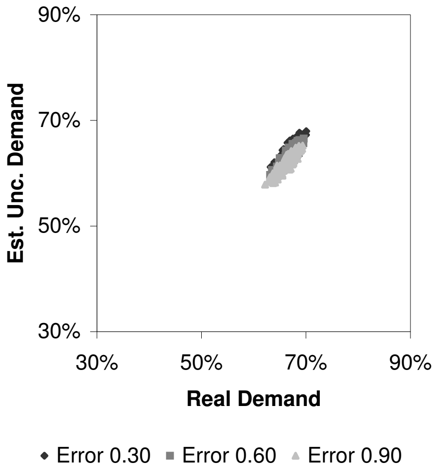

Figure A.27.: Effect of a Biased Overestimation of the Forecasted Buy-down on PARO

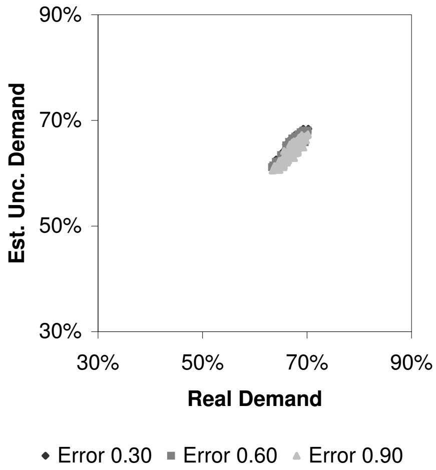

Figure A.28.: Effect of an Unbiased Error of the Forecasted Buy-down on PARO

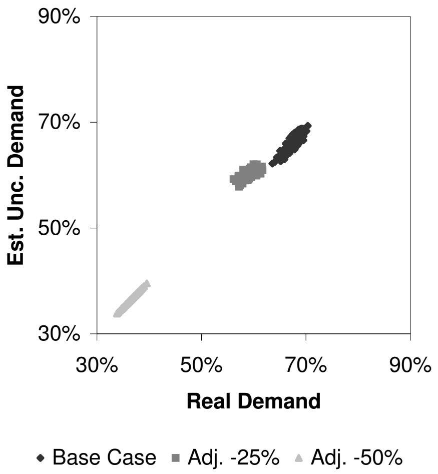

Figure A.29.: Effect of Open RM Controls on PARO

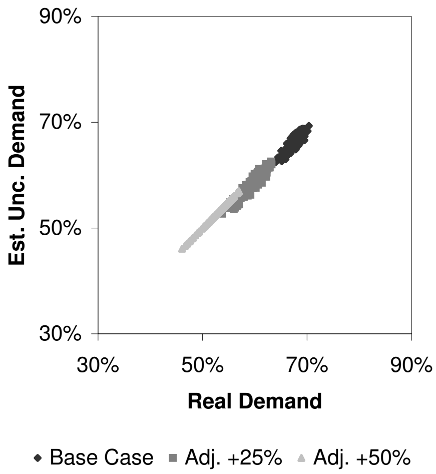

Figure A.30.: Effect of Restrictive RM Controls on PARO

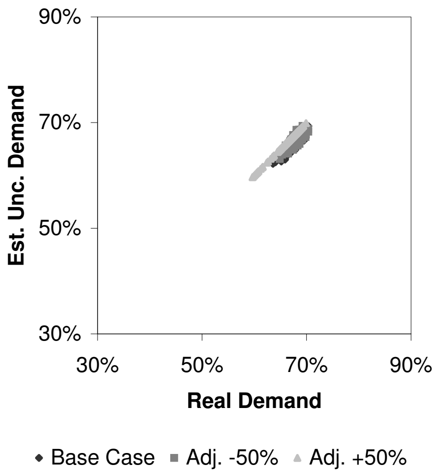

Figure A.31.: Effect of Adjusted Seasonality on PARO

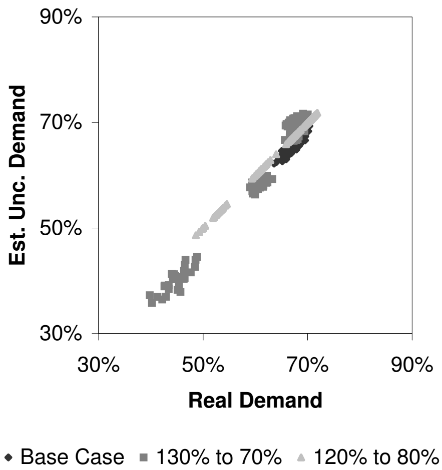

Figure A.32.: Effect of High Deviation in Customer Demand on PARO

Error level	Base Case -	Biased underestimation 30%	60%	90%	Biased overestimation 30%	60%	90%	Unbiased error 30%	60%	90%
$\overline{PARO}^R$ (%)	67.9	64.8	57.8	43.5	67.6	66.0	64.0	67.2	66.4	65.5
$\overline{PARO}^D$ (%)	66.5	66.2	64.6	68.2	61.2	57.2	53.9	63.4	60.6	58.1
$\overline{MAE}^{PARO}$ (%)	1.3	1.5	6.8	24.7	6.4	8.8	10.1	3.9	5.8	7.3
r^{PARO}	0.89	0.75	0.57	0.39	0.96	0.97	0.97	0.90	0.91	0.89
$\overline{ARO}^R$ (million)	5.4	5.2	4.6	3.5	5.4	5.3	5.1	5.4	5.3	5.2
$\overline{ARO}^D$ (million)	5.3	4.4	3.0	1.2	5.9	6.3	6.5	5.3	5.3	5.2
$\overline{MAE}^{ARO}$ (million)	0.1	0.8	1.6	2.3	0.5	1.0	1.4	0.1	0.1	0.1
r^{ARO}	0.97	0.96	0.91	0.74	0.98	0.98	0.98	0.97	0.95	0.92
$\overline{RO}^R$ (million)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{RO}^D$ (million)	8.0	6.6	4.6	1.8	9.7	10.9	12.0	8.3	8.7	9.0
$\overline{MAE}^{RO}$ (million)	0.1	1.4	3.4	6.2	1.7	3.0	4.0	0.3	0.7	1.0
r^{RO}	0.96	0.95	0.89	0.66	0.96	0.96	0.96	0.96	0.93	0.90
$\overline{Rev}^{+,R}$ (million)	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0
$\overline{Rev}^{+,D}$ (million)	47.1	46.4	45.3	43.1	48.2	49.0	49.7	47.4	47.7	48.0
$\overline{MAE}^{Rev^+}$ (million)	0.1	0.6	1.7	3.9	1.2	2.0	2.7	0.4	0.7	1.0
r^{Rev^+}	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.4	44.2	43.6	42.5	44.4	44.3	44.1	44.4	44.3	44.3
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.1	39.8	40.7	41.3	38.5	38.0	37.7	39.1	39.1	39.0
$\overline{MAE}^{Rev^-}$ (million)	0.1	0.8	1.6	2.3	0.5	1.0	1.4	0.1	0.1	0.1
r^{Rev^-}	1.00	0.99	0.99	0.98	0.99	0.99	0.99	0.99	0.99	0.98
$\overline{R}^{td}$ (thousand)	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{D}^{td}$ (thousand)	97.6	89.4	81.7	74.8	110.7	123.6	136.7	100.0	102.5	105.4
$\overline{D}^{yd}$ (thousand)	88.4	79.6	71.5	64.4	101.4	114.4	127.4	90.5	92.7	95.3
$\overline{D}^{bd}$ (thousand)	9.2	9.7	10.2	10.3	9.3	9.3	9.3	9.5	9.8	10.2
$\overline{F}^{td}$ (thousand)	97.6	89.3	81.7	74.8	110.6	123.6	136.6	100.0	102.5	105.4
$\overline{F}^{yd}$ (thousand)	88.4	79.6	71.5	64.4	101.4	114.3	127.4	90.5	92.7	95.2
$\overline{F}^{bd}$ (thousand)	9.2	9.7	10.2	10.4	9.3	9.3	9.3	9.5	9.8	10.1
$\overline{MAE}^{D^{td}}$	1.00	1.10	1.41	1.77	1.50	2.27	3.12	1.30	1.85	2.46
$\overline{MAE}^{D^{yd}}$	0.70	0.84	1.23	1.66	1.18	1.95	2.80	1.01	1.59	2.25
$\overline{MAE}^{D^{bd}}$	0.47	0.49	0.51	0.52	0.47	0.47	0.47	0.48	0.49	0.51
$\overline{PMAE}^{D^{td}}$ (%)	15.1	16.7	21.3	26.7	22.7	34.4	47.2	19.7	27.9	37.2
$\overline{PMAE}^{D^{yd}}$ (%)	11.5	13.9	20.3	27.3	19.4	32.2	46.3	16.6	26.2	37.1
$\overline{PMAE}^{D^{bd}}$ (%)	85.1	88.8	92.7	93.7	85.1	84.9	84.8	87.0	89.5	92.5
$\overline{MAE}^{F^{td}}$	1.98	2.08	2.36	2.65	2.36	3.04	3.84	2.04	2.16	2.32
$\overline{MAE}^{F^{yd}}$	1.85	1.98	2.30	2.64	2.21	2.90	3.70	1.90	2.01	2.16
$\overline{MAE}^{F^{bd}}$	0.50	0.52	0.53	0.54	0.50	0.50	0.50	0.51	0.52	0.53
$\overline{PMAE}^{F^{td}}$ (%)	30.0	31.5	35.7	40.1	35.8	46.1	58.2	30.9	32.7	35.1
$\overline{PMAE}^{F^{yd}}$ (%)	30.6	32.7	38.0	43.6	36.6	47.9	61.1	31.5	33.2	35.7
$\overline{PMAE}^{F^{bd}}$ (%)	90.0	93.3	96.8	97.5	90.0	89.9	89.8	91.7	93.7	96.2

Table A.9.: Effect of Unconstraining Errors of the Yieldable Demand on ROM Measures

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	67.9	68.0	68.2	68.3	67.5	67.2	66.8	67.7	67.7	67.6
$\overline{PARO}^D$ (%)	66.5	66.7	67.1	67.3	65.2	63.8	62.5	65.9	65.5	64.7
$\overline{MAE}^{PARO}$ (%)	1.3	1.3	1.1	1.0	2.4	3.4	4.4	1.8	2.2	2.9
r^{PARO}	0.89	0.89	0.90	0.90	0.90	0.91	0.92	0.89	0.90	0.91
$\overline{ARO}^R$ (million)	5.4	5.4	5.4	5.5	5.4	5.4	5.3	5.4	5.4	5.4
$\overline{ARO}^D$ (million)	5.3	5.3	5.4	5.4	5.3	5.3	5.2	5.3	5.3	5.3
$\overline{MAE}^{ARO}$ (million)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
r^{ARO}	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
$\overline{RO}^R$ (million)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{RO}^D$ (million)	8.0	8.0	8.0	8.0	8.1	8.2	8.4	8.1	8.1	8.2
$\overline{MAE}^{RO}$ (million)	0.1	0.1	0.1	0.1	0.1	0.3	0.4	0.1	0.1	0.2
r^{RO}	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96	0.96
$\overline{Rev}^{+,R}$ (million)	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0
$\overline{Rev}^{+,D}$ (million)	47.1	47.1	47.1	47.1	47.2	47.4	47.5	47.2	47.2	47.3
$\overline{MAE}^{Rev^+}$ (million)	0.1	0.1	0.1	0.1	0.2	0.4	0.5	0.2	0.2	0.3
r^{Rev^+}	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.4	44.5	44.5	44.5	44.4	44.4	44.4	44.4	44.4	44.4
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1
$\overline{MAE}^{Rev^-}$ (million)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
r^{Rev^-}	1.00	0.99	0.99	1.00	0.99	0.99	0.99	0.99	0.99	0.99
$\overline{R}^{td}$ (thousand)	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{D}^{td}$ (thousand)	97.6	95.3	92.9	90.6	100.5	103.5	106.4	97.9	98.2	98.6
$\overline{D}^{yd}$ (thousand)	88.4	88.7	89.0	89.4	88.5	88.6	88.8	88.6	88.8	89.2
$\overline{D}^{bd}$ (thousand)	9.2	6.6	3.9	1.2	12.0	14.8	17.6	9.3	9.4	9.5
$\overline{F}^{td}$ (thousand)	97.6	95.3	92.9	90.6	100.5	103.4	106.4	97.9	98.2	98.6
$\overline{F}^{yd}$ (thousand)	88.4	88.7	89.0	89.3	88.5	88.6	88.8	88.6	88.8	89.1
$\overline{F}^{bd}$ (thousand)	9.2	6.6	3.9	1.2	12.0	14.8	17.6	9.3	9.4	9.5
$\overline{MAE}^{D^{td}}$	1.00	0.98	0.98	1.01	1.06	1.16	1.28	1.02	1.07	1.14
$\overline{MAE}^{D^{yd}}$	0.70	0.70	0.71	0.71	0.70	0.71	0.71	0.70	0.71	0.71
$\overline{MAE}^{D^{bd}}$	0.47	0.45	0.47	0.52	0.55	0.66	0.80	0.50	0.56	0.66
$\overline{PMAE}^{D^{td}}$ (%)	15.1	14.8	14.9	15.2	16.1	17.6	19.4	15.4	16.2	17.2
$\overline{PMAE}^{D^{yd}}$ (%)	11.5	11.6	11.7	11.8	11.6	11.6	11.7	11.6	11.6	11.8
$\overline{PMAE}^{D^{bd}}$ (%)	85.1	80.7	85.0	94.8	99.0	119.9	145.4	89.8	102.2	119.6
$\overline{MAE}^{F^{td}}$	1.98	1.97	1.97	1.98	2.02	2.08	2.15	1.99	2.00	2.01
$\overline{MAE}^{F^{yd}}$	1.85	1.86	1.86	1.87	1.85	1.86	1.86	1.86	1.86	1.86
$\overline{MAE}^{F^{bd}}$	0.50	0.47	0.48	0.53	0.57	0.69	0.83	0.50	0.51	0.52
$\overline{PMAE}^{F^{td}}$ (%)	30.0	29.8	29.8	30.0	30.6	31.5	32.7	30.1	30.2	30.4
$\overline{PMAE}^{F^{yd}}$ (%)	30.6	30.7	30.8	30.9	30.6	30.7	30.7	30.7	30.7	30.8
$\overline{PMAE}^{F^{bd}}$ (%)	90.0	84.8	87.6	95.7	104.1	124.6	149.7	90.7	92.1	94.2

