Revenue Management for Strategic Alliances with Applications to the Airline Industry

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Preface

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Chapter 1

Introduction

In many sectors, in which revenue management procedures are applied or could be applied, it is noticeable that corporations build strategic alliances. Revenue management can be successfully adopted in markets in which customers possess different willingness to pay for the same service or product and, therefore, customer segmentation can be realized by the companies. The objective of revenue management is to control the demand by means of pricing and capacity control decisions to maximize revenues from a limited capacity (compare Talluri and van Ryzin, 2004b, Section 1.1). The implementation of strategic alliances causes new decision problems especially for revenue management. Considering the capacity allocation, in case of alliances, the capacity control not only has to sort out how many capacity units should be allocated to the different customer segments, but also how the capacity is divided among the alliance partners.

So far, existing literature discusses numerous capacity control strategies for single corporations which, in fact, is already a complex problem. There is hardly any literature concerning capacity control decision problems in strategic alliances and practical experience as well does not provide an answer to solve the problem. To overcome the missing attention of capacity control problems in strategic alliances, the major aim of this thesis is the development of a capacity control method which dynamically decides on the acceptance or the rejection of customer requests for products or services of the alliance partners. The goal of the capacity control method is to maximize the combined revenue of the alliance partners.

In this thesis, we focus on strategic alliances in the airline industry. The major strategic alliances in the passenger transport airline industry are Star Alliance, SkyTeam, and oneworld. The deregulation of the airline industry had consequences on the market. Major traditional airlines are confronted with the competition of low-cost carriers entering the markets and, therefore, have to process an increasing amount of their traffic within airline alliances.

The capacity control method proposed in this thesis comprises of an optimization part and a simulation part:

In the optimization part, we consider different optimization techniques as the Deterministic Linear Model (DLP) introduced, e.g., by Williamson (1992), Section 4.1, and the Expected Marginal Seat Revenue heuristics (EMSR) presented by Belobaba (1987, 1989) to calculate booking limits, the control variables of the capacity control, for a single airline on a single flight leg. In this thesis, the DLP model and the EMSR heuristics are extended to fit the requirements of a strategic alliance with two partners. We consider real options to divide the seat capacity in the aircraft among the members of the alliance.

In the simulation part, we adopt event-driven simulation models to simulate the booking process of the partners in the alliance and to evaluate the capacity control strategy determined in the optimization part. The stochastic demand is taken into account in the simulation models to generate a more realistic setting. The perceptions gained by the simulation can be used to improve the optimization. Therefore, a simulation-based optimization procedure is used which updates the calculated control variables within an iterative process.

Additionally, two different genetic algorithm approaches are implemented to search for enhanced booking limits for the alliance partners. To improve the solution of the capacity control method, determined in this thesis, the transfer prices, which the partner airlines pay in the option-based capacity control method to share the capacity, is iteratively updated.

This thesis is organized as follows: In Chapter 2, we will present the conditions for revenue management application and the instruments of revenue management. We will limit the theoretical discussion to the revenue management concepts that are necessary to follow the course of this work. A brief introduction of strategic alliances will be followed by a detailed discussion of strategic alliances in sectors in which revenue management can be applied in Chapter 3. Chapter 4 will introduce an option-based capacity control procedure and will illustrate how the booking limits are determined for the alliance partners. The simulation of the booking processes of the alliance partners considering capacity control with real options will also be described in Chapter 4. In Chapter 5, a simulation-based optimization procedure will be introduced to improve the booking limits for the partners within the strategic alliance. Chapter 6 will present two different types of a genetic algorithm approach to control the capacity of the strategic alliance. A negotiation process will be introduced in Chapter 7 to improve the capacity control by the determination of optimal transfer prices that accrue between the alliance partners. In each chapter, in which new capacity control procedures for strategic alliances will be presented, the results of the procedures will be introduced and discussed. We will summarize our study in Chapter 8 with comments on further research.

Chapter 2

Conceptual Foundation of Revenue Management

In this chapter, selected topics of revenue management will be introduced to provide the theoretical background of the revenue management problems discussed in this thesis. After a brief introduction of the historical development of revenue management (Section 2.1), the conditions for a successful application of revenue management (Section 2.2.1) as well as different revenue management instruments (Section 2.2.2) will be discussed.

2.1 Historical Development of Revenue Management

The origins and history of revenue management theory are closely connected to a single industry: the airline industry. Revenue management is a concept that dates back to the deregulation of fares in the U.S. airline industry in the late 1970's. Until 1978, the U.S. airline industry was regulated by the Civil Aeronautics Board. Thereby, the Civil Aeronautics Board strictly controlled the markets airlines could enter, the destinations airlines could serve, and the fares airlines could charge, based on standardized price and profitability targets. With the Airline Deregulation Act of 1978, the U.S. Civil Aviation Board phased out the governmental control of airline fares and services. Due to deregulation, airlines are free to set prices, schedules and services without the approval of the Civil Aeronautics Board. Compare, e.g., Bailey et al. (1985), Chapter 2, Mayer (2001), Section 2.1, Morrison and Winston (1995), Chapter 2, and U.S. GAO (1996), Chapter 1, for a detailed description of the deregulation of the U.S. air traffic.

The deregulation of the airline industry had further consequences on the market. Major airlines were confronted with the competition of low-cost and charter carriers entering the markets. Most of the low-cost airlines could offer tickets at lower prices compared to the major airlines mainly due to considerably low costs which are, among other things, based on no-frills services, low labor costs, and simpler operations (compare, e.g., Talluri and van Ryzin, 2004b, Section 1.2.1). To respond to the low price strategy of the low-cost airlines, American Airlines, one of the major airlines, adopted a price differentiation mechanism to offer discounts with purchase restrictions. By attaching the discount availability on purchase restrictions as, e.g., the condition that discounted tickets had to be purchased 30 days in advance, business travelers should be deterred from accessing the new low fares. The purchase restrictions enabled American Airlines to successfully compete with the new low-cost airlines by offering discounted flight tickets without loosing revenues generated by business travelers (compare, e.g., Klein, 2005, Section 1.1). The adoption of the segment-orientated price differentiation mechanism, however, required the development and application of other planning instruments. Since most requests for low-priced flight tickets are assumed to occur before the requests for higher-priced tickets during the booking process, it must be ensured that there are enough flight tickets for seats in the aircraft on the considered flight left to meet the demand of the customers with a higher willingness to pay. Otherwise the demand for lower-priced flight tickets pushes aside the demand for higher-priced tickets which leads to revenue losses. Therefore, the capacity needs to be controlled to enable proper decisions about the acceptance or rejection of requests during the booking process. A forecasting system identifies the stochastic demand expected for the flight tickets with different fares to support the decisions to control the capacity (compare Corsten and Stuhlmann, 1999). Cross (2001), Chapter 4, and Talluri and van Ryzin (2004b), Section 1.2.1 and 10.1, describe the historical development of revenue management in the U.S. airline industry.

Although the deregulation of the U.S. airline industry and the resulting price competition between the major airlines and the low-fare airlines caused an intensive development of revenue management techniques, airlines already used the revenue management instrument overbooking before the deregulation to increase their revenue (compare McGill and van Ryzin, 1999).

The briefly discussed revenue management instruments, namely segment-oriented price discrimination, capacity control, and overbooking and the forecasting system which supports the revenue management techniques, will be defined and described in detail in Section 2.2.2.

Smith et al. (1992) point out the successful development and application of the revenue management instruments at American Airlines. The potential of segment-orientated price differentiation and overbooking was already discovered before the Airline Deregulation Act of 1978. However, the advancement of the techniques and development of the capacity control instrument were necessary since the deregulation caused additional complexity in the application of revenue management concepts, e.g., attributable to an increased number and variety of discounted prices.

The application of revenue management instruments by American Airlines lead to an enormous revenue augmentation. American Airlines estimated an increase in revenue of approximately 1.4 billion dollars over a three-year period due to an effective revenue management application (compare Smith et al., 1992). This on the other hand caused that American Airlines crowded out low-cost carriers (e.g., PeopleExpress). As a consequence, revenue management techniques were adapted by airlines worldwide which also noticed increasing revenues without mentionable added costs (compare Klein, 2005, Section 1.1). Klophaus (1998) refers to the Deutsche Lufthansa AG which gained 1.4 billion Deutsche Mark additional revenue with the aid of revenue management in 1997.

Although the concept of revenue management was initially developed to solve problems of the airline industry, revenue management techniques can also be applied by other sectors of the service industry. After other service industry sectors noticed the increasing revenues of the airline industry and the applicability of the revenue management concept in their sectors, revenue management techniques were enhanced and adopted. Section 3.2 addresses the different service industry branches which apply revenue management instruments. The origins of revenue management are described in more detail by Boyd and Bilegan (2003) and Smith et al. (1992).

The successful implementation of revenue management techniques in practice caused an increasing theoretical research activity. Among the first publications dealing with revenue management are papers by Rothstein (1971, 1974) on airline and hotel overbooking and Littlewood (1972) presenting a capacity control approach. Boyd and Bilegan (2003), Cross (1995), McGill and van Ryzin (1999), Tscheulin and Lindenmeier (2003a), and Weatherford and Bodily (1992) present comprehensive reviews of revenue management research history with different primarily focuses. An overview of the most recent research on revenue management is given by Chiang et al. (2007) and Müller-Bungart (2006).

Specific conditions are needed to implement revenue management instruments in the airline industry as well as in other service sectors. These conditions will be presented in the following section as well as some revenue management definitions and the description of the revenue management instruments.

2.2 Theoretical Basics of Revenue Management

Revenue management is also called yield management by some authors (compare, e.g., Kimes, 1989; Netessine and Shumsky, 2002; Tscheulin and Lindenmeier, 2003a; Weatherford and Bodily, 1992). Belobaba (1987), Chapter 1, e.g., defines yield in the airline industry as average revenue gained by an airline per passenger and flown air mile. The term revenue management is predominant in practice and theoretical publications since the factor yield could reach its maximal value if only one single passenger books the observed flight. Therefore, the maximization of the yield factor is not a reasonable objective (compare Kimms and Klein, 2005; Weatherford and Bodily, 1992). The labeling revenue management can be ascribed to the goal of revenue maximization which is aspired by the application of revenue management instruments, e.g., in primary application areas such as the airline industry (compare Klein, 2005, Section 2.1.1).

There are numerous definitions for revenue management in literature which often focus on a specific application area or revenue management instrument. Corsten and Stuhlmann (1999) as well as Kimms and Klein (2005) list several specific and general definitions of revenue management given in relevant literature. They also compare the definitions balancing their assets and drawbacks. A general definition of revenue management is given by Klein (2001) describing revenue management as a management concept for efficiently using the capacity which is largely inflexible and only available in a limited period of time. Thereby, the concept contains quantitative methods for the decision about the acceptance or rejection of uncertain demand which arrives in different points in time and has different revenue values. This definition is taken as a basis for the present work which follows the definition in focusing on quantity-based revenue management. A differentiation between quantity-based and price-based revenue management will be given in the following paragraph.

The present work concentrates on the aim of revenue maximization by applying capacity control mechanisms for strategic alliances. This objective, however, is one of many which can be pursued by revenue management. Alternative objective targets of revenue management are described by Klein (2005), Section 2.2, and Weatherford and Bodily (1992).

A concept that is often mentioned in connection with revenue management is dynamic pricing, compare, e.g., Klein (2005), Section 2.3, and Talluri and van Ryzin (2004b), Chapter 5. Boyd and Bilegan (2003) and Bitran and Caldentey (2003) describe the relationship between revenue management and dynamic pricing: The company applying a dynamic pricing concept defines prices for offered goods and services and indirectly controls the capacity by price modifications. There is no predefined price for the goods and services, the prices are treated as variables. If the company adopts revenue management control, the company sets predefined prices for the goods and services for each customer segment by means of the segment-orientated price differentiation and allocates the capacity to customer segments by means of the revenue management instrument capacity control. If customers recognize different prices for the same service, it is not due to a variable price setting of the company but caused by a changing availability of capacity for the different customer segments. E.g., if an airline defines different booking classes based on the determined customer segments, the capacity that is available in one of the booking classes changes during the booking process due to the capacity usage of accepted requests. As soon as the available capacity is zero the respective booking class will be closed and, therefore, the price for a flight ticket in the closed booking class is no longer available.

There are several preconditions to implement a dynamic pricing concept such as the possibility to adjust prices without significant costs or other efforts and the existing freedom of action to fix the prices not well in advance (compare, e.g., Gallego and van Ryzin, 1994).

Talluri and van Ryzin (2004b), Section 5.1.1, differentiate between quantity-based revenue management and price-based revenue management where the former contains capacity control and overbooking and the latter includes the dynamic pricing concept and auctions. Although many authors share this differentiation (compare, e.g., Boyd and Bilegan, 2003 and Klein, 2005, Section 2.3), others, e.g., Elmaghraby and Keskinocak (2003) and Phillips (2005), Chapter 6, classify capacity control and overbooking as a special case of pricing with constrained supply. For a direct comparison of the revenue management instrument capacity control and the dynamic pricing concept compare Müller-Bungart (2006), Section 1.4.3. Auctions provide another way to dynamically adjust prices compared to dynamic pricing (compare Talluri and van Ryzin, 2004b, Section 6.1). However, applying auctions in revenue management is not a well-discussed topic. Chiang et al. (2007) lists a few publications which discuss auctions in the revenue management concept.

The present work focuses on capacity control mechanisms for strategic alliances and regards capacity control as marked-off from the dynamic pricing concept. For a broader overview of dynamic pricing, we refer to the relevant dynamic pricing literature presented, e.g., by Bitran and Caldentey (2003), Elmaghraby and Keskinocak (2003), as well as Talluri and van Ryzin (2004b), Chapter 5.

To successfully apply revenue management instruments, certain preconditions need to be fulfilled. These will be described in the following.

2.2.1 Characteristics of Revenue Management Problems

Revenue management can be successfully applied to situations which have certain common characteristics. Many publications in revenue management literature describe revenue management by defining these characteristic aspects since there is no short and concise revenue management definition as described before. Kimes (1989) lists the following defining characteristics which are similarly picked up by multiple other publications (compare, e.g., Friege, 1996; Klein, 2001; Talluri and van Ryzin, 2004b, Section 1.3.3; Tscheulin and Lindenmeier, 2003b; Weatherford, 1998; Weatherford and Bodily, 1992): relatively fixed capacity, ability to segment markets, perishable inventory, products sold in advance, fluctuating demand, and high marginal capacity change costs vs. low marginal sales costs. These characteristics will not be further discussed since they can be restructured. Corsten and Stuhlmann (1999) as well as Kimms and Klein (2005) present a different, more advanced categorization of characteristics. Among other improvements, additional factors concerning the successful application of revenue management are taken into account. For an elaborate discussion on the classification criteria and an extensive study of the literature concerning revenue management characteristics compare Kimms and Klein (2005). In the following, the four basic characteristical aspects, established by Corsten and Stuhlmann (1999) and Kimms and Klein (2005), will be described.

2.2.1.1 Requirement of External Factor Integration

The service provision necessitates the integration of an external factor, e.g., because the offered goods and services cannot be stored. The consumer of the goods and services needs to bring in the external factor to the creation process which is why the factor is called extern (compare, e.g., Müller-Bungart, 2006, Section 1.2). The integration of an external factor requires that the goods and services cannot be generated prior to their sale and, therefore, cannot be stored. It is essential to offer the goods and services prior to their creation and sales to induce the customers to provide the required external factors. To give an example: In the airline industry, the product transportation from location A to location B cannot be produced before the departure date of the aircraft. An unsold seat in the aircraft cabin expires and cannot be stored as soon as the aircraft lifts off. The flight tickets, however, are offered and usually purchased long before the departure date which induces and provokes the integration of the external factor by the passengers. The requirement to integrate an external factor is originally defined to be a characteristic aspect of service industries. Compare, e.g., Corsten and Stuhlmann (1997) and Fitzsimmons and Fitzsimmons (2006), Chapter 2, defining the customers as the inputs for services. According to Klein (2005), Section 2.1.2.2, and Müller-Bungart (2006), Section 1.2, the integration of external factors is also necessary in make-to-order manufacturing. In this sector, the production process cannot start prior to the specification of the order by the customer. The mutual characteristic of integrating external factors into the creation process describes one of the parallels between the service industries and the make-to-stock manufacturing sector. Compare the study in Kimms and Müller-Bungart (2003) in which the characteristics of problems requiring the application of revenue management instruments in the service sector are compared to the ones in the make-to-stock manufacturing industry.

2.2.1.2 Restricted Operational Flexibility of Capacity

The second characteristic enabling the efficient application of revenue management instruments is lacking capacity flexibility of the considered resource. Some authors, e.g., Kimes (2002) mention a relatively fixed capacity in this context. This imprecise declaration is criticized by Corsten and Stuhlmann (1999), Kimms and Klein (2005), and Weatherford and Bodily (1992). However, the capacity considered in revenue management application areas cannot be assumed as totally fixed since there are capacity adjustments possible in special situations. Consider, e.g, the airline industry. According to Kimms and Klein (2005), airlines can react to the respective demand to some extent, e.g., by changing the seating in the affected aircraft or by using aircrafts with different seat capacity. Despite this adjustment potential, airlines are often forced to reject requests due to an insufficient capacity that is not flexible enough to be adjusted to the demand. Corsten and Stuhlmann (1999) describe the capacity as lacking flexible (compare also Kimms and Klein, 2005). This means that the available capacity cannot be flexibly adapted to the variable demand in short-term. Thereby, the flexibility of the capacity is dependent on the amount of adjustment, the adjustment costs, and the time available to the adjustment (compare Klein, 2005, Section 2.1.2.3). Pursuing the airline example: If an airline recognizes during the booking process a demand on a specific flight that is higher than forecasted one, the airline cannot spontaneously switch the aircraft. The adjustment costs would be too high and the time available for the adjustment too short. To sum up: In situations which give rise to revenue management problems, the capacity cannot be adjusted in short-term due to technical or economical restrictions which shows the operational inflexibility of the capacity as pointed out by Müller-Bungart (2006), Section 1.2.

So far only capacity enlargements were considered. The limited operational flexibility of the capacity, however, additionally causes a restricted short-term reduction of capacity. The perishable inventory characteristic, mentioned in other publications, can be interpreted in the context of restricted capacity flexibility. The capacity can only be used in a specific period of time. After that period, unused capacity cannot be stored or sold anymore and, therefore, does not gain any income for the company (compare Netessine and Shumsky, 2002). As pointed out by Kimms and Klein (2005), the lacking possibility of short-term capacity reduction causes potential idle time costs in terms of lost benefits like rejected requests. E.g., an unsold seat in an aircraft expires with the aircraft's take off and cannot be stored afterward. This seat is not available and, therefore, cannot be sold by the airline in an aircraft operating a flight in the future. This characteristic induces some authors to refer to revenue management as Perishable-Asset Revenue Management (PARM) as proposed, e.g, by Weatherford and Bodily (1992).

Another characteristic, mentioned in prior publications, is related to the limited operational flexibility of the capacity: high marginal capacity change costs vs. low marginal sales costs. As mentioned above, the limited operational flexibility of the capacity is, among others, caused by the high expenses when providing additional capacity (compare Kimes, 1989). In the airline industry these fixed costs are, e.g, for maintenance of the aircrafts and hubs. Nevertheless, selling an additional unit of inventory and the resulting usage of the already available capacity provokes only low marginal sales costs as pointed out by Kimms and Klein (2005). In the airline industry, these marginal sales costs are, e.g., costs for the passenger's catering on board and the costs for handling the passenger, arising during the passenger transport. Revenue management instruments can be applied to situations in which this characteristic is missing.

2.2.1.3 Heterogeneous Demand Behavior

The consumers prefer different points in time for their purchases. The amount of the service and the individual willingness to pay also varies. These circumstances allow for market segmentation into different types of customers.

For the application of revenue management, the different points in time for purchases represent an important condition. According to Kimms and Klein (2005), the purchase of the product in different points in time can be dependent on the customer's level of information or the customer's need for planning reliability. Kimes (1989) gives an example: Time-sensitive and price-sensitive customers are differentiated in the airline industry, distinguishing business from leisure travelers. Business travelers are more time-sensitive and have a higher willingness to pay, which can be capitalized by the airlines. A more detailed discussion concerning the market segmentation and price differentiation will be given in Section 2.2.2.1, describing the revenue management instrument segment-orientated price differentiation. If the customers' preferences in terms of the point in time of their purchase are not diverse, there is no decision about accepting a request or reserving the capacity for customers with a higher willingness to pay arriving in the future. This decision, however, describes the main problem which can be solved applying the revenue management instrument capacity control. Assuming consumers with different willingness to pay but equal preference to purchase the goods and services at the same point in time, there are procedures that are more efficient than the revenue management concept such as auctions (compare Kimms and Klein, 2005). For an introduction to general aspects concerning the design of auctions compare, e.g., McAfee and McMillan (1987) and Milgrom (1989). Caldentey and Vulcano (2007) and Vulcano et al. (2002) describe auctions in the context of revenue management.

According to Weatherford and Bodily (1992), there is another way to segment customers. In this practice, the business generated by the customer represents the segmentation basis, whereas the selling company offers larger discounts to customers with a higher demand. This quantity discounting is classified to be a marketing tool apart from revenue management by Weatherford and Bodily (1992). However, according to Kimms and Klein (2005), a varying amount of inquired goods and services can generate different valuations of demand which is why this aspect should be considered applying revenue management instruments. Considering, e.g., the cargo transportation sector with its quantity discounts and bonus programs. If the available capacity is less than the total incoming demand, a differing valuation of demand could be the result of a differing scope of services assuming constant prices for each requested unit of goods and services. E.g., considering a hotel, accepting a request for an one-night accommodation could inhibit that the hotel room will be booked for an entire week.