Table A.10.: Effect of Unconstraining Errors of the Buy-down on ROM Measures

	Base	Biased			Biased					
	Case	underestimation			overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	67.9	63.8	55.4	35.7	60.8	45.9	28.4	65.6	61.4	55.7
$\overline{PARO}^D$ (%)	66.5	64.6	62.3	63.1	54.4	39.1	24.3	60.4	53.6	46.0
$\overline{MAE}^{PARO}$ (%)	1.3	1.0	6.9	27.5	6.4	6.8	4.2	5.2	7.8	9.7
r^{PARO}	0.89	0.64	0.29	0.75	0.98	0.97	0.96	0.94	0.94	0.93
$\overline{ARO}^R$ (million)	5.4	5.1	4.4	2.9	4.9	3.7	2.3	5.2	4.9	4.5
$\overline{ARO}^D$ (million)	5.3	4.3	3.0	1.4	5.3	4.4	3.1	5.1	4.7	4.2
$\overline{MAE}^{ARO}$ (million)	0.1	0.8	1.5	1.4	0.4	0.7	0.8	0.2	0.2	0.3
r^{ARO}	0.97	0.96	0.91	0.84	0.98	0.98	0.96	0.97	0.96	0.94
$\overline{RO}^R$ (million)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{RO}^D$ (million)	8.0	6.7	4.7	2.2	9.7	11.3	12.7	8.4	8.7	9.1
$\overline{MAE}^{RO}$ (million)	0.1	1.3	3.3	5.8	1.7	3.3	4.7	0.4	0.7	1.1
r^{RO}	0.96	0.95	0.89	0.80	0.95	0.95	0.94	0.96	0.93	0.88
$\overline{Rev}^{+,R}$ (million)	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0
$\overline{Rev}^{+,D}$ (million)	47.1	46.5	45.2	42.7	48.3	49.6	50.9	47.6	48.0	48.4
$\overline{MAE}^{Rev^+}$ (million)	0.1	0.5	1.8	4.3	1.3	2.5	3.9	0.6	1.0	1.3
r^{Rev^+}	1.00	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	0.99
$\overline{Rev}$ (million)	44.4	44.1	43.5	41.9	43.9	42.7	41.3	44.3	43.9	43.5
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.1	39.8	40.5	40.5	38.6	38.3	38.2	39.2	39.3	39.3
$\overline{MAE}^{Rev^-}$ (million)	0.1	0.8	1.5	1.4	0.4	0.7	0.8	0.2	0.2	0.3
r^{Rev^-}	1.00	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.98
$\overline{R}^{td}$ (thousand)	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{D}^{td}$ (thousand)	97.6	89.5	81.8	73.6	111.1	125.7	141.7	100.1	102.7	105.4
$\overline{D}^{yd}$ (thousand)	88.4	79.7	71.6	61.4	101.8	116.4	132.4	90.6	92.9	95.3
$\overline{D}^{bd}$ (thousand)	9.2	9.8	10.2	12.2	9.2	9.2	9.3	9.5	9.8	10.2
$\overline{F}^{td}$ (thousand)	97.6	88.9	83.1	76.5	124.6	151.4	178.1	106.7	116.9	127.2
$\overline{F}^{yd}$ (thousand)	88.4	76.0	66.0	54.4	115.3	142.2	168.8	95.6	103.6	111.7
$\overline{F}^{bd}$ (thousand)	9.2	12.9	17.1	22.1	9.2	9.2	9.3	11.1	13.3	15.5
$\overline{MAE}^{D^{td}}$	1.00	1.11	1.41	1.92	1.53	2.39	3.43	1.32	1.89	2.57
$\overline{MAE}^{D^{yd}}$	0.70	0.85	1.24	1.91	1.21	2.10	3.16	1.02	1.64	2.37
$\overline{MAE}^{D^{bd}}$	0.47	0.49	0.52	0.59	0.47	0.47	0.47	0.48	0.50	0.51
$\overline{PMAE}^{D^{td}}$ (%)	15.1	16.7	21.3	29.0	23.1	36.2	51.9	19.9	28.6	38.9
$\overline{PMAE}^{D^{yd}}$ (%)	11.5	14.0	20.4	31.5	20.0	34.7	52.2	16.9	27.0	39.1
$\overline{PMAE}^{D^{bd}}$ (%)	85.1	89.3	93.4	107.4	85.0	84.9	84.9	87.2	89.7	92.7
$\overline{MAE}^{F^{td}}$	1.98	2.09	2.38	2.72	2.75	4.20	5.88	2.16	2.55	3.08
$\overline{MAE}^{F^{yd}}$	1.85	2.02	2.42	2.93	2.61	4.07	5.77	1.98	2.28	2.69
$\overline{MAE}^{F^{bd}}$	0.50	0.61	0.82	1.10	0.50	0.50	0.49	0.55	0.63	0.74
$\overline{PMAE}^{F^{td}}$ (%)	30.0	31.6	36.0	41.1	41.8	63.7	89.2	32.7	38.7	46.7
$\overline{PMAE}^{F^{yd}}$ (%)	30.6	33.3	39.9	48.4	43.2	67.4	95.4	32.8	37.8	44.6
$\overline{PMAE}^{F^{bd}}$ (%)	90.0	111.4	147.9	199.7	89.9	89.7	89.6	99.3	114.5	133.3

Table A.11.: Effect of Forecast Errors of the Yieldable Demand on ROM Measures

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^{R}$ (%)	67.9	68.0	68.2	68.3	67.5	67.2	66.8	67.8	67.7	67.6
$\overline{PARO}^{D}$ (%)	66.5	66.7	67.1	67.3	65.1	63.8	62.3	65.8	65.5	64.7
$\overline{MAE}^{PARO}$ (%)	1.3	1.3	1.1	1.0	2.4	3.4	4.4	1.9	2.2	2.9
r^{PARO}	0.89	0.89	0.89	0.90	0.89	0.90	0.91	0.89	0.90	0.90
$\overline{ARO}^{R}$ (million)	5.4	5.4	5.4	5.5	5.4	5.4	5.3	5.4	5.4	5.4
$\overline{ARO}^{D}$ (million)	5.3	5.3	5.4	5.4	5.3	5.3	5.2	5.3	5.3	5.3
$\overline{MAE}^{ARO}$ (million)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
r^{ARO}	0.97	0.97	0.97	0.98	0.97	0.97	0.97	0.97	0.97	0.97
$\overline{RO}^{R}$ (million)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{RO}^{D}$ (million)	8.0	8.0	8.0	8.0	8.1	8.2	8.4	8.1	8.1	8.2
$\overline{MAE}^{RO}$ (million)	0.1	0.1	0.1	0.1	0.1	0.3	0.4	0.1	0.2	0.2
r^{RO}	0.96	0.96	0.96	0.96	0.96	0.96	0.95	0.96	0.96	0.96
$\overline{Rev}^{+,R}$ (million)	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0	47.0
$\overline{Rev}^{+,D}$ (million)	47.1	47.1	47.1	47.1	47.2	47.4	47.5	47.2	47.2	47.3
$\overline{MAE}^{Rev^{+}}$ (million)	0.1	0.1	0.1	0.1	0.2	0.4	0.5	0.2	0.2	0.3
$r^{Rev^{+}}$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.4	44.5	44.5	44.5	44.4	44.4	44.4	44.4	44.4	44.4
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0	39.0
$\overline{Rev}^{-,D}$ (million)	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1
$\overline{MAE}^{Rev^{-}}$ (million)	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
$r^{Rev^{-}}$	1.00	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$\overline{R}^{td}$ (thousand)	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6	95.6
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
$\overline{D}^{td}$ (thousand)	97.6	95.3	92.9	90.6	100.5	103.5	106.5	97.9	98.2	98.6
$\overline{D}^{yd}$ (thousand)	88.4	88.7	89.0	89.4	88.5	88.7	88.8	88.6	88.9	89.2
$\overline{D}^{bd}$ (thousand)	9.2	6.6	3.9	1.2	12.0	14.8	17.7	9.3	9.4	9.4
$\overline{F}^{td}$ (thousand)	97.6	95.3	92.9	90.6	100.5	103.5	106.4	97.9	98.2	98.6
$\overline{F}^{yd}$ (thousand)	88.4	88.7	89.0	89.4	88.5	88.6	88.8	88.6	88.8	89.2
$\overline{F}^{bd}$ (thousand)	9.2	6.6	3.9	1.2	12.0	14.8	17.6	9.3	9.4	9.4
$\overline{MAE}^{D^{td}}$	1.00	0.98	0.98	1.01	1.06	1.16	1.28	1.02	1.07	1.14
$\overline{MAE}^{D^{yd}}$	0.70	0.70	0.71	0.71	0.70	0.71	0.71	0.70	0.71	0.72
$\overline{MAE}^{D^{bd}}$	0.47	0.45	0.47	0.52	0.55	0.66	0.80	0.50	0.57	0.66
$\overline{PMAE}^{D^{td}}$ (%)	15.1	14.8	14.9	15.2	16.1	17.6	19.4	15.5	16.2	17.3
$\overline{PMAE}^{D^{yd}}$ (%)	11.5	11.6	11.7	11.8	11.6	11.7	11.7	11.6	11.7	11.8
$\overline{PMAE}^{D^{bd}}$ (%)	85.1	80.8	85.0	94.8	99.1	119.9	145.6	89.9	102.3	119.7
$\overline{MAE}^{F^{td}}$	1.98	1.97	1.97	1.98	2.02	2.08	2.16	1.99	2.00	2.01
$\overline{MAE}^{F^{yd}}$	1.85	1.86	1.86	1.87	1.86	1.86	1.86	1.86	1.86	1.87
$\overline{MAE}^{F^{bd}}$	0.50	0.47	0.48	0.53	0.57	0.69	0.83	0.50	0.51	0.52
$\overline{PMAE}^{F^{td}}$ (%)	30.0	29.8	29.8	30.0	30.6	31.5	32.7	30.1	30.2	30.4
$\overline{PMAE}^{F^{yd}}$ (%)	30.6	30.7	30.8	30.9	30.7	30.7	30.8	30.7	30.7	30.8
$\overline{PMAE}^{F^{bd}}$ (%)	90.0	84.8	87.6	95.7	104.1	124.7	149.9	90.7	92.1	94.1

Table A.12.: Effect of Forecast Errors of the Buy-down on ROM Measures

	Base Case	Bid price decrease		Bid price increase		Adjust seasonality		Apply saw tooth curve	
Adj. level	-	25%	50%	25%	50%	-50%	+50%	130% - 70%	120% - 80%
$\overline{PARO}^{R}$ (%)	67.9	59.3	34.6	60.1	54.2	68.1	67.4	61.8	65.4
$\overline{PARO}^{D}$ (%)	66.5	60.5	36.9	58.9	52.8	66.9	66.2	61.2	64.4
$\overline{MAE}^{PARO}$ (%)	1.3	1.2	2.3	1.2	1.4	1.3	1.2	2.5	1.7
r^{PARO}	0.89	0.72	0.88	0.95	0.96	0.83	0.94	0.99	0.99
$\overline{ARO}^{R}$ (million)	5.4	4.7	2.8	4.8	4.3	5.4	5.5	5.1	5.3
$\overline{ARO}^{D}$ (million)	5.3	4.8	2.8	4.6	4.1	5.3	5.3	4.8	5.1
$\overline{MAE}^{ARO}$ (million)	0.1	0.1	0.1	0.2	0.2	0.1	0.2	0.4	0.3
r^{ARO}	0.97	0.97	0.95	0.98	0.98	0.95	0.99	1.00	1.00
$\overline{RO}^{R}$ (million)	8.0	8.0	8.0	8.0	8.0	7.9	8.1	7.9	7.9
$\overline{RO}^{D}$ (million)	8.0	7.9	7.7	7.8	7.7	7.9	8.0	7.5	7.8
$\overline{MAE}^{RO}$ (million)	0.1	0.1	0.3	0.2	0.3	0.1	0.2	0.9	0.5
r^{RO}	0.96	0.95	0.94	0.95	0.94	0.89	0.98	1.00	1.00
$\overline{Rev}^{+,R}$ (million)	47.0	47.0	47.0	47.0	47.0	47.1	46.9	46.4	46.8
$\overline{Rev}^{+,D}$ (million)	47.1	46.9	46.6	47.0	47.0	47.2	47.0	46.3	46.8
$\overline{MAE}^{Rev^{+}}$ (million)	0.1	0.1	0.4	0.1	0.1	0.1	0.1	0.5	0.3
$r^{Rev^{+}}$	1.00	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00
$\overline{Rev}$ (million)	44.4	43.8	41.8	43.8	43.4	44.5	44.3	43.6	44.1
$\overline{Rev}^{-,R}$ (million)	39.0	39.0	39.0	39.0	39.0	39.2	38.8	38.5	38.9
$\overline{Rev}^{-,D}$ (million)	39.1	39.0	39.0	39.2	39.3	39.2	39.0	38.8	39.1
$\overline{MAE}^{Rev^{-}}$ (million)	0.1	0.1	0.1	0.2	0.2	0.1	0.2	0.4	0.3
$r^{Rev^{-}}$	1.00	1.00	1.00	0.99	0.99	0.98	1.00	1.00	1.00
$\overline{R}^{td}$ (thousand)	95.6	95.6	95.6	95.6	95.6	95.4	95.8	95.2	95.2
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.4	87.8	87.2	87.2
$\overline{R}^{bd}$ (thousand)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	7.9	8.0
$\overline{D}^{td}$ (thousand)	97.6	97.1	96.2	96.6	96.0	97.9	97.3	93.9	96.1
$\overline{D}^{yd}$ (thousand)	88.4	88.1	87.6	87.5	87.0	88.6	88.0	84.9	87.0
$\overline{D}^{bd}$ (thousand)	9.2	9.0	8.7	9.1	9.0	9.3	9.2	9.0	9.1
$\overline{F}^{td}$ (thousand)	97.6	97.1	96.2	96.6	96.0	97.9	97.2	94.0	96.1
$\overline{F}^{yd}$ (thousand)	88.4	88.1	87.5	87.5	87.0	88.6	88.0	85.0	87.0
$\overline{F}^{bd}$ (thousand)	9.2	9.0	8.7	9.1	9.0	9.2	9.2	9.0	9.1
$\overline{MAE}^{D^{td}}$	1.00	0.97	0.96	0.97	0.97	0.97	1.03	1.09	1.01
$\overline{MAE}^{D^{yd}}$	0.70	0.70	0.71	0.69	0.70	0.67	0.74	0.80	0.72
$\overline{MAE}^{D^{bd}}$	0.47	0.46	0.45	0.46	0.46	0.47	0.47	0.46	0.47
$\overline{PMAE}^{D^{td}}$ (%)	15.1	14.7	14.5	14.7	14.6	14.7	15.6	16.5	15.4
$\overline{PMAE}^{D^{yd}}$ (%)	11.5	11.5	11.6	11.5	11.5	11.0	12.1	13.0	11.8
$\overline{PMAE}^{D^{bd}}$ (%)	85.1	83.4	81.8	84.1	83.5	85.3	85.2	86.2	85.6
$\overline{MAE}^{F^{td}}$	1.98	1.96	1.94	1.96	1.96	1.91	2.08	2.27	2.06
$\overline{MAE}^{F^{yd}}$	1.85	1.84	1.83	1.84	1.84	1.79	1.94	2.12	1.92
$\overline{MAE}^{F^{bd}}$	0.50	0.49	0.48	0.49	0.49	0.49	0.50	0.50	0.50
$\overline{PMAE}^{F^{td}}$ (%)	30.0	29.7	29.4	29.7	29.6	28.9	31.5	35.7	31.8
$\overline{PMAE}^{F^{yd}}$ (%)	30.6	30.4	30.3	30.5	30.4	29.5	32.0	36.2	32.3
$\overline{PMAE}^{F^{bd}}$ (%)	90.0	88.4	86.6	89.0	88.4	89.8	90.8	94.2	91.5

Table A.13.: Effect of Adjusted RM Controls and Seasonality on ROM Measures

A.2.3. Sell-up Rate 50%

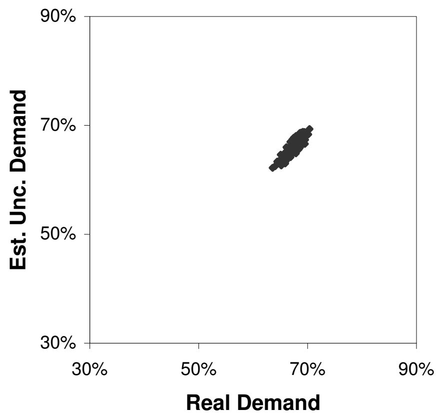

Figure A.33.: Sell-up Rate 50%: Base Case

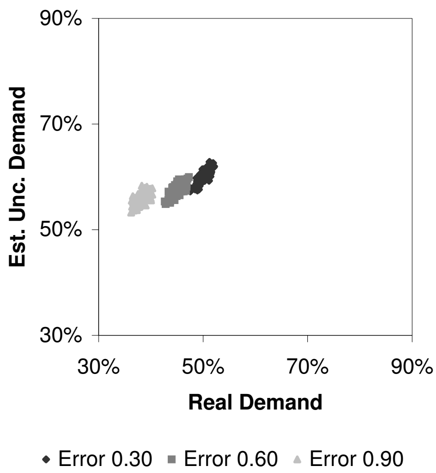

Figure A.34.: Effect of a Biased Underestimation of the Unconstrained Yieldable Demand on PARO

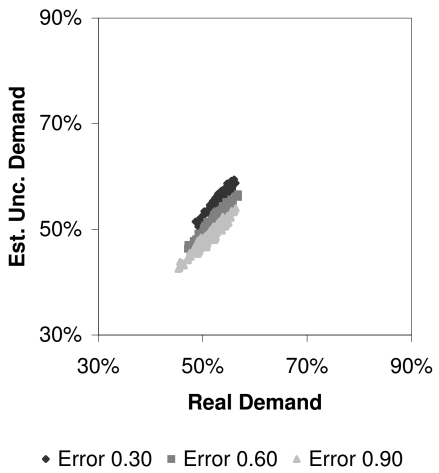

Figure A.35.: Effect of a Biased Overestimation of the Unconstrained Yieldable Demand on PARO

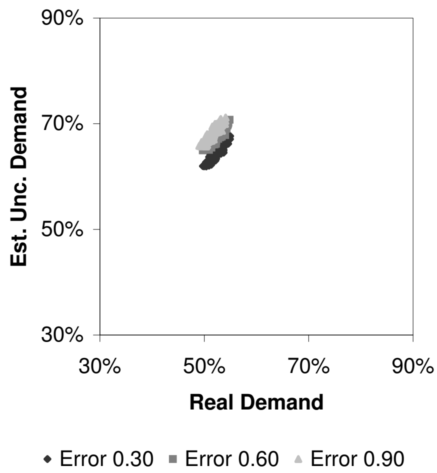

Figure A.36.: Effect of a Biased Underestimation of the Unconstrained Buy-down on PARO

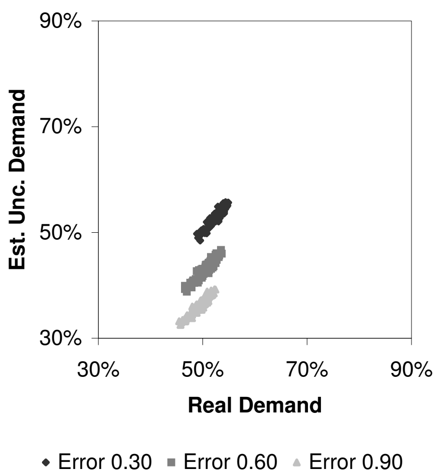

Figure A.37.: Effect of a Biased Overestimation of the Unconstrained Buy-down on PARO

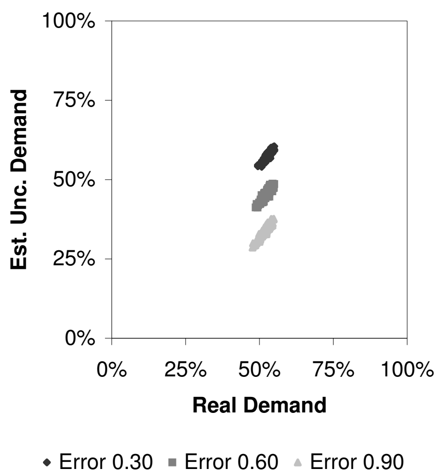

Figure A.38.: Effect of an Unbiased Error of the Unconstrained Buy-down on PARO

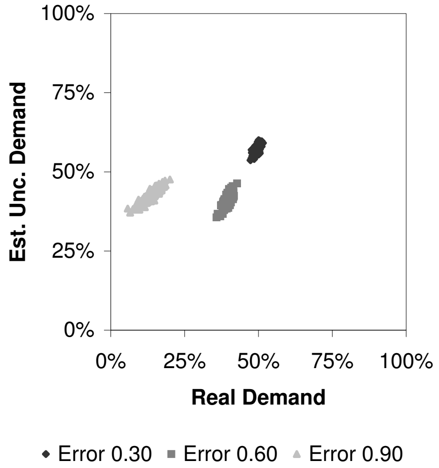

Figure A.39.: Effect of a Biased Underestimation of the Forecasted Yieldable Demand on PARO

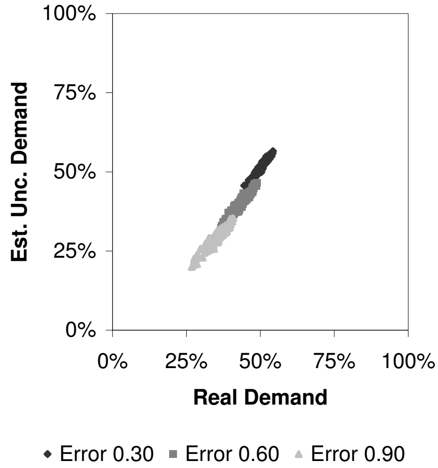

Figure A.40.: Effect of a Biased Overestimation of the Forecasted Yieldable Demand on PARO

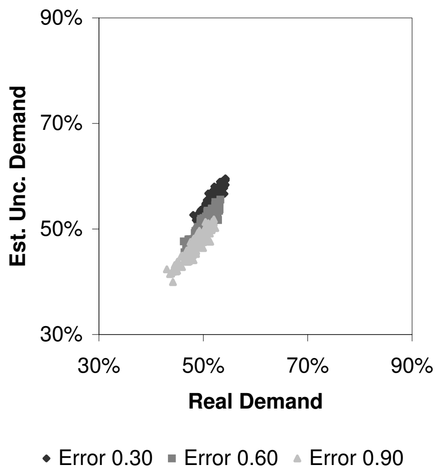

Figure A.41.: Effect of an Unbiased Error of the Forecasted Yieldable Demand on PARO

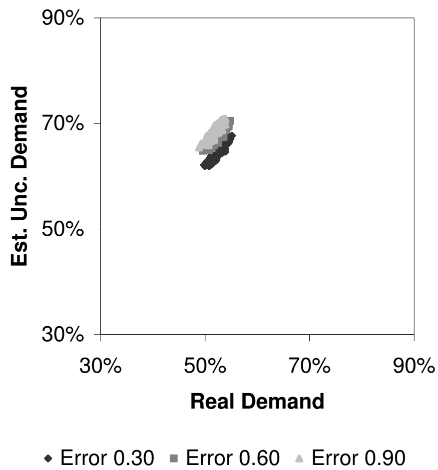

Figure A.42.: Effect of a Biased Underestimation of the Forecasted Buy-down on PARO

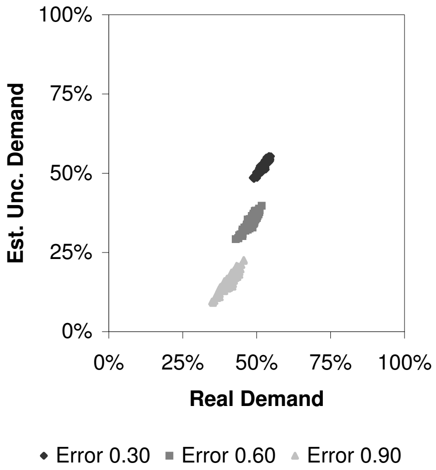

Figure A.43.: Effect of a Biased Overestimation of the Forecasted Buy-down on PARO