The differing willingness to pay of the customers for an identical service is another condition for applying revenue management. The possibility to sell the same goods and services charging different prices in the same market segments results from such differences. As pointed out in Kimms and Klein (2005), the supplier can generate additional requests by lowering the prices and eliminating or shifting demand to resources with left over capacity by increasing the prices. If the demand of all customers would be homogeneous in valuations, there would not be a need for the laborious capacity control. Müller-Bungart (2006), Section 1.2, suggests in this case to accept the incoming requests in a first-come-first-served manner until there is no capacity left. In most sectors, the application of revenue management instruments is essentially motivated by the potential revenue augmentation due to capitalizing the different customers' willingness to pay.

Another characteristic in this context is the existence of varying and uncertain demand. The total demand for the offered goods and services as well as the distribution of incoming requests and the inquired amount is assumed to be non-constant and uncertain, as pointed out by Klein (2001) and Stuhlmann (1999). Although, this stochastic demand characteristic is not a required condition for revenue management application, it highly affects the design of the revenue management instruments, especially capacity control (compare Kimms and Klein, 2005).

2.2.1.4 Standardized Products

In a standardized product range, the scope of services of the products is fixed and well defined and the products are offered for a long period of time. In the airline industry, a product is a combination of a flight from A to B and the booking class offered on the respective flight (compare Müller-Bungart, 2006, Section 1.2). Assuming the characterization of standardized products guarantees two conditions for the application of revenue management. On the one hand, the revenue management instruments segment-orientated price differentiation and capacity control are based on a standardized product range (compare Kimms and Klein, 2005). On the other hand, the expected demand for the different products can only be adequately predicted if the product's attributes are given and fixed. In this case, the continuity of the goods and services within the product range is given which is necessary for the identification of the data base required for the forecast. The effective application of all revenue management instruments is supported by a proper forecast of the customers' willingness to pay and demand behavior, as according to Harris and Pinder (1995).

2.2.2 Revenue Management Instruments

In sectors, in which the aforementioned characteristics and conditions apply, the main object of revenue management is to provide instruments for an effective capacity arrangement and utilization. The revenue management instruments: segment-orientated price differentiation, overbooking, and capacity control will be described in the next sections, following the remarks by Kimms and Klein (2005), considering the forecasting as foundation for the application of revenue management instruments. Since the main focus of this work lies in the conception of capacity control mechanisms for strategic alliances, the description of the revenue management instrument capacity control is emphasized. The product mix is assumed to be well defined when applying the revenue management instruments. In the airline industry, the product mix of an airline defines the air connections offered by the airline with start and destination airports as well as day of departure and departure time. Furthermore, the capacity available for the company and the capacity utilization are assumed to be specified. This corresponds to the allocation of a particular type of aircraft with preexisting capacity to each air connection in the airline industry. Due to these assumptions, the strategical-tactical planning level covering the definition of the product mix and the capacity strategy of the corporation does not need to be carried out within the revenue management concept. Kimms and Klein (2005) as well as Klein (2005), Section 2.2.1, elaborately describe the different planning levels, their correlation, the planning tools arranged, and the objectives pursued on the planning levels. The revenue management instruments described in this section are considered on the tactical-operative planning level.

The forecast, in the context of revenue management, will not be considered as an autonomous revenue management instrument. In fact, forecasting is a component of the other instruments and satisfies diverse functions depending on the revenue management instrument for which the forecast should provide crucial information. According to Chiang et al. (2007), the quality of decisions, made in segment-orientated price differentiation, capacity control, or overbooking, depends on a precise forecast. To apply the segment-orientated price differentiation, forecasting needs to determine appropriate criteria for segmentation and the customer's willingness to pay, according to Kimms and Klein (2005). To give an example: In the airline industry, the airline needs to decide in which segments the passengers will be partitioned. Additionally, the fares customers are willing to pay for a seat on an air connection need to be estimated to implement the segment-orientated price differentiation. The capacity control instrument depends on the prediction of the expected development of the demand for single products. Weatherford and Belobaba (2002) discuss some commonly used heuristic decision rules for seat allocation in capacity control and examine the impact of errors in the willingness to pay forecasts and demand predictions on their revenue performance. The authors state that in airline revenue management the predicted fare value associated with a booking class and the demand forecasted for a fare class on an arranged future flight are critical inputs to any capacity control seat allocation model. For applying the overbooking instrument, additionally to the identification of the expected demand, the amount of cancellations and no-shows needs to be forecasted as precisely as possible (compare McGill and van Ryzin, 1999). Though, a forecast is often difficult due to an unavailable or obsolete data set. Additionally, the future consumer behavior is often poorly predictable since the passengers have multiple behavioral alternatives that are changing in the course of time, especially in the airline sector. As pointed out by McGill and van Ryzin (1999) several thousand price changes reported per day in the U.S. domestic airline industry complicate the forecast. In the publication of Chiang et al. (2007), this dynamic nature of situations in which revenue management instruments are applied, is held responsible for challenging the demand forecast. In the airline industry, the demand forecast is hindered additionally to the various price changes, e.g, by unpredictable changes of flight schedules. There is another challenge occurring: If the determination of data for the demand prediction is based on a historical set, the demand observed in the past, e.g., for an air connection, does not reflect the actual demand. In fact, it corresponds to the amount of bookings and underestimates the actual demand. Since there are no incoming requests for the offered products after closing the booking period, the actual demand cannot be identified by historical information (compare Boyd and Bilegan, 2003). The process of generating true demand history from sales history is called unconstraining. As pointed out by Boyd and Bilegan (2003), unconstraining, which is not unique to revenue management (compare, e.g., Hartley and Hocking, 1971; Little, 1982; Tobin, 1958), has proven to be the most popular technique to account for censored historical data. For elaborate remarks on this technique in the context of revenue management compare McGill (1995), Talluri and van Ryzin (2004b), Section 9.4, and Zeni (2001), Section 2.8. In the simulation models included in the capacity control mechanism proposed in the present work, the demand forecast will not be observed. The demand distribution adopted in the simulation models is implied as already determined by a suitable forecast. Section 4.2.4 covers the discussion concerning a proper choice of demand distribution in this context and the description of simulation models. According to Chiang et al. (2007), all revenue management forecasting tasks need to treat several issues such as the determination of what needs to be forecasted, the choice of the forecasting method, the choice of which data to use, and the definition of the aggregation level and accuracy of the forecast. The references revealed in the following, illustrate diverse forecasting methods applied in revenue management. Beckmann and Bobkoski (1958) compare several frequency distributions of the booking request arrivals in the airline industry. The models introduced by Littlewood (1972) describe a demand estimation including cancellations. Gallego and van Ryzin (1994), Lee and Hersh (1993), and Subramanian et al. (1999) present stochastic processes that model booking requests during the booking process. Boyd and Bilegan (2003), McGill and van Ryzin (1999), Talluri and van Ryzin (2004b), Chapter 9, as well as Zeni (2001), Chapter 2, elaborately describe the varying application of forecasting methods and give an extensive overview of forecasting literature. Boyd and Bilegan (2003) additionally define two forecasting approaches specialized for airlines operating in flight networks.

Several of the revenue management instruments specified in the following paragraphs influence other instruments if they are adopted. For instance, a simultaneous application of segment-orientated price differentiation and capacity control should be preferred. However, in theory and practical experience the simultaneous implementation of the instruments turned out to be too complex. Therefore, most authors and practitioners choose a step-by-step approach. The segment-orientated price differentiation problem is solved first and subsequently the capacity control problem with prices that were determined in the segment-orientated price differentiation follows (compare Kimms and Müller-Bungart, 2003). The segment-orientated price differentiation represents the basis for capacity control (compare Kimms and Klein, 2005). Similarly, the instruments overbooking and capacity control should be adopted simultaneously since the overbooking influences the capacity control. This as well is often not possible due to complexity reasons. Therefore, in most applications, the overbooking level is determined first. Afterwards, the capacity control is implemented on basis of the information gained by solving the overbooking problem (compare Kimms and Klein, 2005).

2.2.2.1 Segment-Orientated Price Differentiation

Segment-orientated price differentiation is essential for application of the revenue management concept. It can be described as fragmentation of the total market into several segments based on customers willing to pay different prices for the product and the isolated pricing of the different segments. In some publications, the segment-orientated price differentiation is presented as basic concept respectively starting point of revenue management rather than as instrument which emphasizes this indispensability (compare Pak (2005), Section 2.2.2, Pak and Piersma (2002), Wiggershaus (2008), Section 3.1.1). The total potential opportunity for profit improvement from price differentiation, established in the field of microeconomics, reaches from the profit the corporation gains by charging a single price for the offered product up to charging each potential customer exactly what the customer is willing to pay. The second procedure is called perfect price differentiation (compare Varian, 1999, Chapter 25). Segmenting the market and charging different prices in the segments for equal or only slightly differing products enables for a skimming of the consumer's surplus which gains profit improvements. Consider, e.g., airlines: Airlines try to smooth the demand by means of segment-orientated price differentiation to use the seat capacity offered in the classes of carriage on the operated flights to full capacity. Klein (2005), Section 3.1.3.1, differentiates between carriage classes and booking classes. A class of carriage is a spatial separated area in the cabin of an aircraft, whereupon the carriage classes differ for the purpose of a product differentiation, e.g., via different service features. The implementation of carriage classes induces the segmentation of consumers. The price differentiation is achieved by assigning different booking classes to each class of carriage. Furthermore, individual rates are assigned to each booking class. Segmenting the passengers into several groups due to their willingness to pay and assigning the groups to defined booking classes with individual ticket rates enables the airline to sell identical seats at divergent prices. Consequently, flight tickets can be sold to low-willingness-to-pay customers to attract passengers that would not pay higher prices to fill up the unsold seat capacity and generate profit improvements. There are several criteria that can be applied for segmenting a market as pointed out in Faßnacht (1996), Section 4.2, as well as Homburg and Krohmer (2009), Section 12.3.1.2.2. Corporations could charge different prices at different points in time. Applying a time-dependent price differentiation implies that the price for a flight ticket that is sold by an airline for seats in an aircraft depends on the time of sale during the booking process (compare Pak and Piersma, 2002). To obtain the mentioned profit improvements, an appropriate market segmentation and sophisticated restrictions to effectively seal off the market segments are required. In Section 4.5.3, Phillips (2005) describes how to find the best segmentation and names the conditions which need to be existent to apply segment-orientated price differentiation. Phillips (2005), Section 4.2, also describes the mentioned restrictions, also referred to as rules or booking fences (compare McGill and van Ryzin, 1999), which are necessary to prevent cannibalization or arbitrage. The demand cannibalization effect appears if customers in high-price segments find a way to pay the lower price. In the airline industry high-willingness-to-pay customers (e.g., business travelers) could purchase discounted tickets under certain circumstances (compare Smith et al., 1992). Arbitrage is another limit to price differentiation. It appears if a third-party finds a way to buy the products in a segment with lower prices and resells them below the market price in another segment to high-willingness-to-pay customers (compare Phillips, 2005, Section 4.2). To provide a proper fencing of the segments, airlines often attach at least one condition to the discounted fares such as linking the purchase of a discounted ticket to a minimum stay of four days at the destination. Since business travelers cannot fulfill this restriction most of the time, these high-willingness-to-pay customers access the higher priced tickets. Furthermore, the airlines prohibit a ticket transfer to other passengers to prevent a circumvention of the airline's efforts to increase revenue by segment-orientated price differentiation (compare Kimms and Müller-Bungart, 2003). Further remarks on the revenue management instrument segment-orientated price differentiation are to be found amongst others in Anjos et al. (2004), Botimer (1996), Botimer and Belobaba (1999), Faßnacht and Homburg (1997), and Klein (2005), Section 3.1.

The capacity control mechanism for strategic alliances presented in this work requires predefined prices for the considered products to calculate the control variables. These prices, which correspond to the revenue the corporations gain by selling the products, need to be determined by a segment-orientated price differentiation prior to capacity control.

2.2.2.2 Overbooking

In addition to variable demand, full capacity utilization is hindered since not every accepted request leads to an occupied capacity unit and corresponding revenue. In the airline industry, this phenomenon occurs since bookings made by passengers can be canceled in the course of the booking period. Additionally, so called no-shows can emerge, where passengers with valid reservations do not show up shortly before the departure of the aircraft without cancellation (compare Kimms and Klein, 2005). Klophaus (1998) states that the Deutsche Lufthansa AG was exposed to more than four million no-shows in 1997, which shows the potential of overbooking. The cancellation and no-show phenomenons also arise in other application areas such as the car rental industry and hotel sector. The capacity reserved for the canceled requests and no-show passengers is not gainfully used which causes that the company runs the risk to face opportunity costs based on the loss of potential profit (Dunleavy, 1995). To face this difficulty, the resources are overbooked beyond the actual existent capacity. Considering airlines, the objective of overbooking is to identify how many bookings will be accepted beyond the existent capacity for each class of carriage on each flight. Basically, the overbooking limit should be defined so that full capacity utilization can be realized without any denied boardings at the departure of the aircraft (compare Klein, 2001). Denied boardings describe the rejection of passengers with valid reservations. The rejection is necessary if, due to overbooking, more passengers with valid reservations show up at flight time than seats are available in the class of carriage on the air connection (compare McGill and van Ryzin, 1999). There is also the possibility of upgrading or downgrading, which means that the passenger is seated in another class of carriage than the class the passenger previously booked. If this is not possible, the airline could search, e.g., by means of auctions (compare Rothstein, 1985) for passengers who agree to switch to a later flight for compensation. These possibilities should be checked by the company previous to a denied service decision, since the degree of dissatisfaction of the passengers and customers in general can be quite significant if the company denies the service. Additionally, denied boardings can lead to costs that accrue, e.g., from compensation payments the airline needs to pay to the rejected passengers. These costs need to be traded off against the additional expected revenue arising from the overbooking and thereby prevented idle capacity (compare Chatwin, 1998). Since there are application areas in which overbooking plays a minor role or is even irrelevant, overbooking is, compared to segment-orientated price differentiation and capacity control, not a general revenue management instrument (compare Klein, 2005, Section 3.3.1). E.g., overbooking methods are of little importance for the make-to-order manufacturing sector, according to Rehkopf (2006), Section 3.3.2, and Wiggershaus (2008), Section 3.4.

The following references discuss approaches for solving the overbooking problem. Littlewood (1972) presents a static decision model to determine the overbooking limit for a limited seat capacity on non-stop flights. In a static model, the overbooking limit is determined without the consideration of incoming bookings or cancellations during the booking period (compare Klein, 2005, Section 3.3.2.1). Further static overbooking models to control the seat capacity of carriage classes are pointed out by Coughlan (1999) as well as Shlifer and Vardi (1975). Stochastic dynamic models for overbooking seat capacity on a non-stop flight are described by Chatwin (1998) and Rothstein (1971). Dynamic models adjust the overbooking limit whenever a request comes in based on the current booking data or forecasts for possible cancellations and no-shows (compare Klein, 2005, Section 3.3.2.1). Aydin et al. (2010) propose new static and dynamic models for single-leg overbooking problems. Chiang et al. (2007) and McGill and van Ryzin (1999) present an extensive list of publications in overbooking.

In the capacity control approaches introduced in this work overbooking is not considered. It is assumed that the given capacity contains the overbooking limit (if necessary) which is determined based on the forecast of cancellations and no-shows. Alternatively, the overbooking and capacity control could be applied simultaneously (compare, e.g., Hersh and Ladany, 1978; Ladany and Bedi, 1977; Subramanian et al., 1999; Zhao and Zheng, 2001). However, in most applications, simultaneous use of overbooking and capacity control is not realizable which is why capacity control is often implemented after the overbooking level was determined based on the information from overbooking.

2.2.2.3 Capacity Control

By applying a capacity control mechanism, the capacity of a single resource or a bundle of different resources is allocated to different market segments or demand classes in order to maximize the expected revenue (compare Chiang et al., 2007). To maximize the revenue of a future flight in the airline industry, the limited capacity available in an aircraft is allocated to different booking classes by means of capacity control (compare Tscheulin and Lindenmeier, 2003a). The instrument capacity control is regarded as the most important new development associated with the revenue management concept and is, therefore, appreciated as primary instrument and core element (compare, e.g., Kimms and Klein, 2005; Pak and Piersma, 2002). In addition to the term capacity control, there are other names in anglophone literature: discount seat allocation (compare, e.g., Smith et al., 1992), passenger mix (compare, e.g., Glover et al., 1982), seat allocation (compare, e.g., Andersson, 1998; Brumelle and McGill, 1993), seat inventory control (compare, e.g., Pak, 2005), and seat management (compare, e.g., Wollmer, 1992). Since the procedures developed in this work are capacity control policies for companies within strategic alliances, the capacity control instrument is described in more detail, especially the basic concepts underlying the newly developed procedures.

Analyzing the capacity control instrument, it is important to differentiate between mathematical optimization methods and control methodologies. In the first step of capacity control, the optimization, varying methods can be used to determine the so called control variables which define the allocation of capacity to different products. The control variables arrange the allocation of seats to the different booking classes on the considered flights in the airline industry (compare Williamson, 1992, Section 4.2). Booking limits, protection levels, and bid prices are so called control variables (compare Müller-Bungart, 2006, Section 2.1) which will be illustrated in the following paragraphs. In the second step of capacity control, control methodologies are adopted to manage the compliance of the capacity allocation by means of control variables determined in the optimization step. To maximize the revenue by managing the capacity, the actual capacity control is just as important as the optimizing process (compare Williamson, 1992, Section 4.2).

Klein (2005), Section 3.2.1.5, describes assumptions underlying the basic capacity control models for both single-resource capacity control and network capacity control. Applying a single-resource capacity control in the airline sector, only single-leg flights can be considered while network capacity control allows for the consideration of multiple flight legs which need to be considered jointly, so called flight networks. The first assumption defines that the stochastic demand for the products is independent and that there are available forecast values indicating the expected, uncertain demand. Additionally, it is assumed that the demand for the different products remains constant even if the capacity control decisions cause that one of the products is not longer available for booking requests. The assumption that the incoming booking requests are all requests for a single capacity unit, e.g., a single seat in the aircraft, allows for incoming group requests which, however, is considered as sequence of single bookings. Furthermore, cancellations and no-shows are assumed to be non-existent which is why an integrated capacity control and overbooking policy is not required. Another assumption supposes that the prices of the products, in the airline industry the flight ticket prices, cannot be adapted to changing basic conditions during the booking process. Moreover, the sale of tickets for products which underly a product differentiation is separately controlled. Passengers in the airline industry, e.g., cannot be upgraded from a class of carriage with lower ticket prices to another carriage class with higher ticket prices to fulfill the high demand for the considered class of carriage with lower ticket prices, even if in consequence of a low demand for the carriage class with higher ticket prices seats remain free in that class. Finally, it is assumed that there is no competition between companies so that the capacity control cannot cause a migration of consumers between the competitors. Other publications, compare, e.g., McGill and van Ryzin (1999) and Talluri and van Ryzin (2004b), Section 2.2, list assumptions that are similarly grouped as in Klein (2005), Section 3.2.1.5. The discussed assumptions are adopted also in the capacity control mechanisms demonstrated in this work.
The optimization approaches for single-resource and network capacity control problems can be differentiated in static and dynamic approaches. Both, static and dynamic approaches, imply the aforementioned assumptions. Static approaches, however, assume an additional specification: The requests for the different products arrive in delimited, non-overlapping intervals and the requests from low-willingness-to-pay segments arrive preliminary to requests from the customers with high-willingness-to-pay which is why the assumption is often called low-to-high-revenue order principle. Dynamic models, however, relax this assumption. They permit an arbitrary arrival order of incoming requests for the different products (compare Talluri and van Ryzin, 2004b, Section 2.2 and Section 2.5).

The capacity control policies can be carried out in different modes. There are booking limit controls, bid price controls, and control policies based on stochastic dynamic optimization (compare Klein, 2005, Section 3.2.1.3). However, as stated by Klein (2005), Section 3.2.1.3, the booking limit control and bid price control are the basic types of capacity control policies. The approaches based on stochastic dynamic optimization are not practice-orientated so far due to the computing time associated with their application. As mentioned before, the problem which necessitates the application of capacity control is linked to the different valuations of demand ascribed to the price differentiation. There could be a loss in sales if the capacity available for the corporation is less than required to handle the total demand and if the demand for the different price segments arises in diverse points in time. There can be a crowding out of sales, assuming that the demand from customers with low-willingness-to-pay arrives at first and the company needs to decide fast about accepting or rejecting the request and, therefore, tends to accept all incoming requests as long as capacity is available (compare Domschke et al., 2005; Friege, 1996; Kimms and Müller-Bungart, 2006). Once the capacity is occupied by customers in the low-willingness-to-pay segment, it cannot be sold to customers willing to pay a higher price arriving later in the booking process. On the other hand, there is a chance of loss in sales and idle time costs if the low-willingness-to-pay customers will be rejected and the customers in the high-willingness-to-pay segment turn out to be fewer than expected. In this scenario, unused capacity will be left over (compare Tscheulin and Lindenmeier, 2003b). To avoid these kinds of losses, the booking limit capacity control compares the capacity units sold for a product until the considered point in time with a given reference value, the booking limit or protection level of the respective products to decide about the acceptance or rejection of incoming requests in order to maximize the expected benefit. Thus, a certain number of capacity units is protected for the customers purchasing the higher priced product from the access of customers willing to pay less but arriving prior in the booking process. The bid price control policy is based on the comparison of the revenue generated by accepting a customer request for a certain product and a bottom price. A bid price describes such a bottom price (compare Klein, 2005, Section 3.2.1.3).