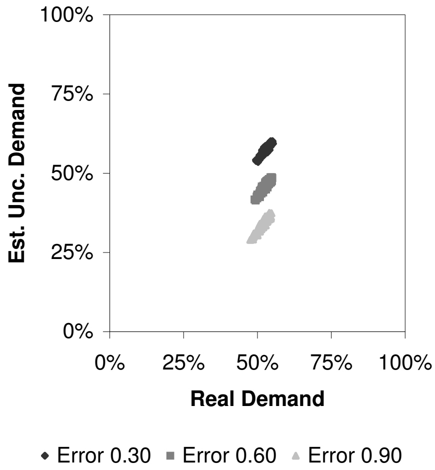

Figure A.44.: Effect of an Unbiased Error of the Forecasted Buy-down on PARO

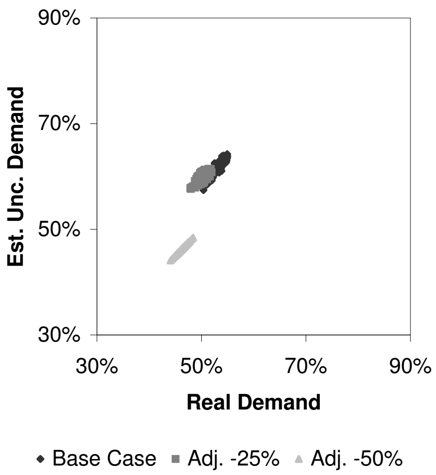

Figure A.45.: Effect of Open RM Controls on PARO

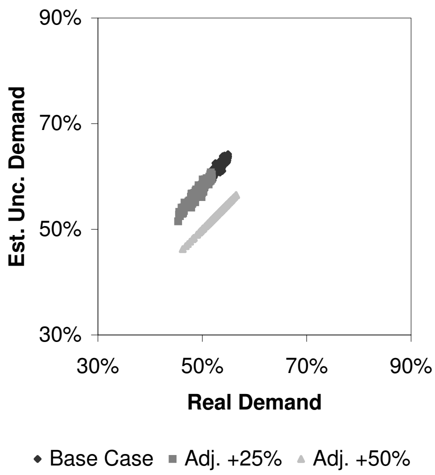

Figure A.46.: Effect of Restrictive RM Controls on PARO

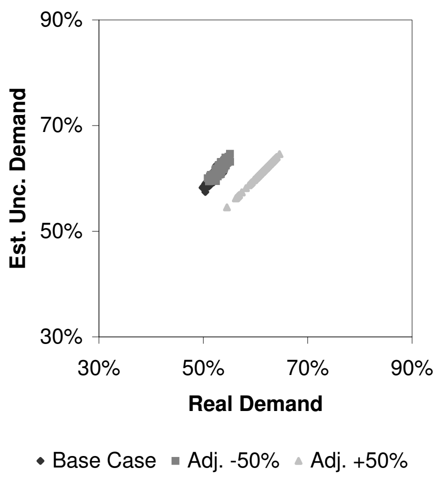

Figure A.47.: Effect of Adjusted Seasonality on PARO

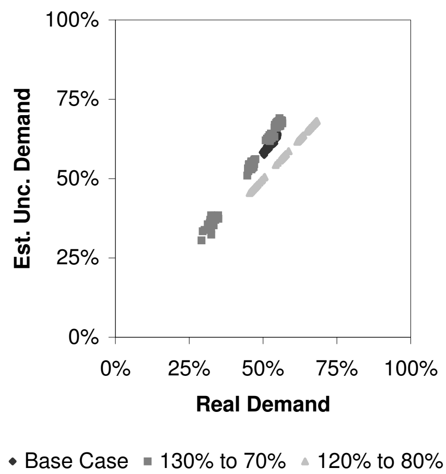

Figure A.48.: Effect of High Deviation in Customer Demand on PARO

Error level	Base Case -	Biased underestimation 30%	60%	90%	Biased overestimation 30%	60%	90%	Unbiased error 30%	60%	90%
$\overline{PARO}^R$ (%)	53.1	50.3	45.1	38.2	53.2	52.7	51.7	52.6	52.1	51.6
$\overline{PARO}^D$ (%)	61.7	60.3	57.6	56.1	55.8	52.0	49.0	58.0	54.9	52.8
$\overline{MAE}^{PARO}$ (%)	8.6	10.1	12.5	17.9	2.7	0.7	2.7	5.4	2.7	1.3
r^{PARO}	0.92	0.86	0.74	0.64	0.95	0.96	0.96	0.92	0.92	0.87
$\overline{ARO}^R$ (million)	6.9	6.5	5.8	5.0	6.9	6.8	6.7	6.8	6.8	6.7
$\overline{ARO}^D$ (million)	6.5	5.4	4.2	3.4	7.1	7.5	7.7	6.4	6.4	6.6
$\overline{MAE}^{ARO}$ (million)	0.3	1.1	1.6	1.6	0.2	0.6	1.0	0.4	0.3	0.1
r^{ARO}	0.98	0.96	0.91	0.86	0.98	0.98	0.97	0.97	0.97	0.94
$\overline{RO}^R$ (million)	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0
$\overline{RO}^D$ (million)	10.6	9.0	7.3	6.0	12.7	14.3	15.7	11.1	11.7	12.5
$\overline{MAE}^{RO}$ (million)	2.4	3.9	5.7	7.0	0.3	1.4	2.7	1.9	1.2	0.4
r^{RO}	0.96	0.93	0.87	0.84	0.96	0.96	0.96	0.95	0.94	0.92
$\overline{Rev}^{+,R}$ (million)	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0
$\overline{Rev}^{+,D}$ (million)	50.0	49.2	48.0	46.7	51.6	52.8	53.8	50.5	51.1	51.7
$\overline{MAE}^{Rev^+}$ (million)	2.0	2.9	4.0	5.4	0.5	0.7	1.7	1.5	0.9	0.4
r^{Rev^+}	1.00	1.00	0.99	0.99	0.99	0.99	0.99	1.00	0.99	0.99
$\overline{Rev}$ (million)	45.9	45.6	44.9	44.0	46.0	45.9	45.8	45.9	45.8	45.8
$\overline{Rev}^{-,R}$ (million)	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1
$\overline{Rev}^{-,D}$ (million)	39.4	40.1	40.7	40.7	38.9	38.4	38.1	39.4	39.4	39.1
$\overline{MAE}^{Rev^-}$ (million)	0.3	1.1	1.6	1.6	0.2	0.6	1.0	0.4	0.3	0.1
r^{Rev^-}	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.98
$\overline{R}^{td}$ (thousand)	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3
$\overline{D}^{td}$ (thousand)	157.1	147.8	139.7	134.6	171.4	185.8	200.1	159.5	162.7	167.4
$\overline{D}^{yd}$ (thousand)	89.1	79.4	71.3	66.4	103.4	117.6	131.9	91.3	94.2	98.4
$\overline{D}^{bd}$ (thousand)	67.9	68.4	68.4	68.2	68.0	68.2	68.3	68.2	68.5	69.0
$\overline{F}^{td}$ (thousand)	157.0	147.8	139.6	134.5	171.3	185.8	200.1	159.4	162.6	167.3
$\overline{F}^{yd}$ (thousand)	89.1	79.4	71.2	66.3	103.3	117.6	131.9	91.3	94.1	98.3
$\overline{F}^{bd}$ (thousand)	67.9	68.4	68.4	68.2	68.0	68.2	68.2	68.2	68.5	69.0
$\overline{MAE}^{D^{td}}$	1.77	1.89	2.13	2.30	2.25	3.03	3.91	2.07	2.60	3.14
$\overline{MAE}^{D^{yd}}$	0.85	1.01	1.36	1.64	1.36	2.20	3.12	1.19	1.79	2.41
$\overline{MAE}^{D^{bd}}$	1.26	1.27	1.27	1.26	1.26	1.26	1.26	1.26	1.27	1.28
$\overline{PMAE}^{D^{td}}$ (%)	16.8	17.8	20.1	21.7	21.3	28.6	37.0	19.6	24.5	29.7
$\overline{PMAE}^{D^{yd}}$ (%)	14.1	16.6	22.4	27.0	22.5	36.2	51.5	19.6	29.5	39.8
$\overline{PMAE}^{D^{bd}}$ (%)	27.8	28.0	28.0	27.8	27.8	27.9	27.9	27.9	28.1	28.3
$\overline{MAE}^{F^{td}}$	2.70	2.81	3.04	3.20	3.08	3.78	4.61	2.77	2.89	3.08
$\overline{MAE}^{F^{yd}}$	1.89	2.03	2.34	2.58	2.30	3.05	3.92	1.95	2.08	2.27
$\overline{MAE}^{F^{bd}}$	1.52	1.54	1.54	1.54	1.52	1.52	1.52	1.53	1.53	1.54
$\overline{PMAE}^{F^{td}}$ (%)	25.6	26.5	28.7	30.2	29.1	35.8	43.7	26.2	27.4	29.2
$\overline{PMAE}^{F^{yd}}$ (%)	31.2	33.5	38.6	42.5	37.9	50.4	64.9	32.2	34.3	37.5
$\overline{PMAE}^{F^{bd}}$ (%)	33.7	34.0	34.1	34.0	33.7	33.7	33.7	33.8	34.0	34.2

Table A.14.: Effect of Unconstraining Errors of the Yieldable Demand on ROM Measures

Error level	Base Case -	Biased underestimation 30%	60%	90%	Biased overestimation 30%	60%	90%	Unbiased error 30%	60%	90%
$\overline{PARO}^R$ (%)	53.1	52.9	52.6	52.0	52.5	50.8	49.6	53.0	52.6	52.0
$\overline{PARO}^D$ (%)	61.7	65.2	68.1	68.7	52.9	43.3	36.4	57.7	45.7	34.0
$\overline{MAE}^{PARO}$ (%)	8.6	12.3	15.4	16.7	0.6	7.5	13.2	4.7	6.9	18.0
r^{PARO}	0.92	0.89	0.87	0.88	0.94	0.94	0.95	0.90	0.92	0.94
$\overline{ARO}^R$ (million)	6.9	6.9	6.8	6.7	6.8	6.6	6.4	6.9	6.8	6.7
$\overline{ARO}^D$ (million)	6.5	6.5	6.5	6.5	6.4	6.0	5.9	6.5	5.8	5.0
$\overline{MAE}^{ARO}$ (million)	0.3	0.3	0.3	0.3	0.4	0.6	0.6	0.4	1.0	1.7
r^{ARO}	0.98	0.98	0.98	0.98	0.97	0.97	0.97	0.98	0.97	0.98
$\overline{RO}^R$ (million)	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0
$\overline{RO}^D$ (million)	10.6	10.0	9.6	9.4	12.0	13.9	16.1	11.2	12.8	14.8
$\overline{MAE}^{RO}$ (million)	2.4	2.9	3.3	3.6	0.9	1.0	3.1	1.7	0.2	1.8
r^{RO}	0.96	0.96	0.96	0.97	0.96	0.96	0.96	0.95	0.95	0.95
$\overline{Rev}^{+,R}$ (million)	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0
$\overline{Rev}^{+,D}$ (million)	50.0	49.4	49.0	48.8	51.5	53.5	55.7	50.7	52.8	55.6
$\overline{MAE}^{Rev^+}$ (million)	2.0	2.6	3.1	3.3	0.5	1.5	3.7	1.3	0.8	3.5
r^{Rev^+}	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.99
$\overline{Rev}$ (million)	45.9	45.9	45.9	45.8	45.9	45.6	45.5	45.9	45.9	45.8
$\overline{Rev}^{-,R}$ (million)	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1
$\overline{Rev}^{-,D}$ (million)	39.4	39.4	39.3	39.3	39.5	39.6	39.6	39.5	40.0	40.8
$\overline{MAE}^{Rev^-}$ (million)	0.3	0.3	0.3	0.3	0.4	0.6	0.6	0.4	1.0	1.7
r^{Rev^-}	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$\overline{R}^{td}$ (thousand)	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3
$\overline{D}^{td}$ (thousand)	157.1	137.8	118.8	100.1	178.3	199.2	218.3	158.0	163.1	172.0
$\overline{D}^{yd}$ (thousand)	89.1	90.0	91.0	92.3	89.7	90.1	89.9	89.9	93.7	100.3
$\overline{D}^{bd}$ (thousand)	67.9	47.9	27.8	7.8	88.6	109.0	128.4	68.2	69.5	71.7
$\overline{F}^{td}$ (thousand)	157.0	137.8	118.8	100.1	178.3	199.1	218.2	158.0	163.1	172.0
$\overline{F}^{yd}$ (thousand)	89.1	90.0	90.9	92.3	89.7	90.1	89.9	89.8	93.7	100.3
$\overline{F}^{bd}$ (thousand)	67.9	47.8	27.8	7.9	88.6	109.0	128.3	68.1	69.4	71.7
$\overline{MAE}^{D^{td}}$	1.77	2.03	2.91	4.03	2.45	3.60	4.82	2.22	3.04	3.94
$\overline{MAE}^{D^{yd}}$	0.85	0.87	0.90	0.96	0.87	0.89	0.88	0.87	1.06	1.47
$\overline{MAE}^{D^{bd}}$	1.26	1.62	2.70	4.00	1.93	3.13	4.41	1.77	2.85	4.04
$\overline{PMAE}^{D^{td}}$ (%)	16.8	19.2	27.5	38.1	23.1	34.1	45.6	21.0	28.7	37.3
$\overline{PMAE}^{D^{yd}}$ (%)	14.1	14.4	14.9	15.8	14.4	14.7	14.5	14.4	17.5	24.2
$\overline{PMAE}^{D^{bd}}$ (%)	27.8	35.9	59.6	88.4	42.8	69.3	97.6	39.2	63.0	89.4
$\overline{MAE}^{F^{td}}$	2.70	2.83	3.48	4.42	3.21	4.14	5.22	2.75	2.88	3.15
$\overline{MAE}^{F^{yd}}$	1.89	1.92	1.95	1.99	1.90	1.90	1.90	1.91	1.97	2.17
$\overline{MAE}^{F^{bd}}$	1.52	1.78	2.74	4.01	2.14	3.24	4.46	1.56	1.68	1.84
$\overline{PMAE}^{F^{td}}$ (%)	25.6	26.8	32.8	41.7	30.4	39.3	49.5	26.0	27.3	29.8
$\overline{PMAE}^{F^{yd}}$ (%)	31.2	31.6	32.1	32.8	31.3	31.4	31.4	31.5	32.6	35.8
$\overline{PMAE}^{F^{bd}}$ (%)	33.7	39.4	60.6	88.6	47.4	71.9	99.0	34.6	37.1	40.8

Table A.15.: Effect of Unconstraining Errors of the Buy-down on ROM Measures

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^{R}$ (%)	53.1	49.6	39.8	14.0	50.3	43.4	34.8	52.1	50.6	48.5
$\overline{PARO}^{D}$ (%)	61.7	57.4	41.7	42.9	51.6	40.2	28.9	56.3	51.5	46.9
$\overline{MAE}^{PARO}$ (%)	8.6	7.8	2.0	28.9	1.3	3.2	5.9	4.2	1.0	1.6
r^{PARO}	0.92	0.68	0.82	0.91	0.97	0.97	0.95	0.93	0.92	0.93
$\overline{ARO}^{R}$ (million)	6.9	6.4	5.2	1.8	6.5	5.6	4.5	6.8	6.6	6.3
$\overline{ARO}^{D}$ (million)	6.5	5.3	3.5	3.7	6.6	5.9	4.8	6.3	6.1	5.9
$\overline{MAE}^{ARO}$ (million)	0.3	1.1	1.6	1.9	0.1	0.3	0.3	0.5	0.5	0.4
r^{ARO}	0.98	0.95	0.93	0.92	0.98	0.98	0.96	0.97	0.95	0.95
$\overline{RO}^{R}$ (million)	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0
$\overline{RO}^{D}$ (million)	10.6	9.2	8.5	8.7	12.8	14.7	16.5	11.2	11.8	12.6
$\overline{MAE}^{RO}$ (million)	2.4	3.7	4.5	4.2	0.2	1.7	3.5	1.8	1.2	0.3
r^{RO}	0.96	0.91	0.89	0.80	0.96	0.95	0.94	0.95	0.93	0.90
$\overline{Rev}^{+,R}$ (million)	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0
$\overline{Rev}^{+,D}$ (million)	50.0	49.4	49.2	45.9	51.8	53.5	55.3	50.7	51.4	52.1
$\overline{MAE}^{Rev^{+}}$ (million)	2.0	2.6	2.9	6.2	0.3	1.4	3.3	1.3	0.7	0.1
$r^{Rev^{+}}$	1.00	0.99	0.99	0.99	1.00	0.99	0.99	1.00	0.99	0.99
$\overline{Rev}$ (million)	45.9	45.5	44.2	40.9	45.6	44.7	43.6	45.8	45.6	45.4
$\overline{Rev}^{-,R}$ (million)	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1
$\overline{Rev}^{-,D}$ (million)	39.4	40.2	40.7	37.1	39.0	38.8	38.8	39.5	39.5	39.4
$\overline{MAE}^{Rev^{-}}$ (million)	0.3	1.1	1.6	1.9	0.1	0.3	0.3	0.5	0.5	0.4
$r^{Rev^{-}}$	0.99	0.99	0.99	0.97	0.99	0.98	0.97	0.99	0.98	0.97
$\overline{R}^{td}$ (thousand)	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3
$\overline{D}^{td}$ (thousand)	157.1	149.1	145.8	129.9	172.2	188.3	205.6	159.7	163.1	168.1
$\overline{D}^{yd}$ (thousand)	89.1	79.7	69.2	51.6	103.9	119.8	137.1	91.4	94.3	98.8
$\overline{D}^{bd}$ (thousand)	67.9	69.4	76.6	78.4	68.3	68.5	68.5	68.3	68.7	69.3
$\overline{F}^{td}$ (thousand)	157.0	142.7	136.5	124.1	184.7	212.1	239.2	162.8	171.2	182.3
$\overline{F}^{yd}$ (thousand)	89.1	71.9	57.5	42.8	116.4	143.7	170.7	93.8	100.5	109.6
$\overline{F}^{bd}$ (thousand)	67.9	70.8	79.0	81.3	68.2	68.4	68.5	69.0	70.6	72.7
$\overline{MAE}^{D^{td}}$	1.77	1.93	2.44	3.09	2.28	3.14	4.19	2.08	2.63	3.21
$\overline{MAE}^{D^{yd}}$	0.85	1.06	1.74	2.85	1.40	2.35	3.49	1.20	1.82	2.49
$\overline{MAE}^{D^{bd}}$	1.26	1.28	1.49	1.58	1.26	1.28	1.29	1.26	1.27	1.29
$\overline{PMAE}^{D^{td}}$ (%)	16.8	18.2	23.0	29.1	21.6	29.7	39.6	19.7	24.8	30.3
$\overline{PMAE}^{D^{yd}}$ (%)	14.1	17.5	28.6	46.9	23.2	38.9	57.6	19.8	30.1	41.0
$\overline{PMAE}^{D^{bd}}$ (%)	27.8	28.4	32.9	35.0	28.0	28.3	28.5	28.0	28.2	28.5
$\overline{MAE}^{F^{td}}$	2.70	2.87	3.20	3.70	3.40	4.75	6.37	2.82	3.08	3.50
$\overline{MAE}^{F^{yd}}$	1.89	2.17	2.76	3.54	2.67	4.16	5.89	2.00	2.25	2.64
$\overline{MAE}^{F^{bd}}$	1.52	1.57	1.78	1.87	1.52	1.52	1.52	1.54	1.56	1.61
$\overline{PMAE}^{F^{td}}$ (%)	25.6	27.1	30.3	34.9	32.2	45.0	60.4	26.7	29.2	33.2
$\overline{PMAE}^{F^{yd}}$ (%)	31.2	35.7	45.4	58.4	44.2	68.8	97.3	33.1	37.2	43.7
$\overline{PMAE}^{F^{bd}}$ (%)	33.7	34.7	39.4	41.4	33.7	33.8	33.8	34.0	34.6	35.6

Table A.16.: Effect of Forecast Errors of the Yieldable Demand on ROM Measures

	Base Case	Biased underestimation			Biased overestimation			Unbiased error		
Error level	-	30%	60%	90%	30%	60%	90%	30%	60%	90%
$\overline{PARO}^R$ (%)	53.1	52.9	52.6	52.0	52.4	48.4	41.3	53.0	52.6	52.0
$\overline{PARO}^D$ (%)	61.7	65.3	68.0	68.7	52.5	35.1	16.6	57.7	45.8	34.0
$\overline{MAE}^{PARO}$ (%)	8.6	12.3	15.4	16.7	0.5	13.3	24.7	4.7	6.8	17.9
r^{PARO}	0.92	0.90	0.88	0.88	0.92	0.93	0.93	0.92	0.93	0.94
$\overline{ARO}^R$ (million)	6.9	6.9	6.8	6.7	6.8	6.3	5.4	6.9	6.8	6.7
$\overline{ARO}^D$ (million)	6.5	6.5	6.5	6.5	6.3	5.1	2.8	6.5	5.9	5.0
$\overline{MAE}^{ARO}$ (million)	0.3	0.3	0.3	0.3	0.5	1.2	2.5	0.4	1.0	1.7
r^{ARO}	0.98	0.98	0.98	0.98	0.97	0.97	0.97	0.98	0.98	0.98
$\overline{RO}^R$ (million)	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0	13.0
$\overline{RO}^D$ (million)	10.6	10.0	9.6	9.4	12.1	14.5	17.0	11.2	12.8	14.8
$\overline{MAE}^{RO}$ (million)	2.4	2.9	3.3	3.5	0.9	1.5	4.0	1.7	0.2	1.8
r^{RO}	0.96	0.96	0.97	0.97	0.95	0.96	0.96	0.95	0.96	0.95
$\overline{Rev}^{+,R}$ (million)	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0	52.0
$\overline{Rev}^{+,D}$ (million)	50.0	49.4	49.0	48.8	51.6	54.7	58.6	50.7	52.8	55.6
$\overline{MAE}^{Rev^+}$ (million)	2.0	2.6	3.1	3.3	0.4	2.7	6.6	1.3	0.8	3.5
r^{Rev^+}	1.00	1.00	1.00	1.00	0.99	0.99	0.99	1.00	0.99	0.99
$\overline{Rev}$ (million)	45.9	45.9	45.9	45.8	45.9	45.3	44.4	45.9	45.9	45.8
$\overline{Rev}^{-,R}$ (million)	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1	39.1
$\overline{Rev}^{-,D}$ (million)	39.4	39.4	39.3	39.3	39.5	40.3	41.6	39.4	40.0	40.8
$\overline{MAE}^{Rev^-}$ (million)	0.3	0.3	0.3	0.3	0.5	1.2	2.5	0.4	1.0	1.7
r^{Rev^-}	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.99
$\overline{R}^{td}$ (thousand)	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0	153.0
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6	87.6
$\overline{R}^{bd}$ (thousand)	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3	65.3
$\overline{D}^{td}$ (thousand)	157.1	137.8	118.8	100.2	178.4	211.3	236.5	158.0	163.1	171.9
$\overline{D}^{yd}$ (thousand)	89.1	90.0	91.0	92.3	89.7	94.5	96.8	89.9	93.7	100.3
$\overline{D}^{bd}$ (thousand)	67.9	47.9	27.8	7.8	88.7	116.8	139.7	68.2	69.4	71.6
$\overline{F}^{td}$ (thousand)	157.0	137.8	118.8	100.1	178.4	211.2	236.4	158.0	163.1	171.9
$\overline{F}^{yd}$ (thousand)	89.1	90.0	90.9	92.3	89.7	94.5	96.8	89.9	93.7	100.3
$\overline{F}^{bd}$ (thousand)	67.9	47.8	27.8	7.8	88.7	116.7	139.6	68.1	69.4	71.6
$\overline{MAE}^{D^{td}}$	1.77	2.03	2.91	4.03	2.45	4.42	6.05	2.22	3.04	3.94
$\overline{MAE}^{D^{yd}}$	0.85	0.87	0.90	0.96	0.88	1.17	1.30	0.87	1.06	1.47
$\overline{MAE}^{D^{bd}}$	1.26	1.62	2.70	4.00	1.94	3.64	5.18	1.77	2.85	4.04
$\overline{PMAE}^{D^{td}}$ (%)	16.8	19.2	27.5	38.1	23.2	41.8	57.3	21.0	28.7	37.2
$\overline{PMAE}^{D^{yd}}$ (%)	14.1	14.4	14.9	15.8	14.5	19.2	21.5	14.4	17.5	24.2
$\overline{PMAE}^{D^{bd}}$ (%)	27.8	35.9	59.6	88.4	42.9	80.5	114.6	39.2	62.9	89.4
$\overline{MAE}^{F^{td}}$	2.70	2.84	3.48	4.43	3.21	4.73	6.21	2.75	2.88	3.15
$\overline{MAE}^{F^{yd}}$	1.89	1.92	1.95	1.99	1.90	2.01	2.05	1.91	1.98	2.17
$\overline{MAE}^{F^{bd}}$	1.52	1.78	2.74	4.01	2.14	3.71	5.20	1.56	1.68	1.84
$\overline{PMAE}^{F^{td}}$ (%)	25.6	26.8	32.8	41.8	30.5	44.9	58.9	26.0	27.3	29.8
$\overline{PMAE}^{F^{yd}}$ (%)	31.2	31.6	32.1	32.9	31.4	33.1	33.9	31.5	32.6	35.8
$\overline{PMAE}^{F^{bd}}$ (%)	33.7	39.4	60.6	88.6	47.5	82.2	115.3	34.6	37.2	40.8

Table A.17.: Effect of Forecast Errors of the Buy-down on ROM Measures

	Base Case	Bid price decrease		Bid price increase		Adjust seasonality		Apply saw tooth curve	
Adj. level	-	25%	50%	25%	50%	-50%	+50%	130% - 70%	120% - 80%
$\overline{PARO}^R$ (%)	53.1	50.2	36.4	49.3	45.8	53.3	52.9	48.4	51.0
$\overline{PARO}^D$ (%)	61.7	60.0	46.3	57.1	52.5	62.0	61.3	57.6	60.1
$\overline{MAE}^{PARO}$ (%)	8.6	9.8	9.9	7.8	6.7	8.7	8.4	9.3	9.0
r^{PARO}	0.92	0.77	0.81	0.95	0.96	0.85	0.95	1.00	1.00
$\overline{ARO}^R$ (million)	6.9	6.5	4.7	6.4	5.9	6.9	6.9	6.5	6.7
$\overline{ARO}^D$ (million)	6.5	6.4	4.8	5.9	5.4	6.6	6.5	6.0	6.3
$\overline{MAE}^{ARO}$ (million)	0.3	0.1	0.1	0.4	0.5	0.3	0.4	0.5	0.4
r^{ARO}	0.98	0.97	0.95	0.98	0.98	0.95	0.99	1.00	1.00
$\overline{RO}^R$ (million)	13.0	13.0	13.0	13.0	13.0	12.9	13.1	12.9	12.8
$\overline{RO}^D$ (million)	10.6	10.7	10.3	10.4	10.3	10.6	10.6	10.0	10.3
$\overline{MAE}^{RO}$ (million)	2.4	2.3	2.7	2.5	2.7	2.3	2.5	2.9	2.5
r^{RO}	0.96	0.96	0.94	0.94	0.94	0.89	0.98	1.00	1.00
$\overline{Rev}^{+,R}$ (million)	52.0	52.0	52.0	52.0	52.0	52.0	51.9	51.4	51.7
$\overline{Rev}^{+,D}$ (million)	50.0	49.8	49.3	49.9	49.9	50.0	49.9	49.0	49.6
$\overline{MAE}^{Rev^+}$ (million)	2.0	2.2	2.7	2.1	2.1	2.0	2.0	2.4	2.1
r^{Rev^+}	1.00	0.99	0.99	1.00	0.99	0.99	1.00	1.00	1.00
$\overline{Rev}$ (million)	45.9	45.6	43.8	45.5	45.0	46.0	45.8	45.0	45.6
$\overline{Rev}^{-,R}$ (million)	39.1	39.1	39.1	39.1	39.1	39.1	38.8	38.5	38.9
$\overline{Rev}^{-,D}$ (million)	39.4	39.2	39.0	39.5	39.6	39.4	39.3	39.1	39.3
$\overline{MAE}^{Rev^-}$ (million)	0.3	0.1	0.1	0.4	0.5	0.3	0.4	0.5	0.4
r^{Rev^-}	0.99	0.99	1.00	0.99	0.99	0.98	1.00	1.00	1.00
$\overline{R}^{td}$ (thousand)	153.0	153.0	153.0	153.0	153.0	152.6	153.2	152.4	152.2
$\overline{R}^{yd}$ (thousand)	87.6	87.6	87.6	87.6	87.6	87.4	87.8	87.3	87.2
$\overline{R}^{bd}$ (thousand)	65.3	65.3	65.3	65.3	65.3	65.2	65.4	65.1	65.0
$\overline{D}^{td}$ (thousand)	157.1	157.4	155.8	155.7	154.5	157.4	156.3	150.6	154.2
$\overline{D}^{yd}$ (thousand)	89.1	89.4	88.5	88.3	87.7	89.3	88.7	85.5	87.6
$\overline{D}^{bd}$ (thousand)	67.9	68.1	67.3	67.4	66.7	68.0	67.6	65.1	66.6
$\overline{F}^{td}$ (thousand)	157.0	157.4	155.7	155.6	154.4	157.3	156.2	150.7	154.3
$\overline{F}^{yd}$ (thousand)	89.1	89.4	88.4	88.3	87.7	89.3	88.7	85.6	87.6
$\overline{F}^{bd}$ (thousand)	67.9	68.0	67.3	67.4	66.7	68.0	67.5	65.1	66.7
$\overline{MAE}^{D^{td}}$	1.77	1.76	1.68	1.74	1.71	1.72	1.84	1.95	1.82
$\overline{MAE}^{D^{yd}}$	0.85	0.85	0.80	0.84	0.83	0.82	0.90	0.97	0.88
$\overline{MAE}^{D^{bd}}$	1.26	1.26	1.23	1.25	1.23	1.24	1.28	1.30	1.27
$\overline{PMAE}^{D^{td}}$ (%)	16.8	16.6	15.9	16.4	16.2	16.3	17.4	18.7	17.4
$\overline{PMAE}^{D^{yd}}$ (%)	14.1	14.0	13.2	13.9	13.7	13.5	14.8	15.7	14.5
$\overline{PMAE}^{D^{bd}}$ (%)	27.8	27.8	27.3	27.6	27.3	27.5	28.3	29.5	28.4
$\overline{MAE}^{F^{td}}$	2.70	2.69	2.65	2.68	2.66	2.58	2.87	3.23	2.87
$\overline{MAE}^{F^{yd}}$	1.89	1.89	1.86	1.88	1.87	1.83	1.98	2.15	1.97
$\overline{MAE}^{F^{bd}}$	1.52	1.52	1.50	1.51	1.50	1.48	1.58	1.69	1.57
$\overline{PMAE}^{F^{td}}$ (%)	25.6	25.5	25.0	25.3	25.2	24.4	27.2	31.8	27.7
$\overline{PMAE}^{F^{yd}}$ (%)	31.2	31.2	30.7	31.1	30.9	30.2	32.7	36.9	33.1
$\overline{PMAE}^{F^{bd}}$ (%)	33.7	33.7	33.2	33.5	33.3	32.8	35.0	38.9	35.5

Table A.18.: Effect of Adjusted RM Controls and Seasonality on ROM Measures

A.3. Disaggregation of ROM Measures to Single Legs

In this section we present additional scatter plots of our analyses of the disaggregation of the ROM measures to single legs. In the main part of the thesis we mainly concentrated on scenarios in which we consider dependent demand. This section mainly focusses on the independent demand scenarios.

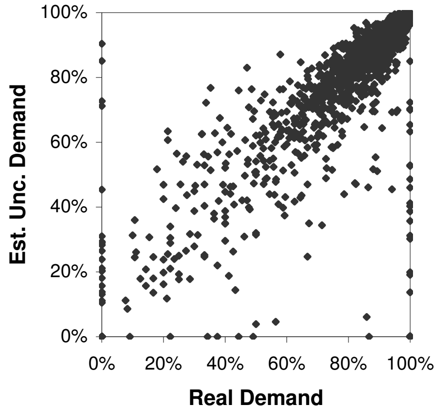

Figure A.49.: No-connecting-traffic Flight Network with Independent Demand

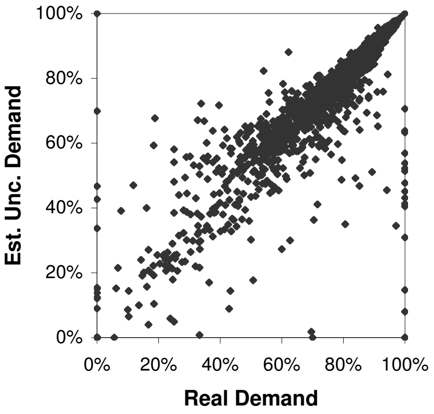

Figure A.50.: No-connecting-traffic Flight Network with Independent Demand - Averaged over 2 Weeks

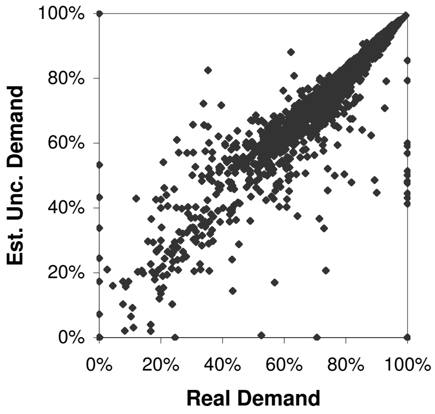

Figure A.51.: No-connecting-traffic Flight Network with Independent Demand - Averaged over One Month

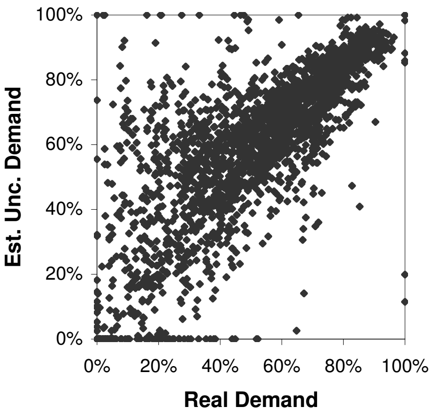

Figure A.52.: Realistic Flight Network with Dependent Demand and a 30% Unbiased Error on Estimated Unconstrained Buy-down - Averaged over One Month