Single-Resource Capacity Control

In booking limit capacity control policy, the available capacity is allocated to the different market segments prior to the booking process. A booking limit control policy confines the capacity which can be sold to a specific market segment (compare Harris and Pinder, 1995). Considering airlines, a booking limit for a particular booking class shows the number of passengers to accept in this booking class and, therefore, the number of seats that are authorized for sale to the booking class (compare Pak, 2005). The single-resource capacity control problem would be trivial if all high fare passengers book before the passengers with low-willingness-to-pay. In this case, the requests could be accepted in order of arrival (in a first-come-first-served manner) until the total capacity of the resource is reached or until there is no future demand, respectively (compare Williamson, 1992, Section 2.1). In the following, the booking limit of product $j = 1, ..., n$ is denoted as b_j. The booking limits are assumed to be nonnegative ($b_j \geq 0$). Booking limits are either partitioned or nested (compare Talluri and van Ryzin, 2004b, Section 2.1.1.1). Partitioned booking limits describe the maximal amount of capacity which is exclusively reserved for the requests for a particular product. There is an optimal capacity control with underlying partitioned booking limits if the demand is certainly known (compare Kimms and Klein, 2005). The available total capacity is partitioned in separate blocks, also called buckets, to determine the partitioned booking limits. The sum of the partitioned booking limits equals the total available capacity which is denoted by C:

$$\sum_{j=1}^{n} b_j = C$$

Every booking limit b_j corresponds to a protection level p_j. A protection level specifies the amount of capacity which is reserved (protected) for a particular product or a group of products and which is exclusively available to these products. Protection levels can be partitioned or nested as well, whereupon the partitioned protection level of a certain product j matches the partitioned booking limit of product j (compare Talluri and van Ryzin, 2004b, Section 2.1.1.2). This correlation is presented in Figure 2.1.

We do not consider group arrivals in the following and, therefore, assume that every incoming request asks for one capacity unit. A booking request for product j is accepted if the amount of requests already

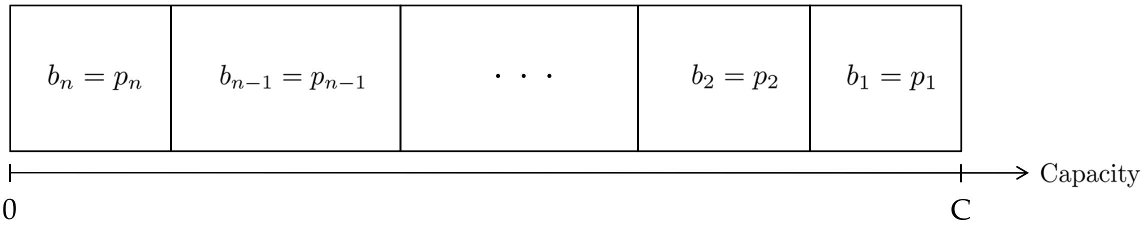

Figure 2.1: Partitioned Booking Limits and Protection Levels (compare Lee and Hersh, 1993)

accepted for product j, h_j, plus the incoming request is less than or equal to the booking limit for the considered product ($h_j + 1 \leq b_j$, for all $j = 1, ..., n$), respectively the protection level for product j ($h_j + 1 \leq p_j$, for all $j = 1, ..., n$).

Partitioned booking limits for a single resource can be determined by means of the following deterministic linear program, presented, e.g., by Bertsimas and Popescu (2003), de Boer et al. (2002), Williamson (1992), Section 4.1, for network capacity control assuming several resources. Let $v_j > 0$ be the revenue the company gains when accepting a booking for product j with $v_1 \geq v_2 \geq ... \geq v_n$. $E[d_j] > 0$ denotes the expected demand for product j.

$$\max \sum_{j=1}^{n} v_j b_j \tag{2.1}$$

subject to

$$b_j \leq E[d_j] \qquad j = 1, ..., n \tag{2.2}$$

$$\sum_{j=1}^{n} b_j \leq C \tag{2.3}$$

$$b_j \geq 0 \qquad j = 1, ..., n \tag{2.4}$$

The objective function (2.1) maximizes the revenue over all booking classes. The condition (2.2) ensures that the booking limits of the single products must not exceed the expected demand for the respective product. Additionally, the partitioned booking limits need to be determined so that the total available capacity is not exceeded (2.3). The booking limits of the booking classes are greater than or equal to zero (2.4).

The models developed in this work to calculate partitioned booking limits for the partners within a strategic alliance are based on the deterministic linear program described above. However, there are other models for booking limit calculations described in literature. E.g., Kimms and Müller-Bungart (2003) present a non-linear probabilistic model with underlying probability distributions assumed to be given for the quantity demanded for the different products. A linear probabilistic model for partitioned booking limit calculation, which is the linear equivalent to the model described by Kimms and Müller-Bungart (2003), is formulated by Müller-Bungart (2006), Section 2.2.1.

According to Talluri and van Ryzin (2004b), partitioned booking limit controls possess methodical drawbacks if the demand is stochastically variable as it is often the case in reality. If there are requests beyond the booking limits of the more profitable products, the additional booking requests for these products are declined even if there are still capacity units available. This can lead to loss of revenue. In a nested booking limit control, capacity allocated to the least profitable products is made available to more profitable products as well (compare McGill and van Ryzin, 1999). Lee and Hersh (1993) specify that nested booking limits can also be described as nested protection levels. As pointed out by Talluri and van Ryzin (2004b), Section 2.1.1.2, nested protection levels are defined as the capacity which is protected for the products $j, j-1, ..., j=1$ from the access of the lower yielding products. Whereupon $j=1$ equals the highest yielding product as defined before. The nested protection levels as well as the nested booking limits are defined for a set of products which is hierarchically arranged in a proper order. The principle of nested booking limits and protection levels by Talluri and van Ryzin (2004b), Section 2.1.1.1 and Section 2.1.1.2, is illustrated in Figure 2.2.

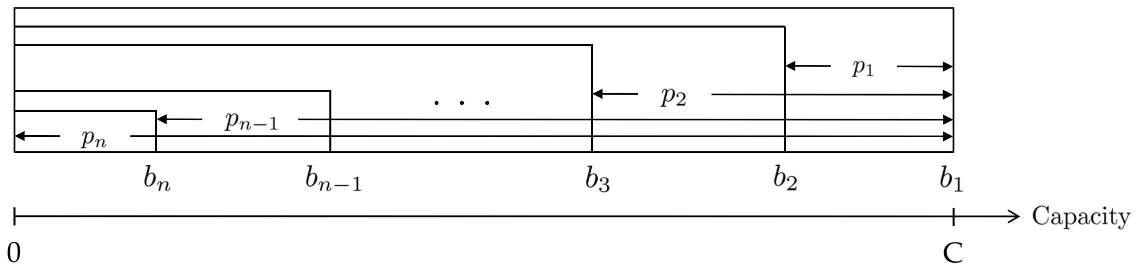

Figure 2.2: Nested Booking Limits and Protection Levels

The nested booking limit b_1 for the highest yielding product is equal to the total capacity ($b_1 = C$) just as the nested protection level p_n which represents the capacity protected for all products $j = 1, j = 2, ..., n$ ($p_n = C$). For the nested booking limits of the products $j = 2, ..., n$ counts: The nested booking limit for product j is equal to the difference between the total capacity and nested protection level of product $j-1$ ($b_j = C - p_{j-1}$, for all $j = 2, ..., n$). The characteristic of the nested booking limits and protection levels compared to the total capacity can be demonstrated as follows:

$$C = \begin{cases} b_j & j = 1 \\ b_j + p_{j-1} & j = 2, ..., n. \end{cases}$$

A nested booking limit of a particular product j is equal to the sum of the partitioned booking limit of that product and the partitioned booking limits of all lower yielding products (compare Klein, 2005, Section 3.2.1.3). The nesting order, which indicates the ranking of products according to their valency, needs to be declared if nested control variables are applied. A permutation of the products is specified so that product j is higher yielding than product k if $j < k$. The nesting order defines that product j can access the capacity reserved or protected for product k if product j is higher yielding than product k (compare Müller-Bungart, 2006, Section 2.2.2). Considering the single-resource capacity control, the identification of the nesting order is trivial if there are no group bookings allowed. Since, without loss of generality, for all products $j \neq k$ can be assumed that $v_j \neq v_k$, the nesting order is defined as $j < k$ if product j is higher yielding than product k, thus, the revenue gained by selling product j is higher than the revenue for selling product k ($v_j > v_k$). The determination of a nesting order is more complicated if there are multiple resources that need to be considered (network capacity control), if group bookings requesting different amounts of capacity units cannot be partially accepted, and if a customer choice behavior needs to be considered (compare Lee and Hersh, 1993; Talluri and van Ryzin, 2004a). Controlling the capacity by nested booking limits, a booking request for product j is accepted if the sum of requests accepted so far for product j and all lower yielding products is smaller than booking limit b_j of product j (compare Talluri and van Ryzin, 2004b, Section 2.1.1.3). Therefore, a booking request for product j is accepted if

$$\sum_{i=j}^{n} h_i + 1 \leq b_j, \quad \text{for all} \quad j = 1, ..., n.$$

Otherwise the request is rejected (compare Lee and Hersh, 1993). If this condition is satisfied, the total capacity is not exceeded since the booking limit of product $j = 1$ characterizes the total capacity. To guarantee that this condition is valid during the entire booking period, the respective nested booking limits need to be decreased after accepting a request for a particular product. If nested booking limits would be handled such as partitioned booking limits, which do not need to be updated after accepting a request, the total capacity could not be adhered to or, with a respective demand for higher yielding products, there would not be capacity left for these from a certain point in time in the booking period (compare Müller-Bungart, 2006, Section 2.2.2). Nested protection levels need to be updated as well after accepting a booking request when controlling the capacity with these control variables. Standard nesting and theft nesting are two methods which can be applied to update nested booking limits, respectively nested protection levels, to execute the capacity control (compare Bertsimas and de Boer, 2005; Talluri and van Ryzin, 2004b, Section 2.1.1.3). In both procedures, the available capacity needs to be decreased by one after accepting a booking request. Therefore, if the q-th request for product j is accepted, the capacity available for request $q + 1$, c^q, is updated by means of the following rule (compare Müller-Bungart, 2006, Section 2.2.2):

$$c^q = c^{q-1} - 1. \tag{2.5}$$

In 2.5, c is denoted as c^q to avoid confusion. The total capacity C corresponds to c^0, the available capacity in the booking process when none of the requests for the products is accepted. In standard nesting control, after accepting a booking request q for booking class k, the booking limit of the requested booking class is reduced by one, as well as the booking limits of all booking classes that are higher yielding than booking class k (neglecting group bookings). The decreased booking limits need to be non-negative in the standard nesting control ($b_j \geq 0$). This condition is fulfilled since the booking limits of the lower nested booking classes are not reduced when accepting a request for a higher nested booking class. Recall, a nested booking limit of any booking class is always higher than the nested booking limits of all lower nested booking classes. However, the booking limits of the higher nested classes need to be higher than or equal to the booking limits of the respective lower nested booking classes after the reduction of the booking limits. To guarantee this condition, the booking limit for the respective lower nested booking classes is updated after the acceptance of a request for class k by setting the booking limits of all lower nested classes equal to the smaller value of the values: the decreased booking limit for the higher nested class b_k^q or the unchanged booking limit for the considered lower nested class b_j^{q-1} (compare Müller-Bungart, 2006, Section 2.2.2). Accepting a request q for booking class k, the booking limits are updated so that

$$b_j^q = \begin{cases} b_j^{q-1} - 1 & j \geq k \\ min\{b_j^{q-1}, b_k^q\} & j < k \end{cases} \qquad j = 1, ..., n. \tag{2.6}$$

In 2.6, b_j is denoted as b_j^q to avoid confusion. The case differentiation in 2.6 is introduced by Müller-Bungart (2006), Section 2.2.2, following the description of Klein (2005), Section 4.3.2.3. In theft nesting control, after accepting a booking request q for booking class k, the booking limit of all booking classes $j = 1, ..., n$ is reduced by one (compare Talluri and van Ryzin, 2004b, Section 2.1.1.3). Consequently, the acceptance of a request for booking class k not only decrements the capacity allocated to booking class k, but also steals capacity units allocated to booking classes that are lower nested than booking class k, even if the capacity allocated to booking class k is still unexhausted. Controlling the capacity by booking limits in the theft nesting approach, it needs to be ensured that the booking limits are non-negative, contrary to the procedure in standard nesting. Accepting a request q for booking class k the booking limits are updated so that

$$b_j^q = max\{0, b_j^{q-1} - 1\}, \quad \text{for all } j = 1, ..., n.$$

When applying a protection limit capacity control, the protection levels also need to be revised after accepting requests. Talluri and van Ryzin (2004b), Section 2.1.1.3 illustrate the procedure in standard and theft nesting considering protection levels.

Other possible control variables underlying capacity control policies are the aforementioned bid-prices. A bid-price represents a minimum price that the company wants to achieve selling a product (compare Boyd and Bilegan, 2003). According to McGill and van Ryzin (1999), some authors refer to bid-prices as minimum acceptable fares, probabilistic shadow prices, displacement costs, or probabilistic dual costs. Considering a single-resource capacity control policy, the bid-price is equal to the price of the lowest nested product for which a positive contingent of capacity units has been allocated (compare Klein, 2005, Section 3.2.1.3). A booking request q for product j is accepted if sufficient capacity units are available and the acceptance of the booking request yields a revenue v_j that is at least equal to the bid-price π_j. Otherwise the request is rejected (compare Talluri and van Ryzin, 2004b, Section 2.1.1.4). In the aviation industry, the airline accepts an incoming request if the remaining seat capacity is greater than zero and the revenue, the airline gains by accepting the booking request, is greater than or equal to the bid-price. Contrary to the calculation of booking limits and protection levels, only one control variable for each resource needs to be determined when calculating the bid-prices underlying the capacity control (compare Pak, 2005, Section 2.3.2), unless bid-prices are time-dependent. However, this advantage involves a shortcoming since bid-prices do not reserve or protect capacity for customers in higher yielding segments from the access of lower yielding customer segments if both customer segments are within the group of segments which are willing to pay a price at least equal to the considered bid-price (compare Klein, 2001). This drawback can be reduced if the bid-prices are updated during the booking process, e.g. after each request acceptance. Several updating possibilities for bid-prices are presented by Klein (2005), Section 4.2.1.1. The number of stored values, necessary for the capacity control considering updated bid-prices, can be very high, which can eliminate the aforementioned advantage of bid-price policies (compare Talluri and van Ryzin, 2004b, Section 2.1.1.4). Williamson (1992), Section 4.4.1, describes the determination of bid-prices for a single resource which are called leg-based bid prices when considering airlines. E.g., Williamson (1992), Section 4.2.3, uses dual prices from a deterministic linear program to determine marginal values for an incremental capacity unit on a resource. Since bid-prices are calculated for each resource separately, the bid-price determination in single resource capacity control and network capacity control are similar. Further information on capacity control with underlying bid-prices and the determination of bid-prices are presented, e.g., by Bertsimas and Popescu (2003), Klein (2005), Section 4.2.1, Müller-Bungart (2006), Section 2.3, Talluri and van Ryzin (2004b), Section 3.2, and Williamson (1992), Section 4.2.3. The following analysis will concentrate on the application of booking limits as variables to control the capacity within strategic alliances.

The control methodologies of capacity control can be classified into a static and dynamic execution of control. In a static control, the control variables determined at first, before the booking process, will stay unchanged during the entire booking process. Considering dynamic control, the booking limits determined at first are revised based on additional information received during the booking process. New information could be provided, e.g., by analyzing the booking requests already received in the booking process and the demand forecasts that can be recalculated based on the new information (compare Belobaba, 1989).

The sequence of incoming booking requests is relevant for the calculation of nested control variables. As described before, the static optimization approaches to determine nested booking limits assume the requests for the particular products to arrive in a low-to-high-revenue order due to simplification reasons. Additionally, it is assumed that the amount and structure of the demand does not change in the course of the booking process. Hence, the nested booking limits obtained by means of static optimization procedures are optimal only if the actual amount and structure of demand during the booking period is just as assumed, as pointed out by (compare Talluri and van Ryzin, 2004b, Section 2.2). In the earliest reference with respect to nested capacity control, a static approach to optimize nested control variables for an airline operating a non-stop flight is described by Littlewood (1972). In the approach, which became famous as Littlewood's Rule, Littlewood considers two booking classes with ticket fares $v_1 > v_2$. The decision rule decides on the acceptance or rejection of a booking request based on the expected revenue resulting from accepting or rejecting the request. Assume that h_2 requests for the second booking class (or product) are already accepted by the airline and the remaining available capacity in the aircraft is defined by c. If an additional request for the second booking class arrives, the revenue v_2 can be collected by accepting the request. This revenue, however, needs to be compared with potential opportunity costs for the first booking class, resulting from the capacity decrement when the request is accepted and so the capacity is not longer available for the access of requests for the first booking class. These opportunity costs occur only if the demand for the first booking class D_1 is greater than or equal to the remaining capacity $c = C - h_2$. $P(D_1 \geq c)$ describes the probability for that case. So, the expected opportunity costs for the second booking class can be described as marginal revenue $v_1 P(D_1 \geq c)$ for the first booking class. The expected revenue from reserving the c-th capacity unit for the first booking class is also called expected marginal revenue. Requests for the second booking class are accepted as long as the revenue gained by accepting the request exceeds the described expected marginal revenue:

$$v_2 \geq v_1 P(D_1 \geq c). \tag{2.7}$$

The right-hand side of 2.7 increases with decreasing remaining capacity c. Assuming a continuous distribution there is an optimal protection level p_1^* satisfying:

$$v_2 = v_1 P(D_1 > p_1^*) \Rightarrow p_1^* = F_1^{-1}(1 - \frac{v_2}{v_1}),$$

with $F_j(\cdot)$ denoting the probability function of the demand for product j. The booking limit for the second booking class results from $b_2^* = c - p_1^*$. For a more detailed description of Littlewood's rule compare Klein (2005), Section 3.2.2.1 and Talluri and van Ryzin (2004b), Section 2.2.1. The EMSR approach (Expected Marginal Seat Revenue approach), described by Belobaba (1987, 1989), is based on the decision rule defined by Littlewood. Belobaba's approach considers more than two nested booking classes, although the approach determines optimal booking limits only in the case of two considered booking classes. The booking limits are heuristically determined if more than two booking classes are present (compare Talluri and van Ryzin, 2004b, Section 2.2.4). Both variants of the EMSR approach, the EMSR-a and EMSR-b heuristic, will be described in Section 4.2.3 in which the capacity control approach for strategic alliances with underlying EMSR heuristics will be introduced. Brumelle and McGill (1993), Curry (1990), as well as Wollmer (1992) describe models to calculate optimal nested booking limits for a single-leg airline revenue management problem with multiple booking classes (also called fare classes) when low fare passengers book before high fare passengers. If the low-to-high revenue order is considered with multiple booking classes, the demand for the different booking classes is assumed to arrive in blocks, which is why the literature speaks of a blocked demand model. Both references prove that the optimal capacity control policy under blocked demand is a nested booking limit method.

So far, only static booking limit control policies have been considered. Dynamic booking limit policies to determine nested booking limit permit an arbitrary order of request arrivals. Therefore, the low-to-high revenue order assumption is relaxed. The nested booking limits and protection levels calculated by means of dynamic models are time-dependent since the incoming demand varies with time during the booking process. This time-dependent demand affects the expected demand and thereby the determined control variables. In most capacity control systems in practice, the booking limits and protection levels determined by the dynamic booking limit policies are fixed and periodically updated since the value function most likely does not change intensely over a short period of time (compare Talluri and van Ryzin, 2004b, Section 2.5.2). McGill and van Ryzin (1999) present an extensive overview of dynamic programming research related to single-resource capacity control. Brumelle and Walczak (2003), Lee and Hersh (1993), Subramanian et al. (1999), and Zhao and Zheng (2001) provide dynamic approaches to determine booking limits for the single-leg case. Lee and Hersh (1993) include group bookings in their approach. In the procedure of Subramanian et al. (1999), group bookings are not considered, however, the authors extend the basic model presented by Lee and Hersh (1993) considering cancellations, no-shows, and overbooking methods. Brumelle and Walczak (2003) introduce a dynamic model considering overbooking and group bookings (also called batch arrivals). Zhao and Zheng (2001) present a dynamic procedure considering a single airline leg with two booking classes and three customer types incorporating customer-choice behavior into the protection level calculation. Another reference considering passengers behavior in the single-leg case is published by Talluri and van Ryzin (2004a). Detailed descriptions concerning single resource capacity control methods and the influence of group bookings and customer-choice behavior on control variable calculations can be looked up in the monograph of Talluri and van Ryzin (2004b), Chapter 2.