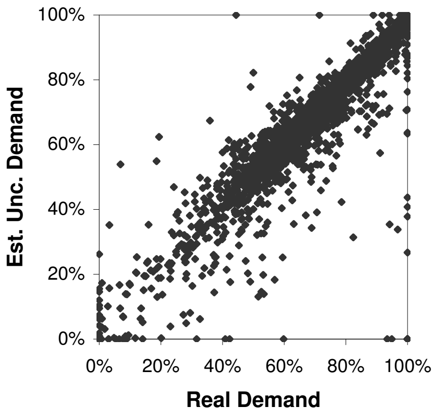

Figure A.53.: Realistic Flight Network with Independent Demand and a 30% Unbiased Error on Estimated Unconstrained Demand - Averaged over One Month

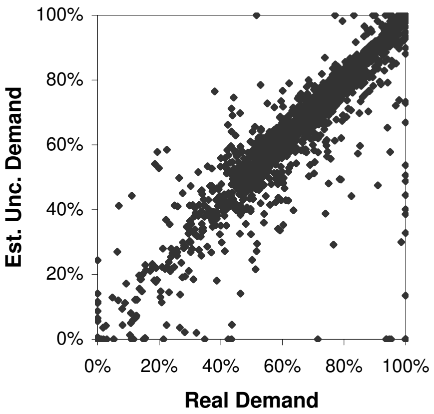

Figure A.54.: Realistic Flight Network with Independent Demand - Bid Price Moderate and Averaged over One Month

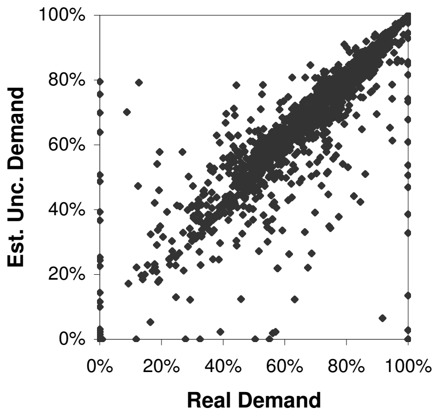

Figure A.55.: Realistic Flight Network with Independent Demand - Bid Price Aggressive and Averaged over One Month

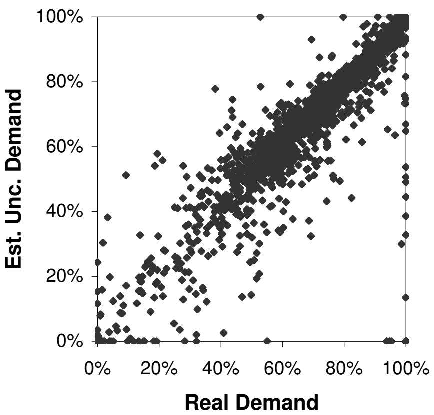

Figure A.56.: Realistic Flight Network with Independent Demand - Continental Flights and Averaged over One Month

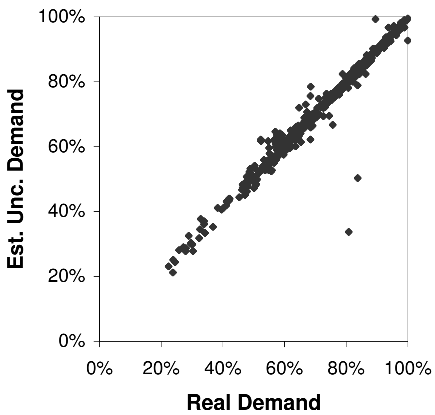

Figure A.57.: Realistic Flight Network with Independent Demand - Intercontinental Flights and Averaged over One Month

A.4. Disaggregation of ROM Measures to Single Components

In Chapter 7 we presented result tables and scatter plots for the realistic flight network scenario considering dependent demand. In this section we list the corresponding result tables for the independent demand case and also show the results of the no-connecting-traffic flight network.

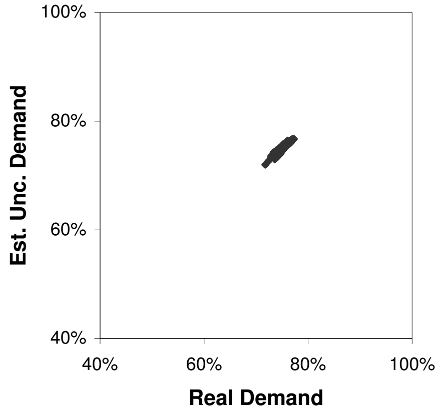

Figure A.58.: Base Case with Independent Demand on Network Level

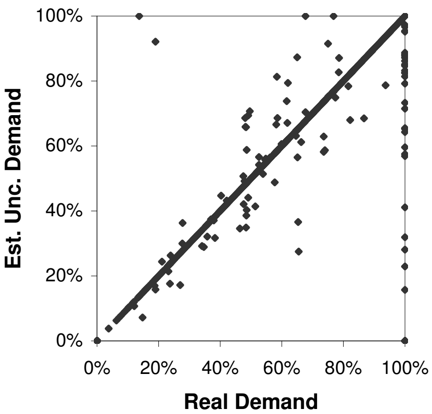

Figure A.59.: Realistic Flight Network with Independent Demand - Overbooking

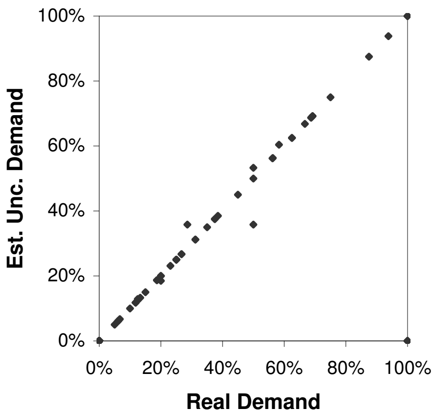

Figure A.60.: Realistic Flight Network with Independent Demand - Upgrading

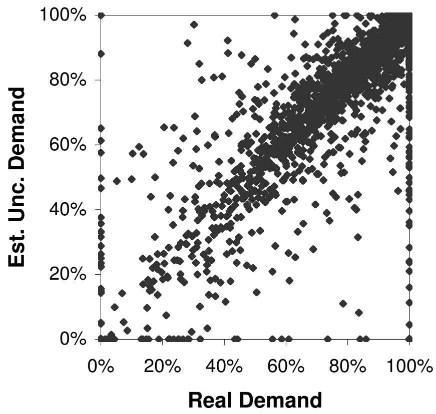

Figure A.61.: Realistic Flight Network with Independent Demand - Fare-mix

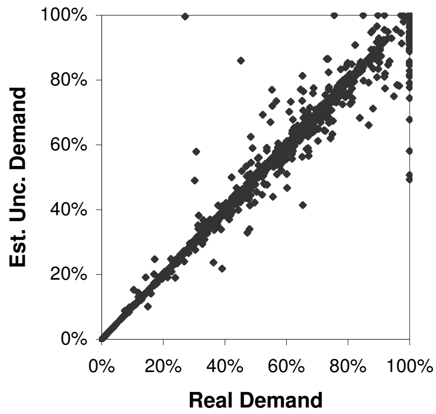

Figure A.62.: Realistic Flight Network with Independent Demand and Averaged over One Month - Overbooking

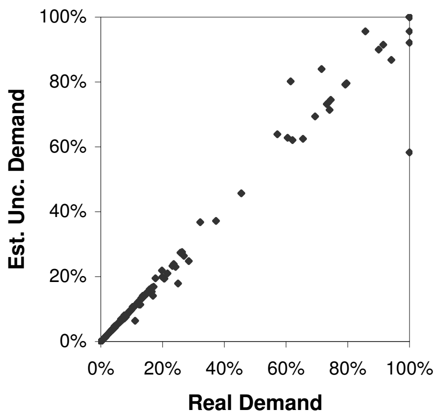

Figure A.63.: Realistic Flight Network with Independent Demand and Averaged over One Month - Upgrading

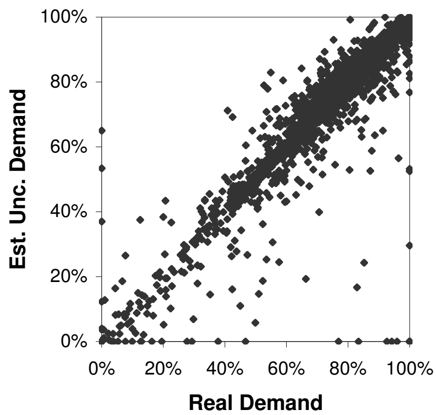

Figure A.64.: Realistic Flight Network with Independent Demand and Averaged over One Month - Fare-mix

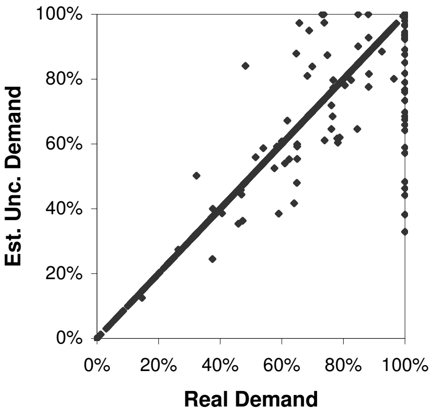

Figure A.65.: No-connecting-traffic Flight Network with Dependent Demand - Overbooking

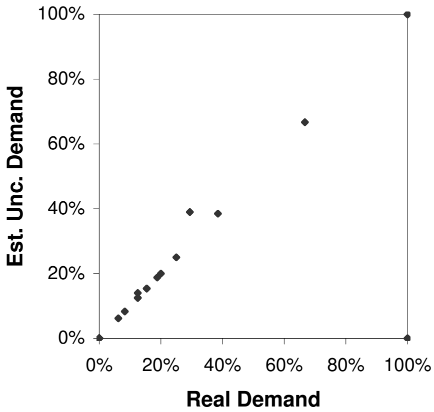

Figure A.66.: No-connecting-traffic Flight Network with Dependent Demand - Upgrading

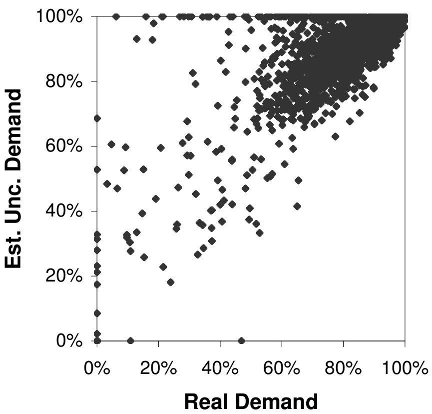

Figure A.67.: No-connecting-traffic Flight Network with Dependent Demand - Fare-mix

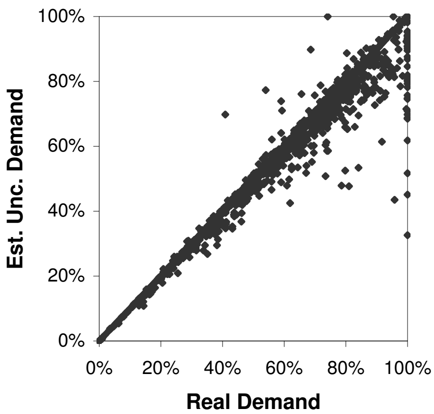

Figure A.68.: No-connecting-traffic Flight Network with Dependent Demand and Averaged over One Month - Overbooking

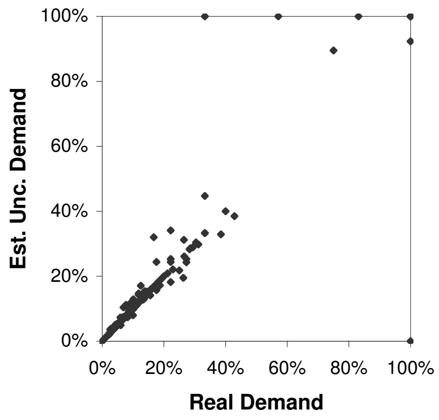

Figure A.69.: No-connecting-traffic Flight Network with Dependent Demand and Averaged over One Month - Upgrading

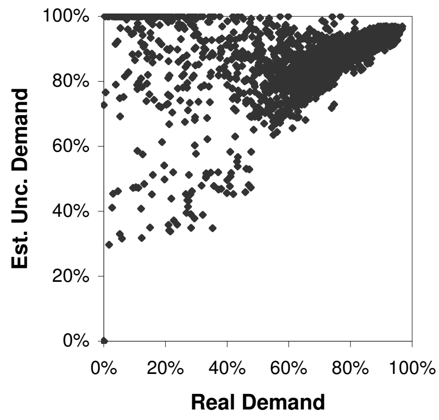

Figure A.70.: No-connecting-traffic Flight Network with Dependent Demand and Averaged over One Month - Fare-mix

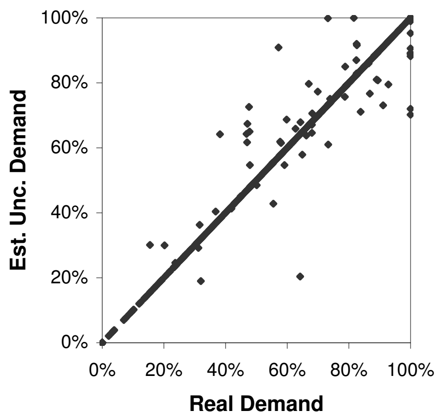

Figure A.71.: No-connecting-traffic Flight Network with Independent Demand - Overbooking

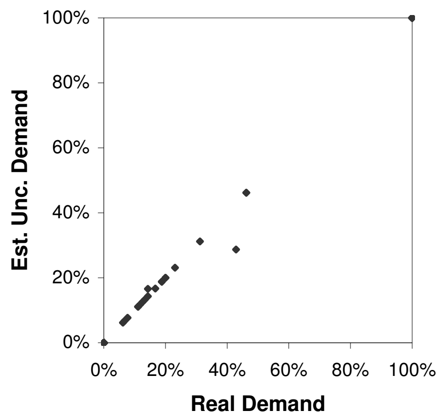

Figure A.72.: No-connecting-traffic Flight Network with Independent Demand - Upgrading

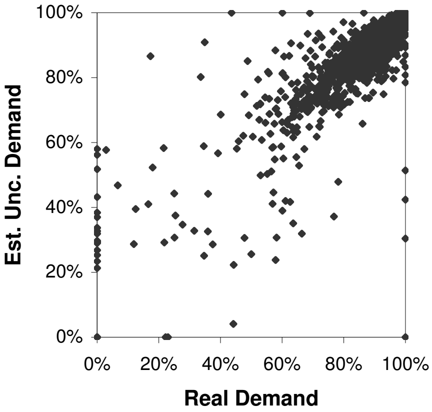

Figure A.73.: No-connecting-traffic Flight Network with Independent Demand - Fare-mix

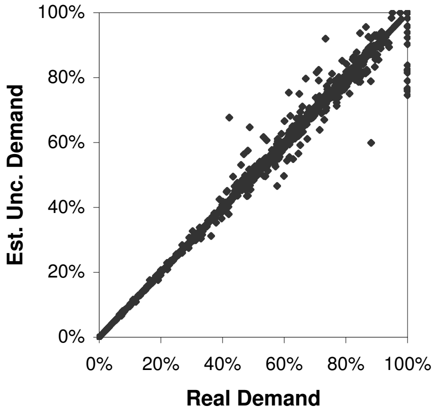

Figure A.74.: No-connecting-traffic Flight Network with Independent Demand and Averaged over One Month - Overbooking

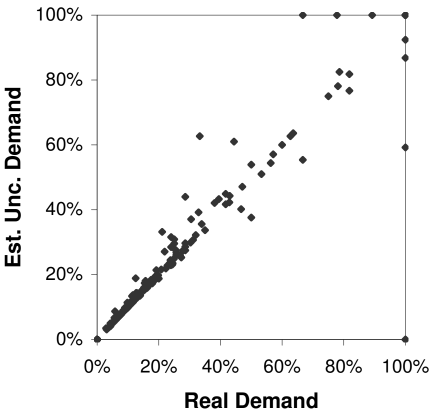

Figure A.75.: No-connecting-traffic Flight Network with Independent Demand and Averaged over One Month - Upgrading

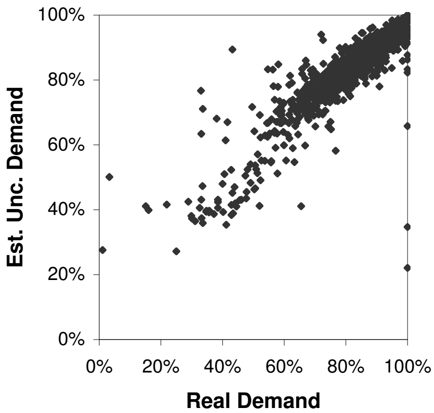

Figure A.76.: No-connecting-traffic Flight Network with Independent Demand and Averaged over One Month - Fare-mix

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
$\overline{PARO}^R$ (%)	75.0	75.0	69.6	73.1	73.1	76.5	71.0
$\overline{PARO}^D$ (%)	75.0	75.0	69.7	73.1	73.0	76.5	71.0
$\overline{MAE}^{PARO}$ (%)	0.3	0.2	0.3	0.3	0.3	0.3	0.3
r^{PARO}	0.94	0.95	0.94	0.94	0.95	0.93	0.94

Table A.19.: PAROs on an Aggregated Network Level with Upgrading and Overbooking Applied - Realistic Flight Network and Independent Demand

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. inc. (%)	53.1	53.1	49.0	-	-	53.1	49.0
$\overline{MAE}^{PARO^O}$ (%)	0.3	0.3	0.8	-	-	0.3	0.8
r^{PARO^O}	1.00	1.00	0.98	-	-	1.00	0.98
flight dep. inc. (%)	14.3	14.3	13.9	0.0	0.0	-	-
$\overline{MAE}^{PARO^U}$ (%)	0.2	0.2	1.5	-	-	-	-
r^{PARO^U}	1.00	1.00	0.06	-	-	-	-
flight dep. inc. (%)	54.9	54.9	54.9	54.6	54.6	54.9	54.9
$\overline{MAE}^{PARO^F}$ (%)	3.7	3.7	4.6	5.0	5.0	3.7	4.6
r^{PARO^F}	0.86	0.86	0.83	0.82	0.82	0.86	0.83

Table A.20.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on No-connecting-traffic Flight Network with Independent Demand

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. inc. (%)	69.5	69.5	69.4	-	-	69.5	69.4
$\overline{MAE}^{PARO^O}$ (%)	0.5	0.5	1.0	-	-	0.5	1.0
r^{PARO^O}	1.00	1.00	0.96	-	-	1.00	0.96
flight dep. inc. (%)	38.5	38.5	37.9	1.1	1.1	-	-
$\overline{MAE}^{PARO^U}$ (%)	3.1	3.1	0.6	6.2	4.8	-	-
r^{PARO^U}	0.93	0.93	0.89	0.94	0.89	-	-
flight dep. inc. (%)	69.5	69.5	69.6	69.9	69.9	69.5	69.6
$\overline{MAE}^{PARO^F}$ (%)	2.2	2.2	2.6	3.1	3.1	2.2	2.6
r^{PARO^F}	0.93	0.93	0.94	0.92	0.92	0.93	0.94

Table A.21.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on No-connecting-traffic Flight Network Using Averaging with Independent Demand

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. inc. (%)	53.0	53.0	49.6	-	-	52.9	49.5
$\overline{MAE}^{PARO^O}$ (%)	0.7	0.7	1.3	-	-	0.7	1.3
r^{PARO^O}	0.99	0.99	0.96	-	-	0.99	0.96
flight dep. inc. (%)	14.3	14.3	13.9	9.1	8.2	-	-
$\overline{MAE}^{PARO^U}$ (%)	6.0	6.0	5.7	1.4	1.6	-	-
r^{PARO^U}	0.65	0.65	0.70	0.99	0.99	-	-
flight dep. inc. (%)	54.6	54.6	54.9	55.6	55.6	54.6	54.9
$\overline{MAE}^{PARO^F}$ (%)	9.5	9.5	9.7	8.4	8.3	9.6	9.8
r^{PARO^F}	0.73	0.73	0.76	0.85	0.85	0.73	0.76

Table A.22.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on No-connecting-traffic Flight Network with Dependent Demand

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. inc. (%)	69.5	69.5	69.3	-	-	69.5	69.3
$\overline{MAE}^{PARO^O}$ (%)	1.4	1.4	1.8	-	-	1.4	1.8
r^{PARO^O}	0.99	0.99	0.96	-	-	0.99	0.96
flight dep. inc. (%)	38.9	38.9	38.5	27.6	26.5	-	-
$\overline{MAE}^{PARO^U}$ (%)	2.1	2.1	1.3	1.1	1.7	-	-
r^{PARO^U}	0.90	0.90	0.89	1.00	0.99	-	-
flight dep. inc. (%)	70.1	70.1	70.1	70.2	70.2	70.1	70.1
$\overline{MAE}^{PARO^F}$ (%)	18.2	18.2	17.0	13.3	13.2	18.1	16.9
r^{PARO^F}	0.45	0.45	0.60	0.83	0.83	0.45	0.60

Table A.23.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on No-connecting-traffic Flight Network Using Averaging with Dependent Demand

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. inc. (%)	39.4	39.5	39.4	-	-	39.3	39.3
$\overline{MAE}^{PARO^O}$ (%)	2.4	2.4	2.9	-	-	2.0	2.6
r^{PARO^O}	0.92	0.92	0.87	-	-	0.94	0.88
flight dep. inc. (%)	30.1	30.1	27.8	2.3	2.3	-	-
$\overline{MAE}^{PARO^U}$ (%)	3.7	3.7	2.3	0.0	0.0	-	-
r^{PARO^U}	0.78	0.75	0.38	1.00	1.00	-	-
flight dep. inc. (%)	61.8	61.6	61.7	60.4	60.2	61.3	61.7
$\overline{MAE}^{PARO^F}$ (%)	9.2	8.7	10.0	10.6	10.3	8.9	10.2
r^{PARO^F}	0.75	0.77	0.74	0.73	0.73	0.75	0.73

Table A.24.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on Realistic Flight Network with Independent Demand

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. inc. (%)	53.6	53.6	53.0	-	-	53.5	53.1
$\overline{MAE}^{PARO^O}$ (%)	1.2	1.2	1.8	-	-	1.2	2.0
r^{PARO^O}	0.99	0.99	0.93	-	-	0.99	0.92
flight dep. inc. (%)	45.5	45.5	44.8	3.6	3.8	-	-
$\overline{MAE}^{PARO^U}$ (%)	0.8	0.7	1.5	0.1	0.5	-	-
r^{PARO^U}	0.99	0.99	0.36	1.00	1.00	-	-
flight dep. inc. (%)	70.9	70.8	70.9	70.0	70.1	70.8	70.9
$\overline{MAE}^{PARO^F}$ (%)	3.6	3.6	4.1	4.2	4.3	3.9	4.4
r^{PARO^F}	0.92	0.91	0.91	0.92	0.91	0.89	0.88

Table A.25.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on Realistic Flight Network Using Averaging with Independent Demand

Overbooking Upgrading	Reg. Reg.	Reg. -50%	-50% Reg.	None Reg.	None -50%	Reg. None	-50% None
flight dep. inc. (%)	53.0	53.0	52.4	-	-	52.9	52.5
$\overline{MAE}^{PARO^O}$ (%)	2.8	2.9	3.8	-	-	2.7	3.7
r^{PARO^O}	0.97	0.96	0.86	-	-	0.97	0.81
flight dep. inc. (%)	38.3	38.5	37.9	33.5	32.8	-	-
$\overline{MAE}^{PARO^U}$ (%)	5.9	5.8	2.4	3.8	2.2	-	-
r^{PARO^U}	0.85	0.79	0.79	0.91	0.95	-	-
flight dep. inc. (%)	72.3	72.4	72.4	71.9	72.0	72.3	72.3
$\overline{MAE}^{PARO^F}$ (%)	14.2	14.0	13.0	12.0	11.9	14.1	12.9
r^{PARO^F}	0.76	0.77	0.78	0.82	0.83	0.76	0.78

Table A.26.: Comparing PAROs for Overbooking, Upgrading and Fare-mix on Realistic Flight Network Using Averaging with Dependent Demand

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Notations

(i, j, t)	A tuple of an itinerary i, a booking class j and a time period $t \in I \times J \times T$.
(i, j)	A tuple of an itinerary i and a booking class $j \in I \times J$.
α	The smoothing parameter used for the forecasting and update of the average historical bookings.
β	The adjustment factor used to modify the bid prices, the overbooking level or the upgrading level.
ϵ^d	The error deviation used in the forecasting and unconstraining error scenarios.
$\epsilon_{i,j,t}$	The error factor applied to itinerary i for booking class j in time period t used in the forecasting and unconstraining error scenarios.
ϵ^l	The average error level used in the forecasting and unconstraining error scenarios.
γ_l	The share of connecting passengers on leg l.
ω	The share of additional buy-down used in the unconstraining algorithm.
$\tilde{\pi}_{l,m}$	The adjusted bid price for compartment m on leg l.
$\pi_{l,m}$	The bid price for compartment m on leg l.
$\rho_{i,j,l}$	The prorate factor to prorate the fare for itinerary i for booking class j related to leg l.
$\theta_{i,j,t}$	The sell-up rate for itinerary i for booking class j into the next higher booking class in time period t.
υ_l	The flight distance of leg l.
$a_{i,j,t}$	$\in \{0, 1\}$: The availability information for itinerary i for booking class j in time period t.
ARO	The ARO for the total flight network.
$\overline{ARO}^D$	The average ARO for the total flight network calculated with the estimated unconstrained demand over all simulation runs.

$\overline{ARO}^O$	The average ARO for overbooking for the total flight network over all simulation runs.
$\overline{ARO}^R$	The average ARO for the total flight network calculated with the real demand over all simulation runs.
$\overline{ARO}^U$	The average ARO for upgrading for the total flight network over all simulation runs.
ARO_l	The ARO for leg l.
ARO_l^F	The ARO for fare-mix for leg l.
ARO_l^O	The ARO for overbooking for leg l.
ARO_l^U	The ARO for upgrading for leg l.
$\hat{b}_{i,j,t}$	The actual bookings for itinerary i for booking class j in time period t after no-shows and cancelations.
$\hat{B}_{l,m}$	The cumulated actual bookings for compartment m on leg l after no-shows and cancelations up to the end of the booking period.
$b_{i,j,t}$	The actual bookings for itinerary i for booking class j in time period t.
B_l	The cumulated actual bookings for leg l up to the end of the booking period.
B_l^γ	The cumulated actual connecting traffic bookings for leg l for booking class j up to the end of the booking period.
$B_{l,m}$	The cumulated actual bookings for compartment m on leg l up to the end of the booking period.
$B_{l,m}^{add}$	The number of additional bookings for compartment m on leg l considered being overbooking and/or upgrading success.
$B_{l,m}^{db}$	The number of denied boarded passengers for compartment m on leg l.
$B_{l,m}^{dg}$	The number of downgraded passengers for compartment m on leg l.
$B_{l,m}^{ex}$	The number of exceeding bookings for compartment m on leg l.
$B_{l,m}^O$	The estimated number of passengers for compartment m on leg l that are a result of overbooking.
$B_{l,m}^U$	The estimated number of passengers for compartment m on leg l that are a result of upgrading.

$B^{up}_{l,m}$	The number of upgraded passengers for compartment m on leg l.
$c_{i,j,j',t}$	The number of booking requests for itinerary i in booking class j' in time period t, with a willingness to pay up to booking class j with dependent demand.
$c_{i,j,t}$	The number of booking requests for itinerary i in booking class j in time period t with independent demand.
cap_l	The total capacity available on leg l.
$cap_{l,m}$	The capacity available in compartment m on leg l.
$cap^f_{l,m}$	The free capacity of compartment m on leg l at the end of the booking period.
$cap^O_{l,m}$	The capacity available in compartment m on leg l after overbooking.
$cap^{O,U}_{l,m}$	The capacity available in compartment m on leg l after upgrading and overbooking.
$cap^U_{l,m}$	The capacity available in compartment m on leg l after upgrading.
$\overline{D}$	The average cumulated estimated unconstrained demand for all itineraries i over all simulation runs with independent demand.
$\overline{D}^{bd}$	The average cumulated estimated unconstrained buy-down for all itineraries i over all simulation runs with dependent demand.
$\hat{d}^{bd}_{i,j,j',t}$	The estimated unconstrained buy-down for itinerary i for booking class j in time period t after no-shows and cancelations with dependent demand.
$\hat{d}_{i,j,t}$	The estimated unconstrained demand for itinerary i for booking class j in time period t after no-shows and cancelations with independent demand.
$\hat{d}^{td}_{i,j,t}$	The estimated unconstrained total demand for itinerary i for booking class j in time period t after no-shows and cancelations with dependent demand.
$\hat{d}^{yd}_{i,j,t}$	The estimated unconstrained yieldable demand for itinerary i for booking class j in time period t after no-shows and cancelations with dependent demand.