Network Capacity Control

According to McGill and van Ryzin (1999), revenue management policies should account for arising network effects. Since these effects cannot be accomplished by single-resource capacity control, special network capacity control policies need to be implemented. The arising network effects can be demonstrated using the example of the airline application area. The number of passenger itineraries that contain different flight legs has dramatically increased due to the expansion of hub-and-spoke networks. An origin-destination itinerary booking class combination, also called origin-destination itinerary fare class combination (ODF) describes a product in the airline network example. Therefore, network capacity control is also called origin-destination control (compare Talluri and van Ryzin, 2004b, Section 3.1 and Vinod, 1995). Since many different origin-destination itineraries involve jointly used flight legs, a booking for a certain itinerary influences the available capacity not only for the booked itinerary but also for all origin-destination combinations which access the respective flight legs. Consider, e.g., two possible origin-destination itineraries: a non-stop flight from Düsseldorf (DUS) to Frankfurt/Main (FRA) and a flight from Düsseldorf via Frankfurt/Main to Bangkok (BKK) which involves the same flight leg as the flight DUS – FRA. Controlling the flight legs separately could cause a lack of capacity on one of the legs involved in the DUS – FRA – BKK itinerary. Since there need to be capacity units available on both flight legs to accept a request for the long haul flight, booking requests for DUS – FRA – BKK, which generate a higher total revenue, cannot be accepted anymore. This can cause a loss in revenue for the airline. To prevent this, airlines need to apply a network capacity control simultaneously considering all respective flight legs (compare Klein, 2001, Section 3.3). Considering the network effects in revenue management applications can lead to high potential revenue benefits. On the other hand, network capacity control policies are challenging due to implementation, methodological, and organizational difficulties, as pointed out by Talluri and van Ryzin (2004b), Section 3.1.1. Since network capacity control problems are already difficult to solve in single airline revenue management policies, the problem gets even more complex if multiple airlines share capacity within a strategic alliance. For that reason, the capacity control procedures implemented in this work focus on single-resource capacity control to develop promising alliance capacity control procedures which can be extended to alliance network capacity control approaches in future research. However, to conclude the theoretical revenue management background, we refer to the elaborate descriptions of network capacity control presented by Boyd and Bilegan (2003) and Talluri and van Ryzin (2004b), Chapter 3. For an overview of network capacity control research we refer to Chiang et al. (2007), and McGill and van Ryzin (1999). Two control methods, namely virtual nesting control and bid-price methods, have been dominating the literature of network capacity control (compare Boyd and Bilegan, 2003). Bid-price methods have already been mentioned for single-resource capacity control. The bid-prices capacity control for multiple resources is a simple extension to the bid-price underlying capacity control considering a single resource (compare Talluri and van Ryzin, 2004b, Section 3.2.1.3). Virtual nesting is a method that reduces the problem size of network capacity control problems which improves the efficiency of procedures applied for network capacity control. Smith and Penn (1988) introduced the Displacement Adjustment Virtual Nesting (DAVN), a control policy to implement virtual nesting capacity control. Other references using DAVN are Bertsimas and de Boer (2005), van Ryzin and Vulcano (2008a,b), and Williamson (1992), Section 4.4.3. Other approaches that are applied in network capacity control are mentioned by McGill and van Ryzin (1999) referring to the respective literature. E.g., Curry (1990) presents a mathematical programming approach combined with a marginal seat revenue approach, capturing several important elements of network capacity control. The combined approach handles large origin-destination problems and accounts for nested booking classes. There are references considering customer-choice behavior also in network capacity control problems, compare Bront et al. (2009) as well as Liu and van Ryzin (2008).

Chapter 3

Remarks on Strategic Alliances

This chapter introduces strategic alliances. Definitions and basic information concerning strategic alliances will be shortly discussed (Section 3.1) before an extensive overview of revenue management application areas, in which corporations form strategic alliances, will be presented (Section 3.2).

3.1 Defining Strategic Alliances

Opdemom (1998), Section 3.1, defines a strategic alliance as a form of cooperation between at least two legally separate corporations operating in the same industry sector that compete on the same market level. Backhaus and Piltz (1990) add that corporations form strategic alliances to combine the individual strengths in the various business segments so that the corporations can realize mutual strategic relevant competitive advantages. There is high potential for success in single business areas which can be ensured or even newly developed if corporations achieve these advantages by forming strategic alliances. Since strategic alliances are cooperations between current or potential competitors in a business sector, all partners within the strategic alliance focus on the same strategic business sector. Therefore, strategic alliances can also be perceived as horizontal cooperations (compare Backhaus and Piltz, 1990). According to Zhang and Zhang (2006) strategic alliances represent an important form of cooperation that can be seen as a weak form of a merger. Since the partners within a strategic alliance stay distinct business entities with own decision-making autonomy, strategic alliances do not arise from a merger. In network-orientated industries, strategic alliances are especially prevalent. Network-orientated industries are, e.g., the airline, logistic, multimodal transport, shipping, and telecommunication industry (compare Zhang and Zhang, 2006). In the following section, the industries in which capacity control concepts for strategic alliances can be applied will be further discussed. Other forms of cooperations, despite from strategic alliances, theoretical theories discussing alliances, basic conditions of cooperations, as well as driving forces of cooperations can be retrieved in Zentes et al. (2005). Casson and Mol (2006) offer an examination of current literature on alliances from a broad theoretical perspective. An extensive discussion of horizontal strategic alliances and the mutual strategic goals of the alliance partners is given by Lutz (1993). In this study, Lutz (1993), Section 2.1.1, lists the main objectives of the alliance partners as: market entry, access to new technologies, risk and cost reduction, realization of synergy effects, and reduction of competition as well as avoidance of competition law or barriers of trade. As pointed out in Zhang and Zhang (2006), corporations can realize advantages by forming strategic alliances, e.g., due to the expansion of their networks, advantages of product complementaries which can be taken, gaining economies of scale and scope, and enhancing product quality and customer services. However, these potential benefits that can inure to the benefit of firms and customers cannot be realized by all corporations since there are restrictions in building strategic alliances due to antitrust aspects. According to Dussauge and Garrette (1999), Chapter 1, antitrust authorities are most suspicious when it comes to alliances between competitors. Consider the airline industry: airlines operating on international routes usually face only few competitors. The degree of competition could be significantly reduced on the respective origin-destination routes if two major competitors form an alliance. Therefore, antitrust authorities need to consider any possible anticompetitive effect when they decide whether domestic airlines should be restricted or encouraged to expand their networks by joining a foreign strategic alliance (compare Zhang and Zhang, 2006). The critical aspect of antitrust law considerations and the legal relevance for cooperations in Europe is outlined by Basedow and Jung (1993) and Schulte (2003). Dussauge and Garrette (1999), Chapter 1, examine the legal context and regulations given to interfirm cooperations. In the publication of Oum et al. (2001), regulatory issues which are related to international airline alliances are surveyed. Chen and Ross (2000) explore strategic alliances in which the partners share production capacity and some possible anticompetitive entry-deterrence effects of these types of alliances. When forming strategic alliances, corporations need to consider additional business requirements which could limit their scope of action. To ensure that all partners within the alliances cooperate fairly, the future alliance members should contract agreements. Several aspects can be modeled in such alliance contracts. E.g., the contract could limit network extensions and frequency of cooperations in the mutual network. Additionally, certain revenue allocation agreements could be established. Other business requirements are, e.g., regulations set by the government or unions (compare O'Neal et al., 2007).

In this work, alliances between rivals which coordinate their revenue management decisions locally are considered. The outcome of the study carried out by Morris and Hergert (1987) shows that alliances between competitors account for more than 70% of all cooperation agreements. Collaborations of corporations in strategic alliances influence the revenue management decisions made by the alliance partners. Vinod (2005) resorts to the airline industry and states that the airlines within an alliance manage the traffic flow in the alliance network to maximize revenues. Capacity control to manage the seat availability and traffic flow, however, is influenced by the collaboration and is, therefore, different to capacity control mechanisms considering only a single airline. According to Vinod (2005), in an optimal environment for revenue management decisions of alliance partners, all partners share data, such as the fares the partners request on the origin-destination combinations and the bookings which were already recorded by the individual revenue management systems. Due to several considerations including, e.g., organizational, geographical, and antitrust aspects, this environment is, however, unrealistic and not arrangeable. Boyd (1998) points out that centralized decisions on the basis of combining flight networks of alliance partners and treating them as a single network cannot be made in alliances in the airline industry. The existence of airline specific, highly complex revenue management IT-systems and the need for processing a large amount of data in real-time makes a centralized control system nearly impossible. Another aspect militates for a decentralized coordination: The airlines (if they do not merge) are autonomous and their revenue management concepts are developed for their special needs which improves the airlines competitive situation. Not only do technical objections lead to a decentralized treatment but also antitrust arguments forbid centralized solutions. Due to these three aspects, only decentralized solutions are of practical relevance.

Netessine and Shumsky (2005) analyze capacity control problems under horizontal and vertical competition. Horizontal competition is defined as the competition between two airlines for passengers on the same flight leg and in the vertical competition scenario the airlines operate different legs on a combined multi-leg origin-destination itinerary.

There are research fields which can be compared to the capacity control problem occurring in strategic alliances. As it is pointed out in Shumsky (2006), the coordination in a strategic alliance can be compared to the coordination in a physical supply chain. In a supply chain for physical goods the supply chain can be regarded as an alliance with manufacturers or suppliers and retailers being the alliance partners. In that case, the products within the alliance are shipped from manufacturers or suppliers to retailers. Of course, there are significant differences between the coordination in supply chains and the capacity control problem in alliance revenue management. Shumsky (2006) lists these differences: First, the products exchanged by the alliance partners are not storable. Consider once again an airline alliance. The seats in the operating carrier's aircraft, corresponding to the products exchanged within the alliance, cannot be held as inventory. Once the aircraft of the operating carrier takes off, the airlines can no longer sell tickets for the possible spare seats in the aircraft on the flight. Second, most of the publications addressing traditional supply chains concentrate on selling one product to one customer type. In airline alliances, the partner airlines can sell a single seat to hundreds of customer types, respectively in network structures to miscellaneous of customer type and itinerary combinations. Third, the traditional supply chain literature usually defines the partners in the supply chain either as manufacturers and suppliers or as retailers. In an airline alliance, a partner airline can operate a flight on a flight leg by providing seat capacity in an aircraft and simultaneously the same airline can act as ticketing carrier, accessing seat capacity from a partner airline on another flight leg. Furthermore, in supply chain management the manufacturers or suppliers are assumed to sell their products only to the retailers in contrast to the partners within an alliance which can sell their products to other partners or customers in the market. However, despite the mentioned differences, capacity control in a strategic alliance can be compared to the coordination in a supply chain by means of contracts. Cachon (2003) offers an overview of literature discussing supply chain coordination with contracts. In Section 7.1 the supply chain coordination by means of contracts will be compared to the capacity control mechanism in strategic airline alliances.

As this work is focused on capacity control, the examples in the following section describe revenue management application areas with strategic alliance occurrence emphasizing the capacity control instrument.

3.2 Application Areas of Revenue Management in Combination with Strategic Alliances

As described before, revenue management problems occur in different industry sectors. The application areas of revenue management instruments are elaborately discussed in previous publications. Comprehensive overviews concerning these application sectors are given by Chiang et al. (2007), Kimms and Klein (2005), Kimms and Müller-Bungart (2003), McGill and van Ryzin (1999), Talluri and van Ryzin (2004b), Chapter 10, and Tscheulin and Lindenmeier (2003a). In the following paragraphs, the existence of strategic alliances in revenue management application areas will be discussed. The passenger airline industry will be discussed more detailed compared to the other industries due to the great importance the revenue management literature attaches to this industry and due to the fact that the capacity control methods in this work are explained for strategic airline alliances.

3.2.1 Passenger Airline Industry

As mentioned before, the origins of revenue management can be traced back to the airline industry. A wide range of publications bear on air passenger transportation to give examples for composed theories or explicitly formulate models and methods for the passenger airline revenue management problem. Compare the examples given in Section 2.2.2 which explain revenue management instruments by means of application in the passenger airline industry.

The deregulation of the airline industry, discussed in Section 2.1, had consequences on the airline market beyond the ones influencing the deployment of revenue management instruments. Major airlines were confronted with the competition of low-cost carriers entering the markets. To meet arising challenges, major airlines, not able to profitably offer flights to markets with low demand, began to cooperate with regional carriers which could meet the demand for low density markets profitably. According to Shumsky (2006), major traditional carriers are forced by low-cost competitors to process an increasing amount of their traffic in airline alliances. Chiang et al. (2007) state that an airline needs to become a member of an alliance to defend market share. Airlines have different incentives to cooperate with other airlines within a strategic alliance due to new expected revenue potentials founded by greater airline networks, coordinated flight schedules, and access to protected markets. Moreover, there are cost-cutting potentials justified by a higher load factor. Another motivation for building strategic alliances could be the generation of market entry barriers. In a competitive environment, airlines can attract more passengers by offering flights to numerous destinations in the world and enhancing services, as pointed out in Oum and Park (1997). By means of combining the partners' flight networks, the respective airlines can expand their service networks. Additionally, the combined flight networks allow major airlines to provide services on markets on which profitable operated flights are not possible for the major airlines without the alliance partners. In some small markets, the total demand for flight tickets is so low that operating these markets with own aircrafts would not be profitable for major airlines (compare Oum and Park, 1997). This application environment is observed in the capacity control mechanisms deployed for strategic alliances in the present work. A single flight leg is assumed on which the considered flight can only be profitably performed by the operating airline if another airline also offers flight tickets for the same flight pooling together the incoming demand. Besides enlarged origin-destination flight offers, customers benefit from airlines building an alliance, e.g., due to shorter traveling times and the eliminated need to re-check baggage, as pointed out by Park et al. (2001). Partners within an alliance are able to coordinate flight schedules better than single airlines which reduces the passengers overall travel time. However, airlines building strategic alliances can also cause disadvantages for customers if the airlines behave anticompetitive. This anticompetitive behavior can result in higher flight ticket fares for the customers (compare Oum et al., 2001). As pointed out before, the antitrust authorities need to distinguish the anticompetitive behavior and take legal action against it. Oum and Park (1997) list further incentives for airlines to join strategic alliances. As pointed out by Oum et al. (1993), single airlines cannot expand their flight network on their own in the amount as it is possible for partner airlines within an alliance due to insufficient financial, organizational, and time resources.

The major strategic alliances in the passenger transport airline industry are Star Alliance, SkyTeam, and oneworld. Historical developments of multiple airline alliances are described by Oum et al. (1993). According to Field and Tacoun (2005), in 2004 alliances carried more than 50% of the world passenger traffic, showing the increasing impact of alliances in the passenger airline traffic. There are several different cooperation forms and types of airline alliances which are categorized, e.g., by Barringer and Harrison (2000), Oum and Park (1997), and Vinod (2005). Oum et al. (2001) affirm that a key characteristic of international airline alliances are so called code-sharing agreements among the partners within the alliance. Flights offered by the alliance are called code-shared flights if an airline within the alliance allows their partner airlines to sell flight tickets for seats on flights operated by the considered airline (compare O'Neal et al., 2007). These code-shared flights are usually offered with different flight numbers since each airline sells flight tickets under its own brand as an own product even if the flight tickets are sold for flights operated by a partner airline (compare Park and Zhang, 1998). Boyd (1998) raises the question that comes up if airlines are in a code-share agreement: how many seats on the considered flight can be accessed by the non-operating partner airlines? This question brings up new decision problems concerning the capacity allocation if airlines build strategic alliances. In case of alliances, the capacity control not only has to sort out how many seats should be allocated to the different fare classes but also how the seats are divided among the alliance partners. A range of possible concepts is imaginable from a free sale to apportioning blocks of capacity among the partners of the alliance. Boyd (1998) specified two common decision control mechanisms used in practice: In a free sale, the airline operating the considered flight provides access to the seats in the aircraft by providing information about seat availability to the non-operating alliance partners. The alliance partner airlines are allowed to access the seats, for example, in a first-come-first-served order. In a blocked seat allotment procedure, each airline individually controls the seats they have been assigned to before the booking process. The drawbacks of capacity control methods so far applied for strategic alliances are: In a free sale setting, no capacity is reserved for higher yielding booking classes while in a blocked seat allotment procedure, each airline individually controls the seats they have been assigned to which leads to static allotments (hard blocks). The allotments assigned to the airlines in a blocked seat allotment procedure should be updated during the booking process depending on the demand observed so far (soft blocks) to overcome the drawback of static allocations (compare Boyd, 1998). Park and Zhang (1998) also bring up the subject of blocked seat allotments, calling them block-space sale agreements, and give an example: Delta Air Lines and Swissair had a block-space agreement on the origin-destination route from New York to Zurich. Swissair was actually operating the flight and Delta Air Lines accessed seats on the flight by buying a block of seats from Swissair. By means of this example, the new capacity control decision mechanism for two partners within an alliance will be introduced in the following.

In the airline alliance literature, there are several publications analyzing general aspects of alliances, but only a few regarding airline alliances combined with aspects that are interesting for revenue management. Oum and Park (1997) analyze diverse alliance aspects, such as, e.g., government policy towards strategic airline alliances and the degree of collaboration between the partners within an alliance, based on an extensive study considering 46 alliances among the world's major 30 airlines. Oum et al. (1996) and Park and Zhang (2000) provide empirical studies discussing the effect of alliances on air fares. Park and Zhang (1998) analyze the effects of airlines building a strategic alliance on the passenger traffic changes of the partner airlines occurring on flights operated by the alliance partners compared to the non-alliance flights. Park (1997) and Park et al. (2001) theoretically examine two types of airline alliances and the different effects they have on air fares, the airlines' profits, and the economic welfare. Brueckner (2001) also studies the effects of alliances on fares, traffic levels, and welfare by means of a simulation analysis. Brueckner and Whalen (2000) also conducted a study analyzing the effects of strategic alliances on carriers' prices. Brueckner (2003) confirms in a follow-up study of the analysis in Brueckner and Whalen (2000) that there are price advantages for passengers on international interline itineraries due to code sharing agreements. O'Neal et al. (2007) developed a system that automatically detects and selects the flights that should be offered as code-sharing flights. The amount of revenue enhancement is dependent on the right choice of these flights. The authors tested their code-share flight-profitability system at Delta Air Lines. Boyd (1998) and Vinod (2005) describe coordination mechanisms for strategic alliances in the airline industry being considered by the carriers in practice. Another field of alliance revenue management research deals with the allocation of alliance revenues to the partner airlines. After the booking period, when all decisions concerning the acceptance or rejection of a request are made, the problem of how the revenue is shared fairly among the airlines in the alliance arises (compare, e.g., Çetiner and Kimms, 2009; Wright et al., 2010). This downstream problem, however, is not an issue in this work. To the best of our knowledge, there is no literature that describes option-based capacity control models or methods for strategic alliances which will be introduced in the following chapters.

3.2.2 Air Cargo Sector

So far, in the examples given to discuss the application of revenue management instruments, passenger air traffic problems were specified. However, revenue management measures can also be exercised in the air cargo business segment. Since cargo claims other air transport conditions than passengers, the revenue management concept needs to be adjusted. According to Kasilingam (1996), the following four characteristics distinguish passenger from cargo revenue management: The total capacity is uncertain since it depends on the amount of baggage the passengers check in, the capacity is tree-dimensional and can be described by weight, volume, and number of container positions, cargo can be shipped on multiple routes as long as it arrives in time, and the allotments which are reserved due to contracts concluded with major shippers and forwarders make an amount of capacity not available for general sale. Billings et al. (2003) also list general air cargo revenue management aspects and discuss business-process solutions available for cargo carrier. A practice paper is presented by Slager and Kapteijns (2004), describing cargo revenue management implementations at KLM. Pak and Dekker (2004) solve a multidimensional on-line knapsack problem to determine a bid-prices capacity control policy for cargo revenue management. Bartodziej et al. (2007) present an air cargo network capacity control approach based on mathematical programming which incorporates capacity allocation decisions already made on a higher management level. Amaruchkul et al. (2007) formulate the cargo booking problem on a single-leg flight as Markov decision process.

Revenue management mechanisms are additionally discussed in literature assuming special situational aspects. Products and services can, e.g., be flexible which means that they can be produced in several ways. A customer buying a flexible (also called opaque) product cannot identify some of the product's characteristics until after purchasing. There are flexible products, for instance, in the air cargo sector since most of the time cargo needs to arrive at the destination airport at a certain point in time but does not need to be transported over a route previously announced by the customer. Therefore, the cargo airline holds several options how to transport the cargo. Gallego and Phillips (2004), Kimms and Müller-Bungart (2007a), Müller-Bungart (2006), and Petrick (2009) discuss revenue management in the existence of flexible products. A capacity control mechanism incorporating opaque products is described by Gönsch and Steinhardt (2010).

Also cargo alliances form strategic alliances. As reported by Karp (2004), the two major strategic alliances in the air cargo sector are SkyTeam Cargo and WOW Alliance. By now, however, the revenue management literature discussing capacity control problems occurring in the air cargo sector refers to single airlines.

3.2.3 Passenger Railroad Sector

Although the conditions for applying revenue management instruments are present in the railroad sector, some special factors complicate revenue management decisions. As stated by Müller-Bungart (2006), at German Railways (Deutsche Bahn AG), e.g., passengers buying a regular ticket can choose the departure time, the respective train, and even the route of travel, considering some limitations. This uncertainty complicates, for instance, capacity control decisions. Ciancimino et al. (1999) incorporate this aspect into a deterministic linear programming model and a probabilistic non-linear programming model to solve network railroad capacity control problems.

Although, there are no horizontal strategic alliances within the passenger railroad sector, some operative cooperations can be noticed. E.g., the European high-speed train Thalys connects the cities Paris, Brussels, Amsterdam, and Cologne. This transportation service is operated jointly by the French, Belgian, Dutch, and German railroad.

3.2.4 Freight Sector

Revenue management cargo problems are rarely discussed for shipping, trucking, freight railroad, and intermodal companies, although revenue management instruments can also be applied in these sectors. Strasser (1996) explores the use of revenue management in the railroad freight market. Revenue management is used to segment the railroad freight market into higher priced high-priority freight and lower priced low-priority freight. A reference considering a sea cargo revenue management problem is given by Lee et al. (2007). The authors solve a single-leg revenue management problem with postponement possibility heuristically.

Sibelit SA is an international alliance with railroad freight partners from different countries. In the shipping industry, there are two major strategic alliances, namely New World Alliance and Grand Alliance. The shipping companies expect to enhance the offered services from building strategic alliances (compare Zhang and Zhang, 2006).

3.2.5 Tourist Sectors

Kimms and Klein (2005) classify the sectors in which the revenue management concept can be adapted in the airline sector, the touristic sector, and the customer make-to-order manufacturing sector. The tourist sector includes the hotel business, the gastronomy industry, and the automobile rental sector. In this classification, cruise liners, tour operators, and casinos can also be added to the tourist sectors applying revenue management procedures. One aspect occurs in most of the tourist businesses that needs to be considered in addition to the standard revenue management aspects: There are additional but uncertain profits possible besides the direct revenues. Consider, for instance, the hotel sector. A guest in a hotel generates additional revenue for the hotel besides the direct revenues paid for the hotel room, e.g., by dining in the restaurants and bars or by booking spa treatments or conference rooms. This extra revenue needs to be considered when applying revenue management procedures (compare Müller-Bungart, 2006). Although there are multiple references in hotel revenue management literature, compare, e.g., Badinelli (2000), Bitran and Gilbert (1996), Bitran and Mondschein (1995), Goldman et al. (2002), Koide and Ishii (2005), and Rothstein (1974), only a few references examine cruise liners (compare Hoseason, 2002), tour operators (compare Hoseason and Johns, 1998), and casinos (compare Hendler and Hendler, 2004). Bertsimas and Shioda (2003), Johns and Rassing (2004), and Kimes et al. (2002) focus on revenue management procedures for restaurant businesses. A typical characteristic of the car rental industry is an asymmetric traffic similar to the air cargo and freight industry. The aspect that a wide range of customers return a rental car at a station that is not the same station which rented out the car needs to be considered in revenue management application. Additionally, car rental companies have to face uncertain rental durations and return stations since customers can return the rental car earlier or later and even at another station than previously announced (compare Müller-Bungart, 2006). References dealing with rental revenue management are Carroll and Grimes (1995) and Geraghty and Johnson (1997). Steinhardt and Gönsch (2009) consider upgrades and capacity control decisions simultaneously in the proposed approach which is applicable to car rental revenue management problems.

Strategic alliances are very rare in the tourist sector. In the hotel sector, however, some hotels form vertical alliances with, e.g., tourist agencies, tour operators, airlines, car rental companies, or credit card companies. Horizontal cooperations in a small setting are sometimes arranged by neighboring hotels if the revenue management instrument overbooking is applied. Some hotels overbook their capacity in the high season and shift customers to another hotel in the neighborhood if customers with valid bookings cannot be served due to overbooking.

3.2.6 Manufacturing Sector

There are further areas in which revenue management instruments can be applied. In the manufacturing sector, revenue management is applicable if customers need to integrate an external factor in the production process. This is necessary in the make-to-order production environment since customers need to specify their order previous to the production process. In make-to-order production, the companies are not able to satisfy the incoming demand from stock (compare Müller-Bungart, 2006). There are some publications considering revenue management in make-to-oder production processes, compare, e.g., Defregger and Kuhn (2007), Hintsches et al. (2009), Kolisch and Zatta (2009), Quante et al. (2009), Spengler and Rehkopf (2005), and Spengler et al. (2008).

Strategic alliances formed by manufacturing corporations are also described in supply chain management literature. In Simchi-Levi et al. (2004), Chapter 5, supply chain-related strategic alliances are pointed out. However, the definition of strategic alliances differs in supply chain literature from the strategic alliance descriptions mentioned above. In supply chain literature also vertical cooperations as retail-supplier partnerships are defined as strategic alliances (compare Simchi-Levi et al., 2004, Section 5.1). Although vertical cooperations build the basis to supply chain management, some authors also consider horizontal cooperations, e.g., alliance purchasing (compare Essig, 2000).

3.2.7 Miscellaneous Sectors

Other areas of application include, e.g., media and broadcasting (extensively discussed in Müller-Bungart, 2006, Chapter 6, and Kimms and Müller-Bungart, 2007a), golf courses (compare Kimes and Schruben, 2002), tickets for sports events (compare Barlow, 2002), and health care (compare Chapman and Carmel, 1992). Strategic alliances, however, cannot be detected in these sectors.

Chapter 4

Capacity Control with Real Options

The fundamental question in revenue management capacity control considering strategic alliances is how to allocate the capacity among the members of the strategic alliance. As mentioned before, real options will be considered in the following to divide the capacity between the alliance partners. As a basis for the later on described solution concepts, the theoretical background of real options will be described in Section 4.1. After this short excursion, the determination of booking limits, the control variables in the developed solution concepts, will be outlined in Section 4.2. The solution concepts will be described by means of an example from the airline industry, following revenue management literature and practice also emphasizing the airline industry. In a computational study in Section 4.3, the performance of the proposed procedures will be discussed. This chapter is based on Graf and Kimms (2009).

4.1 Remarks on Real Option Theory

Real options are derived from financial options which are elaborately discussed in finance literature (compare Hilpisch, 2006, Section 1.4). A financial option is defined by Trigeorgis (1996), Section 3.1, as a right, but not an obligation, to purchase or sell the specified financial asset at or up to a defined date by paying a preassigned price (strike price or exercise price). Amram and Kulatilaka (1999), Chapter 1, define an option in a more general way: Options constitute the right, without an associated obligation, to take an action in the future. An option that justifies to buy the asset is defined as call option whereas a put option permits to sell the financial asset (compare Trigeorgis, 1996, Chapter 1). If an option can be exercised on and additionally at any time before the predefined date, the option is called American option. A European option on the other hand can be exercised only exactly on the previously specified point in time (compare Brealey et al., 2006, Section 20.1). An extensive survey of options in finance is given by Brealey et al. (2006), Chapter 6, and Hull (2008). Myers (1977) transferred the concept of financial options to operational decision practice and real economy for the first time. Due to Trigeorgis (1996), Chapter 3.1, a real asset or capital project is the underlying asset to a real option. A classification of real options as well as a survey of literature, describing industries utilizing real options, is introduced in the monographs of Amram and Kulatilaka (1999) and Trigeorgis (1996). There are also references on real options especially in the context of revenue management. Anderson et al. (2004) present a real option approach to revenue management that is dedicated to the car rental business. Gallego and Phillips (2004) mention real options in the context of flexible products in revenue management. In his thesis, Hellermann (2006) discusses option contracts to develop a capacity-option pricing model for air cargo revenue management. As described before, the capacity control in strategic alliances is similar to the coordination in a supply chain. Barnes-Schuster et al. (2002) present options to coordinate a buyer-supplier system. In this system, the buyer purchases options for supplier capacity. After the first of two considered periods, the buyer exercises some of the options (at a strike price) dependent on the demand observed so far. Rudi and Pyke (2000) use real options to share risk between a manufacturer and a retailer in a newsboy model. These real options are defined as the right, without the obligation to physically receive or deliver a good or service on or before a specific exercise date to a preassigned price, as pointed out by Kleindorfer and Wu (2003).

The underlying idea of real options used in the capacity control procedures proposed in the present work for strategic alliances can be described by means of the airline example as follows: An airline within an alliance can buy an option by paying the option price up front to possess the right of buying a flight ticket for a seat in the partner airline's aircraft (the underlying asset) at a fixed price in the future. The option can be exercised by the airline after the option was purchased until the airplane takes off which classifies the option as an American call option. To actually buy the underlying asset, the airline holding the option has to pay a predefined strike price. The interaction between the airline offering options and the airline purchasing options will be discussed in Section 4.2.1.

4.2 Determination of Booking Limits

The determination of booking limits, the variables to control the capacity in revenue management, will be explained in the following subsections. First, the interaction between the airline partners within the strategic alliance will be outlined, followed by the description of the booking limit calculations by means of deterministic linear models and EMSR heuristics.

4.2.1 Interaction Between Airlines

The following assumptions can be made in order to calculate the booking limits which partition the capacity and allocate the capacity to each fare class, as the control variables in capacity control. An alliance with two airlines is considered. One of the airlines, the operating carrier (OC), provides seats in an aircraft that is operated on a single flight leg. The other airline, the ticketing carrier (TC), can access the seats of the operating carrier by buying call options for the seats. We have chosen the term ticketing carrier based on the remarks of Brueckner (2003). Other references point to the non-operating airline as marketing carrier (compare Shumsky, 2006). In our application, the ticketing carrier does not operate a flight that is a direct substitute to the one operated by the operating carrier. In practice, however, it is not uncommon for both airlines to act as operating and ticketing carriers simultaneously, depending on which flight leg is being considered. That means, if an airline is the operating carrier on a specific flight leg, the airline may serve as ticketing carrier on other flight legs.

Figure 4.1 shows the interaction between the operating carrier and the ticketing carrier before and during the booking process. Before the booking process starts for a particular flight operated by the operating carrier, the operating carrier decides how many options to sell to the ticketing carrier. After the operating carrier announces the number of options available for sale, the option price and the strike price to the ticketing carrier, the ticketing carrier determines how many options to buy from the operating carrier. The number of options ranges from zero to the number of options the operating carrier offers to the ticketing carrier. The ticketing carrier pays the option price per seat to the operating carrier to reserve the seats by using options. During the booking process, the ticketing carrier can exercise an option by paying the strike price to the operating carrier. Consequently, the ticketing carrier can sell a flight ticket for a seat in the aircraft of the operating carrier. If the demand for flight tickets within one of the

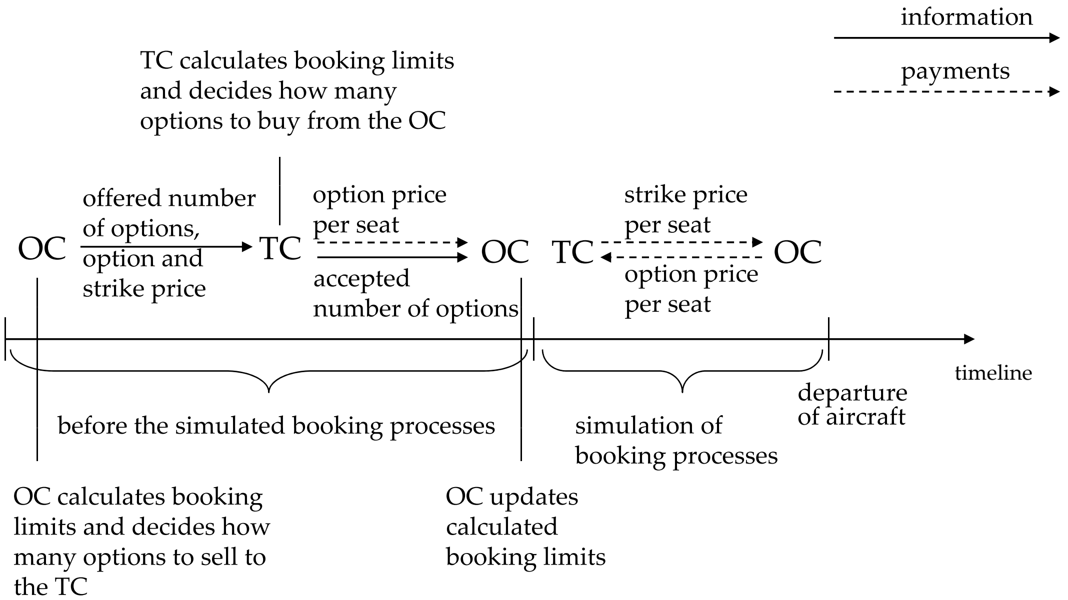

Figure 4.1: Interaction between OC and TC

ticketing carrier's classes is less than assumed, some of the options the ticketing carrier purchased from the operating carrier remain unexercised. To provide a form of re-optimization, the operating carrier has the right to buy back options from the ticketing carrier during the booking process. By paying back the option price to the ticketing carrier, the operating carrier can access the seats reserved for the ticketing carrier. Such a buy-back opportunity can be described as an option on options with option price zero since no option price has to be paid by the operating carrier to the ticketing carrier prior to the buy-back of the option. The strike price for executing the option and buying back the right to sell flight tickets for the seats reserved through the options is equal to the option price payed by the ticketing carrier. Such an option on options is often applied in different resource allocation problems (compare Trigeorgis, 1996, Section 4.7). An option on options is called compound option in the field of real option and financial option theory (compare Geske, 1979, and Moore, 2001, Chapter 11). In an optimal alliance solution, however, the operating carrier only accesses seats reserved for the ticketing carrier if the revenue that the operating carrier receives for accepting a seat request is greater than or equal to the strike price plus the option price. Without the buy-back option for the operating carrier, the introduced method would be similar to a blocked seat allotment which holds the drawback of being inflexible. Once the airlines within the alliance agree how many options to sell and buy, the capacity is fixed during the booking process in a blocked seat allotment procedure. So, there is no possibility to change capacity during the booking process in order to level out varying and unexpected demand. Of course, one can discuss if a buy-back should be penalized by setting the buy-back price higher than the option price so that the operating carrier has to pay more for accessing seats reserved for the ticketing carrier than the operating carrier receives by selling an option to the ticketing carrier. Since implying a penalty is just a special case that can be included easily in our real option approach described in this work, we decided to model the more general case. In Section 4.3.2, the performance of the method with buy-back opportunity of the operating carrier (introduced in our applications) will be compared to the performance of the method without buy-back opportunity.

A brief example in Figure 4.2 clarifies the situation during the booking process: The small boxes in Figure 4.2 illustrate seats in the aircraft of the operating carrier. The color of the seats shows the access rights of the alliance partners during the booking process. The white seats are only available for the operating

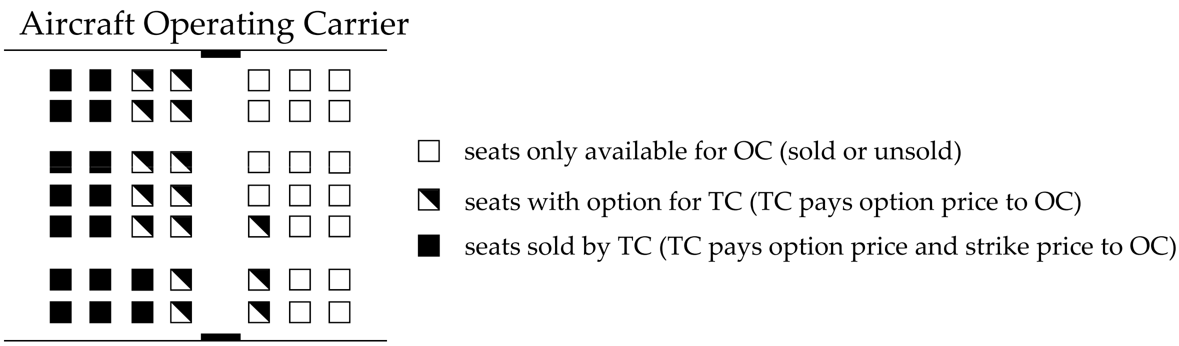

Figure 4.2: An Illustration of the Two-Airline Case

carrier, so the ticketing carrier cannot sell flight tickets for these seats (no matter if the operating carrier already sold the tickets or not). The ticketing carrier bought options for the black/white seats and payed an option price per seat to the operating carrier. By paying a strike price to the operating carrier, the ticketing carrier can sell a ticket for one of these seats. The operating carrier can access the seats reserved for the ticketing carrier by paying back the option price to the ticketing carrier. The ticketing carrier already sold tickets for the black seats. Therefore, the ticketing carrier exercised the options that allowed access to these seats. To actually sell tickets for seats in the operating carrier's aircraft, the ticketing carrier paid the option price and the strike price to the operating carrier. We assumed the access rights of the alliance partners to be given in the described example. In the following subsection, the segmentation of the seats in the aircraft will be illustrated.

4.2.2 Deterministic Models to Calculate Booking Limits

We consider deterministic models to obtain partitioned booking limits for the alliance partners on the considered single flight leg. The models proposed in this work are based on a Deterministic Linear Program (DLP) presented, e.g., by Williamson (1992) and discussed in Section 2.2.2.3.

In the following, the index of the operating carrier is $l = 1$. The ticketing carrier is indexed by $l = 2$. Let n_1 be the number of booking classes of the operating carrier and n_2 be the number of booking classes of the ticketing carrier. Let $v_{jl} > 0$ be the revenue of a single ticket in booking class j of airline l with $v_{1l} \geq v_{2l} \geq ... \geq v_{n_l l}$. The total seat capacity is C and $E[d_{jl}] > 0$ describes the expected demand for tickets in booking class j of airline l. Denote the option price by x and the strike price by s ($x, s \geq 0$). $OP \geq 0$ describes the number of options the ticketing carrier purchases from the operating carrier. The decision variable is the booking limit b_{jl} of booking class j of airline l.

The following linear optimization model determines the optimal number of seats that should be available to each booking class of the operating carrier:

$$\max \sum_{j=1}^{n_1} v_{j1} b_{j1} \tag{4.1}$$

subject to

$$b_{j1} \leq E[d_{j1}] \qquad j = 1, ..., n_1 \tag{4.2}$$

$$\sum_{j=1}^{n_1} b_{j1} \leq C \tag{4.3}$$

$$b_{j1} \geq 0 \qquad j = 1, ..., n_1 \tag{4.4}$$

The objective function (4.1) maximizes the revenue over all booking classes of the operating carrier, assuming that the booking limits of the single booking classes must not exceed the expected demand of the booking classes (4.2). Additionally, the sum of the booking limits of the booking classes has to be smaller than or equal to the available total seat capacity on the single flight leg (4.3). The booking limits of the booking classes are greater than or equal to zero (4.4).

This model can be solved optimally without linear programming: The booking limits of the booking classes can be set equal to the expected demand corresponding to the considered booking class ($b_j = E[d_{j1}]$) in the order of decreasing prices of the booking classes as long as there is enough remaining seat capacity ($c \geq E[d_{j1}]$). As soon as the remaining seat capacity is smaller than the expected demand for the considered class ($c < E[d_{j1}]$), the booking limit of the booking class is set equal to the remaining seat capacity ($b_j = c$). If not all of the booking classes are considered until then, the booking limits of the residual classes are set equal to zero ($b_j = 0$).

In the presence of a ticketing carrier, the operating carrier considers the requests coming from the ticketing carrier as an additional, independent booking class $n_1 + 1$ with its own expected value of demand ($E[d_{n_1+1,1}]$) and revenue ($v_{n_1+1,1}$). The operating carrier forecasts how many flight tickets the ticketing carrier will inquire on the considered flight and regards this forecast as the expected value of demand of the additional class. The revenue of the additional class equals to the sum of option price and strike price ($x + s$), which corresponds to the revenue the operating carrier gains if the ticketing carrier sells one ticket for the considered flight.

$$\max \sum_{j=1}^{n_1+1} v_{j1} b_{j1}$$

subject to

$$b_{j1} \leq E[d_{j1}] \qquad j = 1, ..., n_1 + 1$$

$$\sum_{j=1}^{n_1+1} b_{j1} \leq C$$

$$b_{j1} \geq 0 \qquad j = 1, ..., n_1 + 1$$

After solving the model, the booking limit ($b_{n_1+1,1}$) of the additional class $n_1 + 1$ displays the number of seats the operating carrier should make available to the ticketing carrier.

With the following linear optimization model, the booking limits for the different classes of the ticketing carrier are determined. The ticketing carrier has to decide on the number of options to purchase from the operating carrier. Therefore, the model introduced before has to be modified. The capacity of the ticketing carrier C_{TC} corresponds to the number of seats the operating carrier makes available to the ticketing carrier, i.e. $C_{TC} = b_{n_1+1,1}$.

$$\max \sum_{j=1}^{n_2} (v_{j2} - x - s) b_{j2} \tag{4.5}$$

subject to

$$b_{j2} \leq E[d_{j2}] \qquad j = 1, ..., n_2 \tag{4.6}$$

$$\sum_{j=1}^{n_2} b_{j2} \leq C_{TC} \tag{4.7}$$

$$b_{j2} \geq 0 \qquad j = 1, ..., n_2 \tag{4.8}$$

In the objective function (4.5), the option price and strike price must be subtracted from the revenue the ticketing carrier receives for one flight ticket. The option price and the strike price represent the costs the ticketing carrier has to pay to the operating carrier for one sold seat. The model's objective is the maximization of the ticketing carrier's profit contribution. Constraint (4.6) ensures that the booking limits of the single booking classes do not exceed the expected demand of the booking classes. The sum of booking limits of all booking classes must be less than or equal to the capacity which is available to the ticketing carrier (4.7). In the model for the ticketing carrier, the booking limits of the booking classes are greater than or equal to zero (4.8).

After solving the model for the ticketing carrier, the sum of booking limits indicates how many options the ticketing carrier purchases from the operating carrier ($\sum_{j=1}^{n_2} b_{j2} = OP$).

The above presented model can also be solved optimally without linear programming: If the revenue of a ticket in booking class j is smaller than or equal to the sum of option price and strike price ($v_{j2} \leq x + s$), the booking limit corresponding to the class is zero ($b_j = 0$) since the ticketing carrier's costs are higher than or equal to the revenue the ticketing carrier gains from one sold ticket in that class ($x + s \geq v_{j2}$). The booking limits of the classes, for which $x + s < v_{j2}$ is true, can be set equal to the expected demand corresponding to the considered class ($b_j = E[d_{j2}]$) in the order of decreasing prices of the classes as long as there is enough remaining seat capacity ($c \geq E[d_{j2}]$). As soon as the remaining seat capacity is smaller than the expected demand for the considered class ($c < E[d_{j2}]$), the booking limit of the class will be set equal to the remaining seat capacity ($b_j = c$). If not all of the classes are considered until then, the booking limits of the residual classes will be set equal to zero ($b_j = 0$).

After calculating the booking limits for the operating carrier and the ticketing carrier, there are several booking limits imaginable which could be applied to the two classes of the operating carrier in the booking process. Considering the booking limits calculated by the model which regards the demand of the ticketing carrier as an additional class in the simulation of the booking process might lead to unrealistic results. If the ticketing carrier asks for less tickets than the operating carrier offers ($OP < b_{n_1+1,1}$), less than full capacity is considered when simulating the booking process. Recall that the calculated booking limits partition the capacity so that the sum of the calculated booking limits equals the capacity. We present two procedures which adjust the booking limits of the two classes of the operating carrier to guarantee that the whole capacity is covered by the booking limits of the two airlines.