$\overline{D}^{td}$	The average cumulated estimated unconstrained total demand for all itineraries i over all simulation runs with dependent demand.
$\overline{D}^{yd}$	The average cumulated estimated unconstrained yieldable demand for all itineraries i over all simulation runs with dependent demand.
$D_{i,j}$	The cumulated estimated unconstrained demand for itinerary i for booking class j up to the end of the booking period with independent demand.
$D_{i,j}^{bd}$	The cumulated estimated unconstrained buy-down for itinerary i for booking class j up to the end of the booking period with dependent demand.
$D_{i,j}^{td}$	The cumulated estimated unconstrained total demand for itinerary i for booking class j up to the end of the booking period with dependent demand.
$D_{i,j}^{yd}$	The cumulated estimated unconstrained yieldable demand for itinerary i for booking class j up to the end of the booking period with dependent demand.
$d_{i,j,j',t}^{bd}$	The estimated unconstrained buy-down for itinerary i for booking class j in time period t into the lower booking class j' with dependent demand.
$d_{i,j,t}$	The estimated unconstrained demand for itinerary i for booking class j in time period t with independent demand.
$d_{i,j,t}^{td}$	The estimated unconstrained total demand for itinerary i for booking class j in time period t with dependent demand.
$d_{i,j,t}^{yd}$	The estimated unconstrained yieldable demand for itinerary i for booking class j in time period t with dependent demand.
$\overline{F}$	The average cumulated forecasted demand for all itineraries i over all simulation runs with independent demand.
$\overline{F}^{bd}$	The average cumulated forecasted buy-down for all itineraries i over all simulation runs with dependent demand.

$\overline{F}^{td}$	The average cumulated forecasted total demand for all itineraries i over all simulation runs with dependent demand.
$\overline{F}^{yd}$	The average cumulated forecasted yieldable demand for all itineraries i over all simulation runs with dependent demand.
$f_{i,j,t}$	The forecasted demand for itinerary i for booking class j in time period t with independent demand.
$h_{i,j,t}$	The historical observed bookings for itinerary i for booking class j in time period t.
I	The set of all itineraries in the flight network.
i	An itinerary $\in I$.
I_l	The set of all itineraries in the flight network that contain leg l.
I_l^γ	The set of all connecting traffic itineraries in the flight network that contain leg l.
J	The set of all available booking classes.
j	A booking class $\in J$.
J_i	The set of all booking classes available in itinerary i.
$J_{i,j}$	The set of all booking classes available in itinerary i which are lower than booking class j and in the same compartment.
$J_{i,l}$	The set of all booking classes available in itinerary i which will be booked on leg l.
$J_{i,l,m}$	The set of all booking classes available in itinerary i which will be booked in compartment m on leg l.
$J_{i,m}$	The set of all booking classes available in itinerary i which will be booked in compartment m.
$j_{i,m}^+$	The highest available booking class on itinerary i in compartment m.
$j_{i,m}^-$	The lowest available booking class on itinerary i in compartment m.
$k_{i,j,t}$	The cancelation rate for all bookings for itinerary i for booking class j that were booked up to time period t.

L	The set of all legs in the network.
l	A leg $\in L$.
L_i	The set of all legs that are part of itinerary i.
M	The set of all compartmens.
m	A compartment $\in M$.
M_i	The set of all compartmens available on itinerary i.
M_l	The set of all compartmens that belong to leg l.
m_l^+	The highest valued compartment on leg l.
$m_{l,j}$	The compartment on leg l which is related to booking class j.
$\overline{MAE}^{ARO}$	The average mean absolute error of the ARO for the total flight network over all simulation runs.
$\overline{MAE}^{D}$	The average mean absolute error of the estimated unconstrained demand for all itineraries over all simulation runs with independent demand.
$\overline{MAE}^{D^{bd}}$	The average mean absolute error of the estimated unconstrained buy-down for all itineraries over all simulation runs with dependent demand.
$\overline{MAE}^{D^{td}}$	The average mean absolute error of the estimated unconstrained total demand for all itineraries over all simulation runs with dependent demand.
$\overline{MAE}^{D^{yd}}$	The average mean absolute error of the estimated unconstrained yieldable demand for all itineraries over all simulation runs with dependent demand.
$\overline{MAE}^{F}$	The average mean absolute error of the forecasted demand for all itineraries over all simulation runs with independent demand.
$\overline{MAE}^{F^{bd}}$	The average mean absolute error of the forecasted buy-down for all itineraries over all simulation runs with dependent demand.
$\overline{MAE}^{F^{td}}$	The average mean absolute error of the forecasted total demand for all itineraries over all simulation runs with dependent demand.

$\overline{MAE}^{Fyd}$	The average mean absolute error of the forecasted yieldable demand for all itineraries over all simulation runs with dependent demand.
$\overline{MAE}^{PARO}$	The average mean absolute error of the PARO for the total flight network over all simulation runs.
$\overline{MAE}^{PARO^F}$	The average mean absolute error of the PARO for fare-mix for the total flight network over all simulation runs.
$\overline{MAE}^{PARO^O}$	The average mean absolute error of the PARO for overbooking for the total flight network over all simulation runs.
$\overline{MAE}^{PARO^U}$	The average mean absolute error of the PARO for upgrading for the total flight network over all simulation runs.
$\overline{MAE}^{Rev^+}$	The average mean absolute error of the potential revenue for the total flight network over all simulation runs.
$\overline{MAE}^{Rev^-}$	The average mean absolute error of the no RM revenue for the total flight network over all simulation runs.
$\overline{MAE}^{RO}$	The average mean absolute error of the RO for the total flight network over all simulation runs.
MAE^D	The mean absolute error of the estimated unconstrained demand for all itineraries.
MAE^{PARO}	The mean absolute error of the PARO.
$p_{i,j,l,t}$	The prorated fare for itinerary i for booking class j in time period t related to leg l.
$p_{i,j,t}$	The fare for itinerary i for booking class j in time period t.
$p_{l,m}^{avg}$	The average revenue or yield related to compartment m on leg l.
$p_{l,m}^{db}$	The denied boarding costs associated to compartment m on leg l.
$p_{l,m}^{dg}$	The downgrading costs associated to compartment m on leg l.

$p^{inc}_{l,m}$	The incremental revenue related to compartment m on leg l as a result of overbooking or upgrading.
$p^{min}_{l,m}$	The minimum fare related to compartment m on leg l.
$PARO$	The PARO for the total flight network.
$\overline{PARO}^D$	The average PARO for the total flight network calculated with the estimated unconstrained demand over all simulation runs.
$\overline{PARO}^R$	The average PARO for the total flight network calculated with the real demand over all simulation runs.
$PARO^D$	The PARO for the total flight network calculated with the estimated unconstrained demand.
$PARO^F$	The PARO for fare-mix for the total flight network.
$PARO_l$	The PARO for leg l.
$PARO^O$	The PARO for overbooking for the total flight network.
$PARO^R$	The PARO for the total flight network calculated with the real demand.
$PARO^U$	The PARO for upgrading for the total flight network.
$\overline{PMAE}^D$	The average percentage mean absolute error of the estimated unconstrained demand for all itineraries over all simulation runs with independent demand.
$\overline{PMAE}^{D^{bd}}$	The average percentage mean absolute error of the estimated unconstrained buy-down for all itineraries over all simulation runs with dependent demand.
$\overline{PMAE}^{D^{td}}$	The average percentage mean absolute error of the estimated unconstrained total demand for all itineraries over all simulation runs with dependent demand.
$\overline{PMAE}^{D^{yd}}$	The average percentage mean absolute error of the estimated unconstrained yieldable demand for all itineraries over all simulation runs with dependent demand.
$\overline{PMAE}^F$	The average percentage mean absolute error of the forecasted demand for all itineraries over all simulation runs with independent demand.

$\overline{PMAE}^{F^{bd}}$	The average percentage mean absolute error of the forecasted buy-down for all itineraries over all simulation runs with dependent demand.
$\overline{PMAE}^{F^{td}}$	The average percentage mean absolute error of the forecasted total demand for all itineraries over all simulation runs with dependent demand.
$\overline{PMAE}^{F^{yd}}$	The average percentage mean absolute error of the forecasted yieldable demand for all itineraries over all simulation runs with dependent demand.
$PMAE^{D}$	The percentage mean absolute error of the estimated unconstrained demand for all itineraries.
$\mathbb{P}_{l,m}$	The set of all tuples (i, j) booked on leg l in compartment m ordered by the fare of the respective itinerary i ascending.
$\mathbb{P}_{t}$	The set of all tuples (i, j, t) in time period t ordered by the fare of the respective itinerary i ascending.
$q_{i,j}$	The show-up rate for itinerary i for booking class j.
$q_{l,m}$	The average show-up rate for compartment m on leg l.
$\overline{R}$	The average cumulated real demand for all itineraries i up to the end of the booking period over all simulation runs with independent demand.
$\overline{R}^{bd}$	The average cumulated real buy-down for all itineraries i up to the end of the booking period over all simulation runs with dependent demand.
$\overline{R}^{td}$	The average cumulated real total demand for all itineraries i up to the end of the booking period over all simulation runs with dependent demand.
$\overline{R}^{yd}$	The average cumulated real yieldable demand for all itineraries i up to the end of the booking period over all simulation runs with dependent demand.
r^{ARO}	The correlation coefficient for the ARO over all simulation runs.
$R_{i,j}$	The cumulated real demand for itinerary i for booking class j up to the end of the booking period with independent demand.

$R^{bd}_{i,j}$	The cumulated real buy-down for itinerary i for booking class j up to the end of the booking period with dependent demand.
$R^{td}_{i,j}$	The cumulated real total demand for itinerary i for booking class j up to the end of the booking period with dependent demand.
$R^{yd}_{i,j}$	The cumulated real yieldable demand for itinerary i for booking class j up to the end of the booking period with dependent demand.
$r^{bd}_{i,j,j',t}$	The real buy-down for itinerary i for booking class j in time period t into the lower booking class j' with dependent demand.
$r_{i,j,t}$	The real demand for itinerary i for booking class j in time period t with independent demand.
$r^{td}_{i,j,t}$	The real total demand for itinerary i for booking class j in time period t with dependent demand.
$r^{yd}_{i,j,t}$	The real yieldable demand for itinerary i for booking class j in time period t with dependent demand.
r^{PARO}	The correlation coefficient for the PARO over all simulation runs.
r^{PARO^F}	The correlation coefficient for the PARO for fare-mix over all simulation runs.
r^{PARO^O}	The correlation coefficient for the PARO for overbooking over all simulation runs.
r^{PARO^U}	The correlation coefficient for the PARO for upgrading over all simulation runs.
r^{Rev^+}	The correlation coefficient for the potential revenue over all simulation runs.
r^{Rev^-}	The correlation coefficient for the no RM revenue over all simulation runs.
r^{RO}	The correlation coefficient for the RO over all simulation runs.
Rev	The actual revenue for the total flight network.
$\overline{Rev}$	The average actual revenue or the total flight network over all simulation runs.
$\overline{Rev}^{+,D}$	The average potential revenue for the total flight network calculated with the estimated unconstrained demand over all simulation runs.

$\overline{Rev}^{+,R}$	The average potential revenue for the total flight network calculated with the real demand over all simulation runs.
$\overline{Rev}^{-,D}$	The average no RM revenue for the total flight network calculated with the estimated unconstrained demand over all simulation runs.
$\overline{Rev}^{-,R}$	The average no RM revenue for the total flight network calculated with the real demand over all simulation runs.
Rev^{+}	The estimated potential revenue for the total flight network.
$Rev^{+,O}$	The estimated potential revenue with overbooking for the total flight network.
$Rev^{+,O,U}$	The estimated potential revenue with overbooking and upgrading for the total flight network.
$Rev^{+,U}$	The estimated potential revenue with upgrading for the total flight network.
Rev^{-}	The estimated no RM revenue.
$Rev^{-,N}$	The estimated no RM revenue after consideration of cancelation and no-shows.
Rev_l	The actual revenue for leg l.
Rev_l^{+}	The estimated potential revenue for leg l.
Rev_l^{-}	The estimated no RM revenue for leg l.
Rev^{N}	The actual revenue for the total flight network after consideration of cancelations, no-shows and denied boardings.
RO	The RO for the total flight network.
$\overline{RO}^{D}$	The average RO for the total flight network calculated with the estimated unconstrained demand over all simulation runs.
$\overline{RO}^{R}$	The average RO for the total flight network calculated with the real demand over all simulation runs.
RO_l	The RO for leg l.
RO_l^{F}	The RO for upgrading for leg l.
RO_l^{O}	The RO for overbooking for leg l.
RO_l^{U}	The RO for upgrading for leg l.
S	The set of all available simulation runs.

s	A simulation run $\in S$.
T	The set of all available time periods.
t	A time period $\in T$.
T_t	The set of all time periods after time period t up to the end of the booking period.
$x^{+}_{i,j,t}$	The number of estimated bookings for the potential revenue for itinerary i for booking class j in time period t.
$x^{+,O}_{i,j,t}$	The number of estimated bookings for the potential revenue with overbooking for itinerary i for booking class j in time period t.
$x^{+,O,U}_{i,j,t}$	The number of estimated bookings for the potential revenue with overbooking and upgrading for itinerary i for booking class j in time period t.
$x^{+,U}_{i,j,t}$	The number of estimated bookings for the potential revenue with upgrading for itinerary i for booking class j in time period t.
$x^{-}_{i,j,t}$	The number of estimated bookings for the no RM revenue for itinerary i for booking class j in time period t.
$x^{-,N}_{i,j,t}$	The number of estimated bookings for the no RM revenue after no-shows and cancelations for itinerary i for booking class j in time period t.
$X^{+,O}_{l,m}$	The number of cumulated estimated bookings for the potential revenue with overbooking related to compartment m on leg l up to the end of booking period.
$X^{+,O,U}_{l,m}$	The number of cumulated estimated bookings for the potential revenue with overbooking and upgrading related to compartment m on leg l up to the end of booking period.
$X^{+,U}_{l,m}$	The number of cumulated estimated bookings for the potential revenue with upgrading related to compartment m on leg l up to the end of booking period.
$X^{O}_{l,m}$	The estimated number of potential additional bookings related to overbooking in compartment m on leg l.

$X^U_{l,m}$	The estimated number of potential additional bookings related to upgrading in compartment m on leg l.
$y_{i,j,t}$	The availability of booking class j for itinerary i in time period t.

Acronyms

ARO	achieved revenue opportunity.
DAVN	displacement adjustment virtual nesting.
DCP	data collection point.
DLP	deterministic linear program.
DP	dynamic programming.
EMSR	expected marginal seat revenue.
FCFS	'first come, first served'.
GDS	global distribution system.
LBH	low-before-high.
LP	linear program.
MAE	mean absolute error.
O&D	origin & destination.
PARO	percentage achieved revenue opportunity.
PM	performance measurement.
PMAE	percentage mean absolute error.
PODS	passenger origin-destination simulator.
RASK	revenue per available seat kilometer.
RLP	randomized linear program.
RM	revenue management.
RMS	revenue management system.
RO	revenue opportunity.
ROM	revenue opportunity model.

SLF	seat load factor.

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