Procedure 1
The model of the operating carrier could be solved considering the additional class of the ticketing carrier. After the ticketing carrier decided how many options will be purchased from the operating carrier, the spare seats (if they exist) could be assigned to the class of the operating carrier with the maximum revenue for one sold ticket that is smaller than or equal to the option price plus the strike price ($\max \{v_{j1} : j=1, ..., n_1, v_{j1} \leq (x + s)\}$). If the revenue for one sold ticket of the lowest yielding class of the operating carrier is greater than the option price plus the strike price ($v_{n_1 1} > (x + s)$), the spare seats could be assigned to the booking limit of the lowest yielding class of the operating carrier. The

described procedure (Procedure 1) will be illustrated using an example at the end of this section.

Procedure 2
After solving the model of the operating carrier with the additional class of the ticketing carrier to determine how many sets the operating carrier makes available to the ticketing carrier, the model of the operating carrier could be solved a second time without considering the additional class representing the demand coming from the ticketing carrier. The booking limits that are reached after solving the model without the additional class divide the capacity of the operating carrier's aircraft. This procedure (Procedure 2) as well will be illustrated in the following with an example (compare the end of the example at the end of this section). In Section 4.3.2 the performance of the two different procedures will be analyzed.

A small example is used to illustrate the procedures. Assume two booking classes for each airline ($n_1 = 2, n_2 = 2$) and $C = 100$ available seats. Let the option price be 20€ and the strike price be 150€. The revenue of the tickets in the different classes is shown in Table 4.1 and the expected demand is given in Table 4.2. In this small example, the demand for the ticketing carrier in the higher yielding fare class is assumed to be higher than the demand for the higher yielding fare class of the operating carrier, although v_{11} is lower than v_{12}. This assumption can be made since higher demand could occur for example due to a frequent flyer program that binds customers to the ticketing carrier (compare the segmentation mechanisms discussion in Talluri and van Ryzin, 2004b, Section 11.1.1.2).

	v_{jl}	l = 1	2
j	1	200	250
	2	100	150

Table 4.1: Revenue of the Tickets

	$E[d_{jl}]$	l = 1	2
j	1	30	50
	2	80	70

Table 4.2: Expected Values of Demand

In this example, the operating carrier forecasts that the ticketing carrier will ask for 60 options on the considered flight and regards this forecast as the expected demand for the additional class. The request coming from the ticketing carrier is considered as an additional, independent booking class with an expected value of demand $E[d_{31}] = 60$ and a revenue of $v_{31} = 170$€. The revenue is the sum of option price and strike price which equals the revenue that the operating carrier gains if the ticketing carrier exercises an option.
The model of the operating carrier considering the demand of the ticketing carrier is solved to determine how many seats the operating carrier should make available to the ticketing carrier. Since the described model determines partitioned booking limits, the seat capacity of the operating carrier is divided into seats exclusively available for the different booking classes of the operating carrier. Solving the model with the assumed parameters results in a booking limit vector: $\mathbf{b}_1 = (30, 10, 60)^T$. That means the operating carrier makes 60 seats available to the ticketing carrier.

Solving the model for the ticketing carrier with the capacity the operating carrier provides for the ticketing carrier $C_{TC} = b_{31} = 60$, yields the partitioned booking limits for the ticketing carrier $\mathbf{b}_2 = (50, 0)^T$. As a result, we gain the booking limit vector for the alliance $\mathbf{b} = (\mathbf{b}_1, \mathbf{b}_2)^T$ where $\mathbf{b}_1 = (b_{11}, b_{21})^T$ and $\mathbf{b}_2 = (b_{12}, b_{22})^T$, which equals to $\mathbf{b} = ((30, 10)^T, (50, 0)^T)^T$ in the described example. Note that in this case the booking limit for the second class of the ticketing carrier is zero since the ticketing carrier's revenue for the second class is less than the option price plus the strike price, equal to the costs for the ticketing carrier. If the ticketing carrier decides not to buy options for all of the seats offered by the operating carrier ($b_{31} > b_{12} + b_{22}$), not the whole capacity is considered in simulating the booking process. In the described example, the sum of the booking limits ($\mathbf{b} = ((30,10)^T, (50,0)^T)^T$) equals 90 which leads to unrealistic results since the sum is less than the capacity $C = 100$.

If the ticketing carrier asks for less tickets than the operating carrier offers, the operating carrier has two options as described above:

Procedure 1: The operating carrier could add the spare seats, the ticketing carrier did not buy options for, to the class with the maximum revenue for a sold ticket that is smaller than or equal to the option price plus strike price, in this example the lowest yielding class (v_{21}), resulting in booking limits for the operating carrier: $\mathbf{b}_1 = (30,20)^T$ ($\mathbf{b} = ((30,20)^T, (50,0)^T)^T$).

Procedure 2: The model of the operating carrier is solved a second time assuming that the operating carrier can access the total capacity (ignoring the demand coming from the ticketing carrier). After solving the model for the two classes of the operating carrier with the assumed parameters, we receive the partitioned booking limits vector $\mathbf{b}_1 = (30,70)^T$, tolerating to accept more requests of the lower ordered class of the operating carrier ($\mathbf{b} = ((30,70)^T, (50,0)^T)^T$).

4.2.3 EMSR Heuristics to Calculate Booking Limits

An interesting question is how the performance of the option-based capacity control procedure changes if heuristics instead of deterministic linear programs are used to calculate the booking limits for the operating carrier and the ticketing carrier. As described in Section 2.2.2.3, the two versions of the EMSR heuristics developed by Belobaba (1987, 1989) can be applied to determine nested booking limits for multiple booking classes in single-resource capacity control problems.

We replace the deterministic linear models with the booking limit calculation procedure in the EMSR heuristics and include our real option idea in both versions of the EMSR heuristic. First, the booking limits for the operating carrier are calculated by means of the EMSR heuristics, considering the requests coming from the ticketing carrier as an additional, independent booking class. As described in Section 4.2.2, the operating carrier offers the ticketing carrier options for seats in the amount of the booking limit of the additional class. Second, the booking limits for the ticketing carrier are calculated with the EMSR heuristics. In doing so, the capacity of the ticketing carrier corresponds to the number of options the operating carrier makes available. If the ticketing carrier purchases less options than the operating carrier offers, the spare seats are added to one of the booking limits of the operating carrier (compare Procedure 1 in Section 4.2.2). The option-based procedures with underlying EMSR heuristics and included real option idea are referred to as EMSR-a+Options and EMSR-b+Options, respectively.

EMSR-a (Expected Marginal Seat Revenue – Version a)

The EMSR-a heuristic is based on the idea of approximating the n-class problem in solving two-class problems by means of Littlewood's Rule, considering each pair of booking classes $j+1 (2 \leq j+1 \leq n)$ and $k (1 \leq k \leq j)$. The protection level for each pair of booking classes p_k^{j+1} is calculated as described in Section 2.2.2.3 mentioning Littlewood's Rule. The determined protection level p_k^{j+1} shows how much capacity needs to be reserved for booking class k from the access of booking class $j+1$. The protection level p_j, describing the capacity that needs to be protected for booking class j and all higher yielding booking classes, is equal to the sum of the respective protection levels calculated for the booking class pairs:

$$p_j = \sum_{k=1}^{j} p_k^{j+1}.$$

The EMSR-a heuristic is precisely described in Talluri and van Ryzin (2004b), Section 2.2.4.1.

In the example introduced in Section 4.2.2, the operating carrier and the ticketing carrier offer two booking classes ($n_1 = 2, n_2 = 2$) on a flight with seat capacity $C = 100$. Since the operating carrier considers the ticketing carrier's demand as additional booking class ($n + 1 = 3$), three pairs of booking classes need to be considered calculating the protection levels p_{k1}^{j+1} for the operating carrier (p_{11}^2, p_{11}^3 , and p_{21}^3) by means of Littlewood's Rule. The demand for the booking classes of the operating carrier is assumed to be independent and normally distributed with positive mean μ_{j1} and standard deviation σ_{j1}. In the unlikely event of the demand being negative, the demand is set equal to zero. The demand behavior for the operating carrier's booking classes as well as the flight ticket revenues v_{j1} of the operating carrier's booking classes are presented in Table 4.3. The booking classes need to be sorted according to their flight ticket revenue in order to compare the booking class pairs with each other. Due to the sorting process, the additional booking class with flight ticket revenue $v_{31} = 170$, normally labeled as booking class $j = 3$ of the operating carrier, is now considered as second booking class $j = 2$ of the operating carrier.

j	μ_{j1}	σ_{j1}	v_{j1}
1	16.99	5.67	200
2	48.46	9.93	170
3	55.73	7.47	100

Table 4.3: Mean, Standard Deviation, and Revenue for Booking Classes of Operating Carrier

The resulting protection levels for each pair of booking classes are $p_{11}^2 = 11, p_{11}^3 = 17$, and $p_{21}^3 = 46$. To determine the protection levels for each booking class of the operating carrier, the respective protection levels are aggregated: The protection level $p_{11}^2 = 11$ is equal to the protection level of booking class $j = 1$, $p_{11} = 11$. The aggregated protection levels $p_{11}^3 = 17$ and $p_{21}^3 = 46$ specify the protection level for booking class $j = 2$ of the operating carrier, $p_{21} = 63$ and the protection level for the lowest yielding class of the operating carrier is equal to the assumed capacity $p_{31} = 100$. Converting the protection levels into booking limits by means of $b_{j1} = C - p_{j-1,1}$, for all $j = 2, ..., n$ and $b_{11} = C$ results in the following booking limits: $b_{11} = 100, b_{21} = 89$, and $b_{31} = 37$. The booking limit corresponding to the additional booking class b_{21} provides the information about the number of seats the operating carrier should make available to the ticketing carrier. After the operating carrier communicates the number of seats the ticketing carrier can access ($b_{21} = C_{TC}$), the ticketing carrier calculates the protection levels for the ticketing carrier's booking class pairs. The demand behavior for the ticketing carrier's booking classes as well as the flight ticket revenues v_{j2} of the ticketing carrier's booking classes are presented in Table 4.4.

j	μ_{j2}	σ_{j2}	v_{j2}
1	12.89	4.66	250
2	40.95	6.37	150

Table 4.4: Mean, Standard Deviation, and Revenue for Booking Classes of Ticketing Carrier

Only one pair of booking classes (p_{12}^2) needs to be considered in calculating the respective protection level by means of Littlewood's Rule since the ticketing carrier offers two booking classes. The resulting protection level is $p_{12}^2 = 12$ which is equal to the protection level for the first booking class of the ticketing carrier. For the lowest yielding booking class and all higher booking classes, the full, capacity the ticketing carrier can access, is protected: $p_{22} = 89$. The corresponding booking limits of the ticketing carrier, determined by $b_{j2} = C_{TC} - p_{j-1,2}$, are $b_{12} = 89$ and $b_{22} = 77$.

EMSR-b (Expected Marginal Seat Revenue – Version b)

The EMSR-b procedure is similar to the one of the EMSR-a heuristic. Instead of aggregating the protection levels as described in the EMSR-a heuristic, the demand of all higher yielding booking classes is aggregated. To determine the protection level p_j for booking class j, the aggregated future demand for classes $j, j-1, ..., 1$ is defined by

$$S_j = \sum_{k=1}^{j} D_k,$$

considering each booking class $j+1 (2 \leq j+1 \leq n)$. By means of the aggregated demand, the weighted-average revenue (denoted by $\overline{v}_j$) needs to be calculated by:

$$\overline{v}_j = \frac{\sum_{k=1}^{j} v_k E[D_k]}{\sum_{k=1}^{j} E[D_k]}.$$

Thereafter, the protection levels y_j are determined by means of Littlewood's Rule (described in Section 2.2.2.3), considering again pairs of booking classes. Booking class $j+1$ with flight ticket revenue v_{j+1} is compared to the aggregated booking class with demand S_j and flight ticket revenue $\overline{v}_j$.

As stated in Talluri and van Ryzin (2004b), Section 2.2.4.2, it is common to assume the demand for each booking class j to be independent and normally distributed with mean μ_j and variance σ_j^2 when applying the EMSR-b heuristic. Consider the example given above, demonstrating the EMSR-a procedure. First, the weighted-average revenues for the booking classes of the operating carrier are calculated: $\overline{v}_{11} = 200$ and $\overline{v}_{21} = 177.8$. The resulting protection levels of the operating carrier are $p_{11} = 11, p_{21} = 64$, and $p_{31} = 100$ which correspond to the following booking limits: $b_{11} = 100, b_{21} = 89$, and $b_{31} = 36$. The ticketing carrier can access ($b_{21} = 89$) seats in the operating carrier's aircraft. Second, after calculating the weighted-average revenues for the booking classes of the ticketing carrier ($\overline{v}_{12} = 250$), the protection levels are determined by means of Littlewood's Rule: $p_{12} = 12$ and $p_{22} = 89$ with the corresponding booking limits $b_{12} = 89$ and $b_{22} = 77$.

Compare Talluri and van Ryzin (2004b), Section 2.2.3.2, for a detailed description of the EMSR-b heuristic. Although, the booking limit results of the EMSR-a and EMSR-b heuristic are very similar in this example, the results can be significantly different in other examples. As stated in Talluri and van Ryzin (2004b), Section 2.2.4.2, the EMSR-b heuristic is more popular in practice than EMSR-a. In a study by Belobaba (1992), in which both EMSR heuristics perform well, the EMSR-b heuristic performs better than the EMSR-a heuristic. However, neither EMSR heuristic is dominating the other in general as stated in other computational studies in revenue management literature. We compare the performance of the procedure based on booking limits calculations by means of the EMSR-a heuristic and the EMSR-b heuristic to the results of the procedure with underlying DLPs for booking limit calculations in Section 4.3.2.

4.2.4 Simulation of Booking Processes

In general, the term simulation indicates the implementation of a system which imitates the characteristics of a real system with suitable input data typically using computers and adequate software as well as the analysis of the respective results. Simulations are normally used for real-world systems beeing too complex to be evaluated analytically (compare Law, 2007, Section 1.1). Other aspects of simulations, such as different simulation types, verification and validation of simulation models, the generation of random numbers, and the analysis of simulation output are characterized by Bratley et al. (1987). Law (2007) additionally describes different simulation software and probability distributions of the simulation's input data. The booking processes of the alliance partners are simulated in this work in order to represent customer requests arriving in different points in time and the acceptance and rejection decisions made by the alliance partners. By means of the simulation processes described in this section, the booking limits calculated in Section 4.2.2 and 4.2.3, underlying the capacity control procedure, can be evaluated.

The simulation of the booking processes of the partner airlines within the alliance considering real options that help to divide the capacity among the alliance partners will be described in this section. The booking processes are modeled as discrete event-driven simulations. In our setting, the state variables of the simulation models represent the state of the systems in period t during an ongoing booking process of length T. Two discrete variables are defined: the capacity availability of the aircraft at t and the number of bookings at time t. The state variables change if a request is accepted by one of the airlines. The simulations are discrete since the time of the booking process is divided in a countable number of points in time in which the state variables of the systems can change. If the state variables vary continuously over time, the simulations are classified as continuous simulations (compare Law, 2007, Section 1.2). Discrete simulations can be further distinguished depending on different occasions which change the system in discrete points in time. In the discrete-event simulation, the state variables may change in the case of an occurring event whereas the state variables change in predefined time intervals in the fixed-increment time simulation (compare Kuhn and Wenzel, 2008). Other classifications of simulations are described by Kelton et al. (2004), Section 1.2.3.

During the booking processes, requests for flight tickets of the two airlines arise at different points in time. Therefore, it is necessary to model the uncertain demand for the flight tickets regarding the total amount of demand and its temporal distribution (compare Klein, 2005, Section 5.1.1). According to McGill and van Ryzin (1999), the implementation of a Poisson distribution to model the demand distribution is recommended so that inter-arrival times are exponentially distributed. The inter-arrival times, matching a Poisson process with arrival rate λ, are exponentially distributed with the parameter $\frac{1}{\lambda}$. In reality, the arrival rate is rarely constant. In this case, a non-stationary Poisson process with arrival rate $\lambda(t)$ is used. A non-homogeneous Poisson process to model the arrival of booking requests in their simulation of the booking process is applied by de Boer et al. (2002), Gosavi et al. (2007), and Klein (2005, 2007). Kimms and Müller-Bungart (2007b) specify an algorithm to generate random streams of demand data for test-instances needed to evaluate network revenue management procedures. The authors use a Beta distribution with different parameters in order to model the passenger arrivals throughout the reservation period. In the simulation models described in this work, the booking processes of the alliance partners are divided in three time intervals (typically called Data Collection Periods (DCP's)) with different request arrival rates. The latter are constant within a particular time interval to approximate a non-stationary Poisson process. The simulations of the booking processes start by generating the arrival times of the requests according to the exponentially distributed inter-arrival times. Thereafter, the requests are sorted according to their arrival times in chronological order and numbered with index m. The request numbered with zero is the first request arriving at the airline's reservation system. After the airline's decision whether to accept or to reject the customer request, the index m is increased by one and the next request, according to the sorted arrival times, can be handled by the airline. The arrival time of incoming requests is set equal to the simulation time every time a new request arrives. The simulation process ends if the arrival time of the next incoming request and, therefore, the simulation time is greater than or equal to the predefined duration of simulation which corresponds to the departure of the operating carrier's aircraft. The described simulation course is pictured in Figure 4.3 and Figure 4.4.

Due to the methodical drawbacks discussed by Talluri and van Ryzin (2004b), Section 2.1.1.1, and mentioned in Section 2.2.2.3, we apply nested booking limits in the simulation of the booking processes of the airlines. The partitioned booking limits, calculated in Section 4.2.2 and 4.2.3, are converted to nested booking limits according to the revenue order. Thus, the operating carrier's highest yielding booking class has access to the whole capacity of the operating carrier and the ticketing carrier's most profitable booking class has access to the capacity the ticketing carrier bought options for. Note that only booking classes within the different airlines are nested. Since the two carriers do not share information concerning their ticket prices, the booking classes within the alliance cannot be nested (with one exception: the operating carrier is able to access the seats assigned to the ticketing carrier in class $n_1 + 1$). As described in Section 2.2.2.3, there are two different control policies adopting nested booking limits: standard and theft nesting (compare Talluri and van Ryzin, 2004b, Section 2.1.1.3). Both control policies can be included into the simulation of the booking processes. The performance of the control policies will be analyzed in the computational study in Section 4.3.2.

The decision process determining whether to accept or to reject a request is equal for all booking classes of the operating carrier. The same applies to the booking classes of the ticketing carrier, whereas the processes of the operating carrier and the ticketing carrier differ. In the following, the decision processes of the two considered carriers will be described assuming a standard nesting control policy.

The Decision Process of the Operating Carrier

After receiving a request for a certain booking class j, the operating carrier checks if the booking limit for the booking class is greater than zero and if the available seat capacity is greater than zero ($b_{j1} > 0$ and $c > 0$). If at least one of the two conditions is false, the operating carrier has to reject the request. Otherwise, the operating carrier checks if the remaining capacity in the aircraft is greater than the number of unexercised options (op) the ticketing carrier holds ($c > op$). If yes, the request can be accepted. If the remaining capacity is less than or equal to the number of options, the operating carrier has to check if the revenue of the received request is greater than or equal to the sum of transfer prices ($v_{j1} \geq x + s$). If yes, the request is accepted and the number of unexercised options is decreased by one (the operating carrier is re-buying the option from the ticketing carrier). If no, the operating carrier rejects the request because it is expected that higher revenues can be gained by selling the seat to the ticketing carrier. For every request accepted by the operating carrier, the booking limit for the booking class j the request occurred in, the booking limits for all higher yielding booking classes ($j-1, j-2, ..., 1$), and the remaining capacity are decreased by one. To guarantee the right accept/reject decision, the booking limits for the lower yielding booking classes must not be higher than the booking limits for the higher yielding booking classes ($b_{j1} \geq b_{j+1,1}$, for all $j = 1, ..., n_1 - 1$). To guarantee this condition, the booking limits for the lower yielding booking classes are set equal to the smaller of the values: the decreased booking limit for the higher yielding booking class or the unchanged booking limit for the considered lower yielding booking class ($b_{j+1,1} = min\{b_{11}, b_{21}, ..., b_{j+1,1}\}$). The decision process of the operating carrier is presented in Figure 4.3.

The Decision Process of the Ticketing Carrier

The decision process of the ticketing carrier differs from the process of the operating carrier. If a request for a certain booking class j occurs, the ticketing carrier checks if the revenue for accepting this request is higher than the sum of option price and strike price ($v_{j2} > x + s$). If no, the ticketing carrier rejects the request since the ticketing carrier's costs are higher than or equal to the revenue the ticketing carrier gains from selling the ticket in that booking class. If yes, the ticketing carrier checks if the booking limit for that booking class and the number of unexercised options are greater than zero ($b_{j2} > 0$ and $op > 0$). If at least one of the conditions is false, the request is rejected. Otherwise, the request is accepted and the booking limit for the booking class j the request occurred in, the booking limits for all higher yielding booking classes ($j-1, j-2, ..., 1$), and the number of unexercised options are decreased by one. To guarantee the right accept/reject decision also for the ticketing carrier, the booking limits

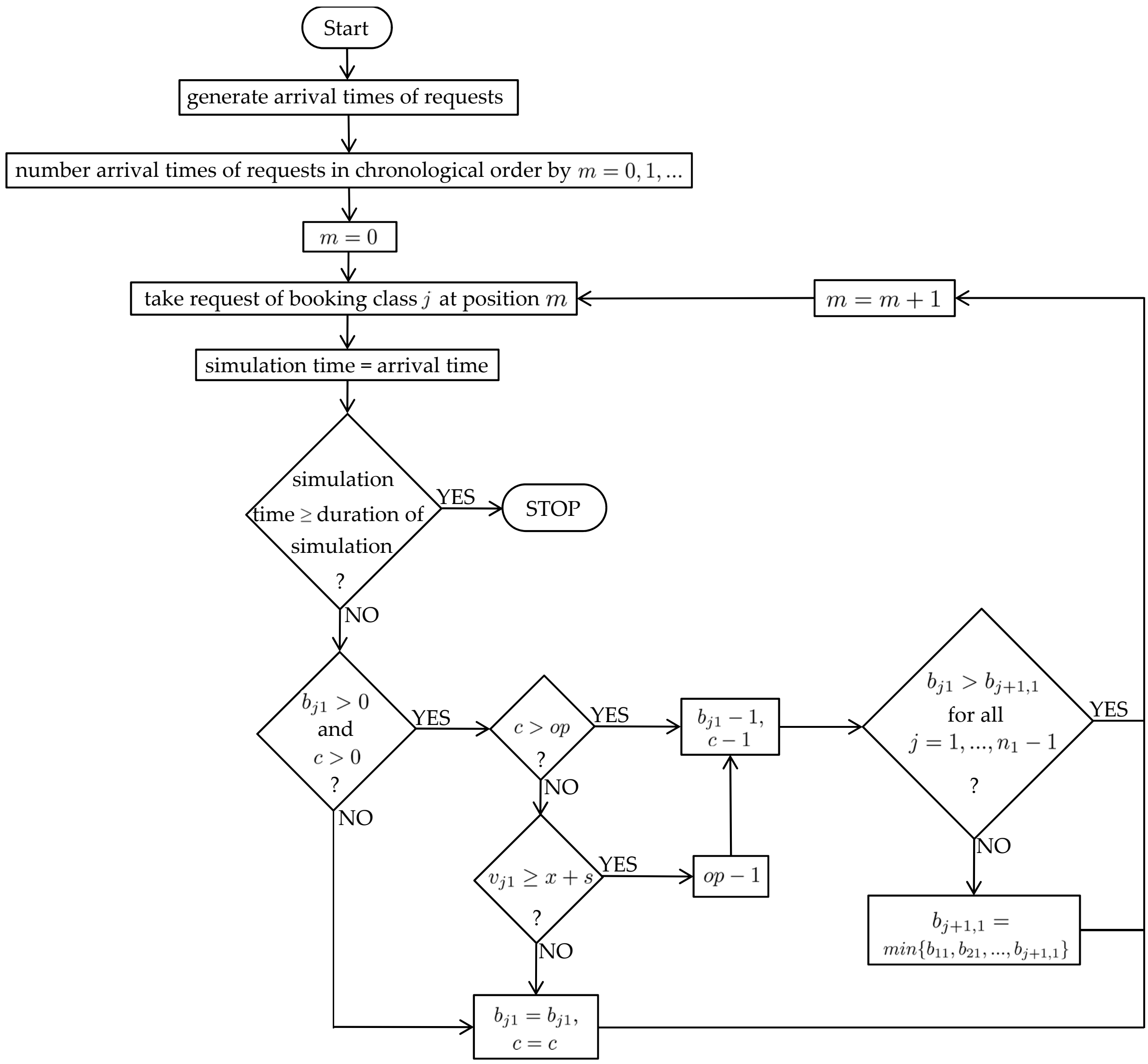

Figure 4.3: The Simulation Process of the Operating Carrier

for the lower yielding classes must not be higher than the booking limits for the higher yielding classes ($b_{j2} \geq b_{j+1,2}$, for all $j = 1, ..., n_2 - 1$). To guarantee this condition, the booking limits for the lower yielding booking classes are set equal to the smaller value of the values: the decreased booking limit for the higher yielding booking class or the unchanged booking limit for the considered lower yielding booking class ($b_{j+1,2} = min\{b_{12}, b_{22}, ..., b_{j+1,2}\}$). In Figure 4.4 the decision process of the ticketing carrier is demonstrated.

As already explained in Section 2.2.2.3, the decision processes of the airlines change with using the theft nesting control. In that case, after each request acceptance not only the booking limit for the class the request occurred in and the booking limits for all higher yielding classes are decreased by one but also the number of booking limits for all lower yielding classes.

To calculate the operating carrier's expected revenue after the simulation of the booking process, the operating carrier multiplies the number of requests accepted in the different booking classes of the operating carrier with the flight-ticket revenue for one ticket in the corresponding booking class and adds up the resulting products. Additionally, the operating carrier gains the transfer payments of the ticket-

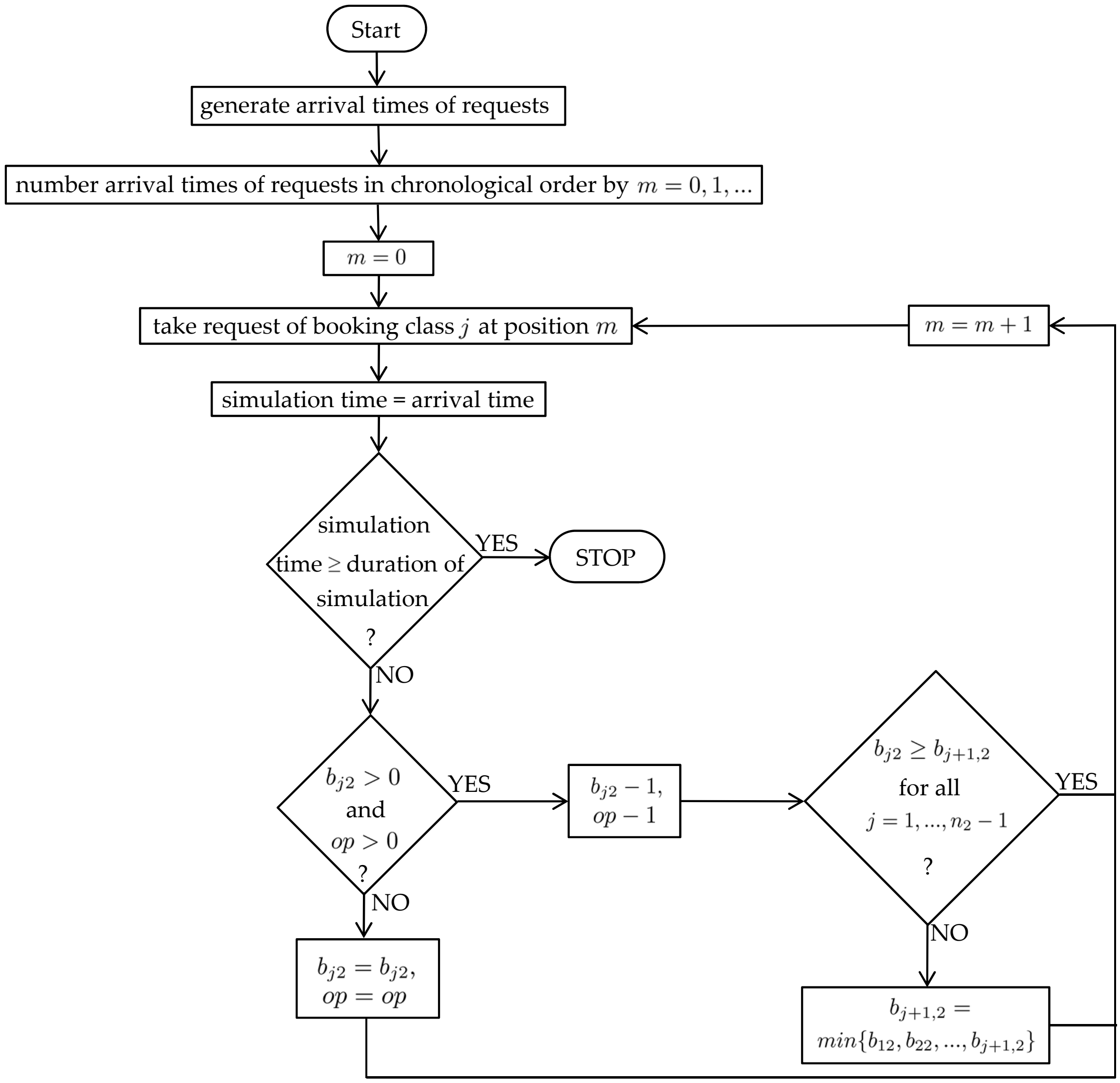

Figure 4.4: The Simulation Process of the Ticketing Carrier

ing carrier, hence, increasing the expected revenue of the operating carrier. The ticketing carrier pays to the operating carrier the option price multiplied by the number of options the ticketing carrier exercised during the booking process or still holds after the booking process. This number of options equals to the number of options the ticketing carrier bought from the operating carrier before the booking process, subtracted by the number of options the operating carrier bought back from the ticketing carrier during the booking process. Furthermore, the ticketing carrier pays the strike price multiplied by the number of accepted requests in all booking classes of the ticketing carrier.

To calculate the ticketing carrier's expected revenue after the simulation of the booking process, the ticketing carrier multiplies the number of requests accepted in the different booking classes of the ticketing carrier with the flight-ticket revenue for one ticket in the corresponding booking class and adds up the resulting products. However, the ticketing carrier has to pay the transfer payments to the operating carrier which decrease the expected revenue of the ticketing carrier. These transfer payments of the ticketing carrier were already mentioned above in the explanation of the operating carrier's expected revenue calculation.

We will explain the calculation of the expected revenues of the partner airlines within the alliance by means of the example described in Section 4.2.2: Let the number of requests accepted by the operating carrier ($l = 1$) in booking class j be denoted by h_{j1}. According to this, the number of requests accepted by the ticketing carrier ($l = 2$) in booking class j are denoted by h_{j2}. The number of options the ticketing carrier exercised during the booking process ($\sum_{j=1}^{n_2} h_{j2}$) added to the number of options the ticketing carrier holds at the end of the booking process is denoted by r.
The calculation of the expected revenue of the operating carrier is, therefore, described by:

$$\sum_{j=1}^{n_1} v_{j1} * h_{j1} + x * r + s * (\sum_{j=1}^{n_2} h_{j2}).$$

And the calculation of the expected revenue of the ticketing carrier is described by:

$$\sum_{j=1}^{n_2} v_{j2} * h_{j2} - (x * r + s * (\sum_{j=1}^{n_2} h_{j2})).$$

4.3 Computational Study for the Option-Based Procedures

The proposed option-based procedures with underlying DLPs and underlying EMSR heuristics were implemented in C++ in order to test the procedures. In the following, the performance of the option-based approach with underlying DLPs is extensively studied and compared to the results of the EMSR-a+Options approach and EMSR-b+Options procedure. To simplify the nomenclature, the option-based procedure with underlying DLPs is referred to as option-based procedure.

In the following subsections, the test bed for the analysis of the option-based procedures will be introduced at first, followed by the demonstration and interpretation of the results gained in the computational study of the option-based procedures. We will discuss the insights gained about the performance of our procedures.

4.3.1 Test Bed for Option-Based Procedures Analysis

After solving the optimization models introduced in Section 4.2.2 and the EMSR heuristics described in Section 4.2.3, the programs pass the calculated booking limits to the simulation. The programs simulate the booking processes of the two carriers according to the models outlined in Section 4.2.4 to determine the revenue obtained with the computed booking limits. Since the goal of the option-based mechanisms is to maximize the combined revenue of the alliance partners, we refer to the alliance revenue in the computational study, which is the sum of the revenues of the alliance partners.

We used standard nesting control in the simulation to implement the nested booking limits since standard nesting is the most common method in revenue management practice (compare Talluri and van Ryzin, 2004b, Section 2.1.1.3). To create pseudo-random numbers for the stochastic request arrivals, we used the random number generator boost::random::ranlux64_base_01 (compare www.boost.org) in the programs. Closing with the departure of the airplane, the duration of the simulation accounts for 150 periods and it shows the booking process of the alliance partners. We simulated 5000 booking processes of the airlines taking the stochastic demand into account. The revenue measurements achieved by the 5000 simulation-replications are averaged, obtaining the result conceived with the inserted booking limits for the considered instance.
In all instances considered in the computational study, the booking limits for the operating carrier were calculated by means of the procedure described in Section 4.2.2 which assigns the spare seats, the ticketing carrier does not buy options for (if they exist), to a class of the operating carrier (Procedure 1).

We compared the results of the introduced option-based procedure to the results of a FCFS approach and ex post optimal solutions. In the FCFS approach, the booking requests are accepted in the order of their appearance at the two airlines as long as they can be served with remaining capacity. The ex post optimal solution represents the optimal revenue obtained with full information on demand after the booking process. To generate the ex post optimal solutions, we simulated the booking process of the operating carrier and the ticketing carrier and counted the total incoming requests depending on their revenue. We filled the seat capacity of the aircraft, starting with the most profitable requests, continuing with the second profitable requests, and so on, until there was no remaining seat capacity. The ex post optimal solution corresponds to the revenue achieved by a central decision maker with full information and defines an upper bound to the result of the option-based procedures. The computational study was done on an AMD Athlon(tm) 64X2 Dual Core Processor 4600+ 2.41 GHz PC with 1,96 GB RAM running Windows XP.

In the computational study of the option-based procedures, the following parameters are systematically varied: the number of total available seat capacity C, the revenue for the tickets in booking class j of airline l, v_{jl}, the option price x and strike price s, and the expected value of demand for tickets in booking class j of airline l, $E[d_{jl}]$. We assumed the seat capacity of the operating carrier to be 100, 120, or 150. Table 4.5 shows the different revenue and price instances underlying the computational study.

Revenue/Price Instance	v_{11}	v_{21}	v_{12}	v_{22}	x	s
1a	350	100	400	150	20	120
1b	350	100	400	150	30	40
1c	350	100	400	150	50	50
1d	350	100	400	150	20	200
2a	400	150	350	100	10	80
2b	400	150	350	100	50	60
2c	400	150	350	100	75	75
2d	400	150	350	100	100	150
3a	350	100	450	200	30	160
3b	350	100	450	200	30	40
3c	350	100	450	200	50	50
3d	350	100	450	200	110	160
4a	200	100	250	150	20	120
4b	200	100	250	150	30	40
4c	200	100	250	150	50	50
4d	200	100	250	150	20	200

Table 4.5: Revenue and Price Instances

The test bed contains four different revenue instances and, for each of these instances, four different option price and strike price values. We ensured that it is more profitable for the airlines to sell a ticket in their first than in their second booking class but changed the gap between the revenues of the different booking classes of the two airlines. We have chosen the option price and the strike price so that the sum of the two prices is higher, lower, much higher than, and equal to the lowest revenue value of the classes. It is possible to determine the optimal option price and strike price for each revenue and demand instance. Therefore, we could for example systematically change the prices step by step and calculate the corresponding expected revenue in each step for each instance. We tested this procedure using one demand and one revenue instance. Starting with an initial value for both prices and increasing the prices in nine steps to their maximum values, it took nearly two hours to determine the optimal prices. As presented in Section 4.3.2, the run-time of the proposed option-based procedure for one instance with a fixed option price and strike price is less than a second. Considering the much faster run-time and the acceptable results, we decided to vary the option price and the strike price systematically in the computational study rather than step by step for each instance.

We assumed the expected value of total demand for tickets in all booking classes of both airlines to be 10%, 20%, 30%, and 40% higher than the specified capacity, that means the demand intensity varies between 1.1 and 1.4. If the capacity is 120, the total demand is 132, 144, 156, and 168. There is no revenue management problem if the capacity is equal to or higher than the demand (compare Klein, 2005, Section 6.2.2). As one of the main assumptions of the applicability of revenue management instruments, the assumption of scarce capacity, is not existent in that case. However, in Section 4.3.2 (Table 4.9) we show the performance of the introduced option-based procedure in a low demand setting, in which the total demand is 90% of the capacity (demand intensity 0.9), to determine the performance of the option-based procedure in a setting in which the actual demand is unexpectedly much lower than the predicted demand.

In each demand scenario, capturing the total demand for all booking classes, we assumed different demand instances with varying demand for the booking classes of the airlines. Considering the demand for one airline, the demand for the expensive flight tickets is lower than the demand for the cheaper tickets in every demand instance. The values underlying the demand instances are presented in Table A.1, A.2, A.3, and A.4 in the Appendix A.1.

4.3.2 Evaluation of the Option-Based Procedures

The revenue, generated by the option-based procedure, aggregated over all instances is 5.26% higher than the revenue generated by the FCFS approach and 16.17% lower than the revenue generated in the ex post optimal solution. The program achieves the result for one instance in less than a second. Therefore, we do not specify the program's run-time for each instance.

The percentage gap ($gap1$) between the solution of the option-based procedure (OBP) and the FCFS approach is computed by:

$$gap1 = \frac{OBP - FCFS}{FCFS} * 100.$$

The percentage gap ($gap2$) between the ex post optimal solution and the solution of the option-based procedure is computed by:

$$gap2 = \frac{ex\ post - OBP}{OBP} * 100.$$

Table 4.6 shows the average revenue aggregated over all instances in one capacity scenario gained from the option-based procedure, the FCFS approach, and the ex post optimal solution as well as the gap between the results of the option-based procedure and the other approaches. The option-based procedure leads to better results than the FCFS procedure in all three capacity settings, whereas there is still the possibility to improve the results towards the ex post optimal solutions. Increasing the capacity leads to a better performance of the option-based procedure compared to the FCFS approach and also to results of the option-based approach that are closer to the ex post optimal solutions. The solution space increases in instances with higher seat capacity which explains the improved performance of the option-based procedure compared to the FCFS method. In an increased solution space, it is unlikely that the FCFS procedure accidentally finds a good solution than in a small solution space.

Capacity	$gap1$	$gap2$
100	0.86	20.60
120	3.69	17.66
150	6.57	15.40

Table 4.6: OBP – Results Aggregated over Demand, Revenue, and Price Instances

The revenue per seat increases slightly as the number of seats in the aircraft increases. The ratio of demand and seat capacity remains constant in all tree capacity instances being 110%, 120%, 130%, and 140% of the assumed capacity. The total demand, however, scales up in instances assuming a higher seat capacity compared to the instances with lower seat capacity. This and the increased seat capacity cause an expanded solution space which explains the slightly higher revenue per seat in high capacity settings. Table 4.7 contains the revenue per seat performance.

Capacity	$gap1/C$	$gap2/C$
100	0.01	0.21
120	0.03	0.15
150	0.04	0.10

Table 4.7: OBP – Results Aggregated over Demand, Revenue, and Price Instances Per Seat

In a first observation, we fixed the demand and aggregated the computed results over all revenue and price instances to evaluate the estimated revenue values.

Table 4.8 contains aggregated results for the assumed capacity of 100, 120, and 150 seats in the aircraft. Scenario 110 (demand in %), e.g., shows the average revenue achieved by the option-based procedure aggregated over all demand instances assuming the total demand to be 110% of the capacity. It can be noticed that the FCFS approach performs better than the option-based procedure in low demand settings since in this case it is more profitable to accept all incoming requests than reserve seats for higher yielding requests. Due to the stochastic demand, the possibility of the demand being less than the capacity is higher in low demand instances than in demand settings with greater total demand. As soon as the demand intensity is 1.3 or higher, considering an airplane with 100 seats, the option-based procedure yields higher revenues than the FCFS approach, whereas the results are still lower than the ex post optimal solutions. If we consider an aircraft with 120 or 150 seats, the option-based procedure achieves higher results than the FCFS approach for the demand being 120% of the capacity or higher since the reservation for higher yielding requests pays off.

The ex post optimal solution is higher in instances with a greater total demand since there are more higher yielding requests in these settings compared to the instances with low total demand.

To show the performance of the option-based procedure in a low demand setting, we calculated the expected revenue for 13 demand instances assuming the total demand to be 90% of the capacity.

Table 4.9 shows the results for the seat capacity being 100, 120, and 150. The average revenue of the option-based procedure over all 13 demand instances and 16 revenue and price instances (compare Table 4.5) is in all capacity instances much lower than the revenue generated by the FCFS approach and much lower than the ex post optimal solution. This insight supports the argument that there is no revenue management problem in case of the demand being lower than the capacity. In all instances in which we assumed the total demand to be 90% of the capacity, it would be the right choice to accept all requests in a first-come-first-served order to fill the capacity of the airplane rather than reserve seats for

Capacity	Demand in %	$gap1$	$gap2$
100	110	-9.54	20.14
	120	-3.08	19.61
	130	4.97	18.96
	140	14.27	17.74
120	110	-8.21	17.34
	120	1.23	16.07
	130	9.56	15.31
	140	18.11	15.39
150	110	-4.61	14.12
	120	3.30	13.49
	130	13.30	12.94
	140	21.57	13.57

Table 4.8: OBP – Results Aggregated over Revenue and Price Instances

Capacity	Demand in %	$gap1$	$gap2$
100	90	-16.62	24.91
120	90	-15.52	22.55
150	90	-13.90	18.86

Table 4.9: OBP – Results Aggregated over Revenue and Price Instances in Instances with Demand Intensity 0.9

higher yielding booking classes.

We fixed the revenue and aggregated the computed results over all price and demand instances in a second survey to evaluate the effect of the revenue variation among the tested instances.

Table 4.10 presents the results for capacity 100, 120, and 150. The revenue gained from the option-based approach is lower than the revenue gained by the FCFS procedure in the fourth revenue instance for all declared capacities. The fourth revenue instance differs from the other three instances in the interval of the flight-tickets' revenues in the first and second booking classes of the two considered airlines. The option-based approach yields better in revenue instances with a larger gap between the ticket revenue of the classes since it is more profitable to reserve seats in the aircraft for the higher yielding booking classes.

Capacity	Revenue Instance	$gap1$	$gap2$
100	1	4.75	17.62
	2	9.73	12.60
	3	-0.80	24.31
	4	-7.07	21.91
120	1	8.52	14.63
	2	12.63	10.32
	3	3.37	20.40
	4	-3.83	18.76
150	1	11.77	12.29
	2	15.83	8.42
	3	6.80	17.39
	4	-0.85	16.03

Table 4.10: OBP – Results Aggregated over Demand and Price Instances

We fixed the option price and the strike price and aggregated the computed results over all revenue and demand instances in a third survey to evaluate the effect of price variations.

Table 4.11 shows the results for the seat capacity being 100, 120, and 150. The revenue achieved by the option-based approach is lower than the revenue gained from the FCFS procedure in price instance d for the capacity being 100 and 120. In all revenue instances combined with price instance d, the sum of option price and strike price is much higher than the revenue the ticketing carrier receives for one sold ticket in the second booking class ($x + s > v_{22}$). In that case, the ticketing carrier will not buy any options for the demand of the second booking class, even if this would increase the total alliance revenue. The option-based approach yields better in price instances in which the sum of option price and strike price is lower than v_{22}. The performance of the option-based procedure depends on the right choice of the option price and the strike price. It is noticeable that the revenue gained from the option-based approach in price instance b is equal to the revenue in price instance c. In price instance b, the sum of option price and strike price is lower than the revenue achieved by the operating carrier selling a flight ticket for the lowest yielding booking class ($x + s < v_{21}$). The sum of option price and strike price is equal to the revenue gained by selling a flight ticket in the operating carrier's lowest yielding class ($x + s = v_{21}$) in price instance c. During the simulation of the booking process, the remaining seat capacity can be less than or equal to the number of unused options held by the ticketing carrier. In that case, the operating carrier checks if the revenue of the received request is greater than or equal to the sum of option price and strike price. The operating carrier accepts the request in both cases since the revenue gained from accepting the request is higher than or equal to the revenue the operating carrier gains if the ticketing carrier executes an option in the uncertain future. This and the fact that the sum of option price and strike price in both price instances (b and c) is simultaneously lower or higher than the revenue achieved by selling a flight ticket in the ticketing carrier's lowest yielding booking class (v_{22}), depending on the considered revenue instance, explains the equal results for price instance b and c. The equal results could indicate that the alliance revenue achieved by the option-based procedure changes only if the sum of option price and strike price differs in certain intervals. This phenomenon will be further discussed in Section 7.2.2. The results of the FCFS approach and ex post optimal solutions are constant in all price instances since these methods do not consider our option theory with its option price and strike price.

Capacity	Price Instance	$gap1$	$gap2$
100	a	10.42	8.41
	b	1.97	17.63
	c	1.97	17.63
	d	-7.73	32.79
120	a	13.01	7.10
	b	5.30	15.07
	c	5.30	15.07
	d	-2.93	26.87
150	a	15.50	5.89
	b	8.33	13.00
	c	8.33	13.00
	d	1.40	22.33

Table 4.11: OBP – Results Aggregated over Demand and Revenue Instances

As described in Section 4.2.2, there are two possible procedures to determine the booking limits for the operating carrier. The performance of the option-based method depends on the selected procedure. As mentioned before, the procedure, which assigns the spare seats the ticketing carrier does not buy options for (if they exist) to a class of the operating carrier was considered in the instances of the computational study (Procedure 1). The revenue gained from Procedure 1, averaged over all instances considering the capacity to be 120, is 1.43% higher than the revenue gained from Procedure 2, which solves the model of the operating carrier twice, not considering the additional class of the ticketing carrier in calculating the booking limits for the operating carrier. The booking limits calculated by Procedure 1, compared to the ones achieved by Procedure 2, differ in the amount of the operating carrier's booking limits (b_{11} and b_{21}). It can be noticed that the booking limit for the operating carrier's higher yielding booking class determined by Procedure 1 almost always corresponds to the one calculated by Procedure 2. This is plausible since the calculation of the booking limit of the operating carrier's first booking class only differs between Procedure 1 and 2 if there is a difference in calculating the booking limits of the operating carrier for three or two considered booking classes (recall that the demand coming from the ticketing carrier is not considered in an additional booking class when calculating the booking limits by Procedure 2 for the two booking classes of the operating carrier). If the sum of option price and strike price is lower than v_{11}, the position in the nesting order of the highest yielding booking class of the operating carrier does not change no matter whether the booking limits are calculated for three or two booking classes. In our test bed, there is only one price and revenue instance which describes the circumstance that the option price plus the strike price exceeds the revenue gained by selling a flight ticket in the first booking class of the operating carrier. The booking limits of the second booking class of the operating carrier, however, often change when comparing Procedure 1 and 2. In most of the incorporated instances, the demand for the second booking class of the operating carrier is lower than the remaining capacity after allocating seat capacity to the first booking class of the operating carrier. Therefore, the booking limit of the operating carrier's second booking class is not much higher after calculating the booking limit for two instead of three classes. In the revenue and price instances in which the sum of option price and strike price is higher than v_{22}, the ticketing carrier will not buy options for the second class and, therefore, the booking limit of the second class of the operating carrier is increased in Procedure 1. That causes the booking limit of the operating carrier's second booking class calculated by means of Procedure 1 to be often higher than the booking limit achieved by Procedure 2 which implies more flexibility for the operating carrier during the booking process since the operating carrier has the opportunity to buy-back options if the revenue gained from accepting a request is higher than or equal to the option price plus the strike price.

We compared the performance of the option-based procedure using standard nesting with the performance applying a theft nesting control for capacity instance 120. No global declaration can be made about the comparative performance of the two nesting controls, but exercising the standard nesting control in the option-based procedure results in a revenue being 2.27% higher than the results of the option-based procedure with underlying theft nesting control aggregated over all instances assuming the capacity to be 120. According to Talluri and van Ryzin (2004b), Section 2.1.1.3, theft nesting protects more capacity for higher yielding classes which seems to be a drawback in our application area.

Furthermore, we compared the performance of the option-based method with buy-back opportunity of the operating carrier (OBP+BB) to the performance of the method without buy-back opportunity (OBP-BB). The revenue generated by the OBP+BB approach, averaged over all instances considering the capacity to be 120, is 0.36% higher than the revenue calculated by the OBP-BB. The reason for the inferior performance of the option-based procedure without allowing the operating carrier to buy-back options is, as mentioned in Section 4.2.1, the inflexibility within this procedure. It can be noticed that the option-based procedure allowing the operating carrier to buy-back options never performs worse than the option-based method which forbids the buy-back of options. In the revenue and price instance 4d, however, both procedures (OBP+BB and OPB-BB) perform equally in all demand instances. An explanation can be found since in the revenue and price instance 4d, the sum of option price and strike price is higher than the revenue the operating carrier earns by selling a flight ticket in both booking classes ($x + s > v_{11}$ and $x + s > v_{21}$). In that case, the operating carrier would never use the buy-back possibility since the expected revenue, the operating carrier achieves if the ticketing carrier sells a flight ticket and, therefore, executes an option, is higher than the revenue the operating carrier earns by accepting a booking request in both booking classes in all demand instances.

As outlined in Section 4.2.3, the booking limits underlying the option-based procedure can be calculated by means of EMSR heuristics instead of the deterministic linear programs introduced in Section 4.2.2. In the following, the performance of the option-based procedure (with underlying DLPs) will be compared to the EMSR-a+Options approach and the EMSR-b+Options approach, both described in Section 4.2.3. The real option idea was included in both versions of the EMSR heuristic. We changed the simulation of the booking process and eliminated the nesting of the booking limits since the booking limits achieved by the EMSR heuristics are already nested. After averaging the expected revenue of all instances with seat capacity 120, we gained an expected revenue from the EMSR-a+Options procedure that is slightly lower than the revenue achieved by the EMSR-b+Options approach. This outcome supports the statement of Belobaba (1992) that EMSR-b provides better revenue performance compared to EMSR-a, which means that this statement can be transfered to the scenario in which the EMSR heuristics are combined with our option idea. The result of the option-based method with the underlying deterministic linear programs is 32.01% higher than the revenue calculated by the EMSR-a+Options approach. A similar result can be noticed considering the EMSR-b+Options approach. We received an expected revenue from the DLP underlying option-based method beeing 26.42% higher than the revenue achieved by the EMSR-b+Options procedure. The EMSR heuristics perform worse in many of the observed instances but it can be noticed that the option-based procedure with underlying DLP gains inferior results compared to the EMSR heuristics in instances which assume the demand for the ticketing carrier's first booking class to be high. The superior expected revenue calculated by the EMSR heuristics compared to the revenue gained by the DLP underlying option-based procedure can be explained by the booking limit of the first booking class of the ticketing carrier which is often higher in the results achieved by the EMSR-heuristics than in the DLP underlying option-based procedure's results. Since the performance of the DLP underlaying option-based procedure is better than the results gained by the EMSR-a+Options approach and the EMSR-b+Options method, the deterministic linear programs with included options idea will be applied to calculate the initial booking limits for the procedures presented in the following.

Chapter 5

Booking Limit Improvement

The following chapter will introduce a simulation-based optimization approach to improve the booking limits calculated by means of the deterministic linear programs introduced in Section 4.2.2. At first, the basics of simulated-based optimization methods will be shortly discussed (Section 5.1) followed by the specification of the simultaneous perturbation stochastic approximation (SPSA) approach introduced by Spall (1992) which will be applied for booking limit improvement in the capacity control mechanisms for partners within a strategic alliance introduced in this thesis (Section 5.2). In a computational study, the performance of the procedure with booking limit improvement will be analyzed (Section 5.3). This chapter is based on Graf and Kimms (2009).

5.1 Simulation-Based Optimization

As already described in Section 4.2.4, simulations can be applied to evaluate the behavior of complex systems. Beyond that, simulations can help optimization methods to determine optimal values for the considered decision variables. In revenue management capacity control, the control variables, in our procedures the booking limits, describe the decision variables which need to be optimized. Carson and Maria (1997) describe simulation optimization as a process in which an optimization strategy uses the output of a simulation model as input to evaluate the search for the optimal solution. Whereas the input for that simulation model is gained by the output of the optimization strategy. As pointed out in Azadivar (1999), an optimization problem is a simulation optimization problem if the objective function and/or constraints of the problem can only be evaluated by computer simulation. Azadivar (1999) compares the stochastic optimization problem with deterministic and stochastic optimization problems and lists the major differences. There is a large body of literature on simulation-based optimization. A comprehensive review of simulation optimization literature is provided by Swisher et al. (2000). The simulation-based optimization topic is extensively described in Gosavi (2003), Law (2007), Chapter 12.5, and Spall (2003). April et al. (2003) as well as Fu (2002) present some of the most relevant approaches developed for simulation-based optimization, describe the application of these procedures in practice, and discuss their implementation in commercial software. The four main methods for simulation-based optimization are, as identified and described by Fu (2002), stochastic approximation (gradient-based approaches), (sequential) response surface methodology, random search, and sample path optimization.

The capacity control problem is a restricted, stochastic maximization problem with an objective function that cannot be described with a formula. Instead, an approximation of the objective function can be evaluated by simulation. Robinson (1995) introduced the idea of simulation-based optimization in a revenue management context. Gosavi et al. (2007), Klein (2005), Section 5.1, Müller-Bungart (2006), Section 5.1.2, and van Ryzin and Vulcano (2008b) describe simulation-based optimization in the context of revenue management as well. Bertsimas and de Boer (2005) published an approach which uses a combination of simulation and optimization to solve the capacity control problem for non-allied carriers. To improve the calculated booking limits, the authors use a stochastic gradient algorithm. Inspired by the revenue enhancements gained by the simulation-based booking limit procedure, as presented in the computational study of Bertsimas and de Boer (2005), we apply a stochastic approximation procedure to improve the booking limits determined beforehand by the deterministic linear programs.

As pointed out by April et al. (2003), stochastic approximation procedures try to imitate the process of gradient search methods applied to solve non-linear programming problems. A gradient is a vector pointing in the direction of the steepest ascent of a function in a maximization problem (compare, Domschke and Drexl, 2005, Section 8.3.2, and Spall, 2003, Section 1.4.1). Considering a minimization problem, the gradient points in the direction of the steepest descent of a loss function. The gradient search procedure (also called hill climbing, steepest ascent, or steepest decent method) proceeds in following the gradient in the direction the gradient points as long as the (loss) function can be improved in doing so (compare Spall, 2003, Section 1.4.1). Efficient approximations of the gradient need to be developed to be able to apply stochastic approximation procedures (compare Klein, 2005, Section 5.1.3). The finite-difference algorithm, discussed in Spall (2003), Chapter 6, is the simplest approach for stochastic approximation. The decision variables are systematically varied by a fixed amount. The booking limit for a single product or booking class b_j, for all $j = 1, ..., n$, considered in our procedures, therefore, would be increased and decreased by a predefined amount Δ_i. To determine the approximation of the gradient $\mathbf{g}(\mathbf{b})$ for the decision variables, the problem needs to be simulated first with the increased decision variable and second with the decreased decision variable, whereas the other decision variables remain constant: $(b_1, ..., b_j + \Delta_j, ..., b_n)$ and $(b_1, ..., b_j - \Delta_j, ..., b_n)$. If $V(\mathbf{b})$ is the result of the simulations for the solution $\mathbf{b}$, the approximation of the gradient can be determined by:

$$\boldsymbol{g}(\boldsymbol{b}) = \frac{(V(b_1, ..., b_j + \Delta_j, ..., b_n) - V(b_1, ..., b_j - \Delta_j, ..., b_n))}{2\Delta_j}.$$

Compare Klein (2005), Section 5.1.3, and Spall (2003), Section 6.3, for the above described finite-difference algorithm. A more sophisticated stochastic approximation procedure, introduced by Spall (1992), is the simultaneous perturbation stochastic approximation procedure (SPSA). The SPSA procedure increases and reduces all considered decision variables simultaneously by a predefined amount $(b_1 + \Delta_j, ..., b_j + \Delta_j, ..., b_n + \Delta_j)$ and $(b_1 - \Delta_j, ..., b_j - \Delta_j, ..., b_n - \Delta_j)$. Thus, the gradient approximation requires only two measurements of the underlying function which makes the SPSA procedure more efficient than the finite-difference method, requiring $2n$ simulation runs for the gradient approximation.

The SPSA procedure is applied in this work to improve the results discussed so far. In the following section, the problem-specific SPSA approach will be described using an example.

5.2 Booking Limit Improvement by Simultaneous Perturbation Stochastic Approximation

As stated in Spall (1998b), there is a great need for mathematical algorithms that detect the solution iteratively since in many real-world optimization problems an analytical (closed-form) solution cannot be determined. The SPSA procedure can be applied to respond to these requirements. Both, Spall (1998b) and Spall (2003), Chapter 7, present an overview of the simultaneous perturbation stochastic approximation procedure for efficient optimization. In Abdulla and Bhatnagar (2006) and Spall (1997), variants of the SPSA procedure are outlined. The SPSA method can be used in various application areas, (compare Spall, 2003, Section 7.1), including revenue management capacity control problems. Gosavi et al.

(2007) introduce a simulation-based optimization model for airline capacity control problems considering cancellations and overbooking. The simulation-based optimization is carried out by means of the simultaneous perturbation stochastic approximation approach.

In the following, the implementation of a problem-specific version of the SPSA principle will be specified in five steps. Compare Spall (1998a) for a detailed description of a general SPSA algorithm implementation. The simulation-based optimization improves the booking limits calculated using the deterministic linear models described in Section 4.2.2 iteratively. Therefore, the booking limits calculated by means of the DLPs are the initial solution of the problem-specific SPSA approach.

Step 1: Initialization
Let $N = \{(j,l)|j \in \{1,...,n\}$ and $l \in \{1,2\}\}$ denote the set of products. In the first step of the SPSA method, the iteration counter k is set equal to zero ($k = 0$) and the booking limits for the products are set to a feasible initial guess $\mathbf{b}^0$. The booking limits $\mathbf{b}^0$ can be calculated, for instance, as described in Section 4.2.2 and be used as initial booking limit values for the SPSA procedure. To continue the example from Section 4.2.2, the booking limit vector $\mathbf{b}^0 = ((b_{11}^0, b_{21}^0)^T, (b_{12}^0, b_{22}^0)^T)^T$ equals to $((30,20)^T, (50,0)^T)^T$. According to Spall (1998a), further parameters are necessary to calculate the sequences $a_k = \frac{a}{(A+k+1)^\alpha}$ and $c_k = \frac{R}{(k+1)^\gamma}$, needed in Step 3 and Step 5 of the SPSA algorithm. The parameters are initialized as follows: $\alpha = 0.602, \gamma = 0.101, a = 0.5, A = 10$, and $R = 5$. In the test bed of the computational study outlined in Section 5.3.1, the determination of these parameters will be shortly discussed.

Step 2: Generation of Simultaneous Perturbation Vector
A simultaneous perturbation vector $\mathbf{\Delta^k}$ is generated in the second step. As pointed out in Spall (1998a), for each component (j,l) of the random number Δ_{jl}^k, a Bernoulli ±1 distribution with probability of $\frac{1}{2}$ for each ±1 outcome is used (e.g., $\mathbf{\Delta^0}= ((1,-1)^T, (-1,-1)^T)^T$).

Step 3: Perturbation and Loss Function Evaluation
Based on the simultaneous perturbation around the current booking limit vector, two measurements y of the loss function are obtained by simulation. Therefore, the current booking limit vector $\mathbf{b}^k$ is simultaneously perturbed in Step 3 by adding and subtracting the perturbation vector $\mathbf{\Delta^k}$ generated in Step 2 as follows: ($y(\mathbf{b}^k + c_k\mathbf{\Delta^k})$ and $y(\mathbf{b}^k - c_k\mathbf{\Delta^k})$).

In the example: $y\left(\left(\begin{Bmatrix} 30 \\ 20 \\ 50 \\ 0 \end{Bmatrix}\right) + 5\left(\begin{Bmatrix} 1 \\ -1 \\ -1 \\ -1 \end{Bmatrix}\right)\right)$ and $y\left(\left(\begin{Bmatrix} 30 \\ 20 \\ 50 \\ 0 \end{Bmatrix}\right) - 5\left(\begin{Bmatrix} 1 \\ -1 \\ -1 \\ -1 \end{Bmatrix}\right)\right)$.

Step 4: Gradient Approximation
A simultaneous perturbation approximation to the unknown gradient $\mathbf{g}^k(\mathbf{b}^k)$ is generated in the fourth step of SPSA as follows:

$\mathbf{g}^k(\mathbf{b}^k) = \frac{y(\mathbf{b}^k+c_k\mathbf{\Delta}^k)-y(\mathbf{b}^k-c_k\mathbf{\Delta}^k)}{2c_k} \begin{bmatrix} \left(\Delta_1^k\right)^{-1} \\ \left(\Delta_2^k\right)^{-1} \end{bmatrix}$, where $\mathbf{\Delta_l^k}$ is the component vector of the $\mathbf{\Delta^k}$ vector.

In the example: $\mathbf{g}^0(\mathbf{b}^0) = \begin{pmatrix} \begin{pmatrix} -100 \\ 100 \end{pmatrix} \\ \begin{pmatrix} 100 \\ 100 \end{pmatrix} \end{pmatrix}.$

Note that the numerator of the fraction is equal in all four components of $\mathbf{g}^k$ which reflects the simultaneous perturbation of all components in the booking limit vector in contrast to the component-by-component perturbations in the standard finite-difference approximation.

Step 5: Updating b_{jl}^k Estimate

The booking limit vector b_{jl}^k is updated to a new value b_{jl}^{k+1} in Step 5 by using the standard stochastic approximation form:

$$\mathbf{b}^{k+1} = \mathbf{b}^k + a_k \mathbf{g}^k(\mathbf{b}^k).$$

To determine the booking limit vector of iteration $k+1$, the gain sequence a_k calculated in Step 1 is multiplied by the gradient vector $\mathbf{g}^k$ and added to the booking limit vector of iteration k.

In the example: $\mathbf{b}^1 = \begin{pmatrix} \begin{pmatrix} 30 \\ 20 \end{pmatrix} \\ \begin{pmatrix} 50 \\ 0 \end{pmatrix} \end{pmatrix} + 0.118 \begin{pmatrix} \begin{pmatrix} -100 \\ 100 \end{pmatrix} \\ \begin{pmatrix} 100 \\ 100 \end{pmatrix} \end{pmatrix}.$

The sum of the booking limits stored in the booking limit vector of the new iteration $k+1$ could be unequal to the assumed capacity. However, since the booking limits are nested in the simulation, simulating the booking process with the booking limits received from the simultaneous perturbation stochastic approximation approach ensures to consider total capacity. Additionally, the nesting control policy in the simulation ensures not to accept incoming request if there is no capacity available.

Step 6: Iteration or Termination

In the last step of the SPSA method, the algorithm returns to Step 2 with $k+1$ replacing k or is terminated if there is little change in several successive iterates or the maximum allowable number of iterations is reached.

Spall (2003), Section 7.3, describes the basic assumptions underlying the SPSA approach and the convergence conditions of the SPSA iterate. The solution of each iteration $\mathbf{b}^{k+1}$ converges to the optimal solution $\mathbf{b}^*$ as the iteration counter k converges to ∞. Compare also Spall (1988, 1992) for a discussion of convergence conditions. Maryak and Chin (2001) discuss the application of a SPSA procedure for global optimization if there are multiple local optima. In their publication, Maryak and Chin (2001) inject noise in the updating step (Step 5) of the basic SPSA approach to convert the SPSA method to a global optimizer. Additionally, Maryak and Chin (2001) show that the basic SPSA approach (without injecting noise in Step 5) can be a global optimizer under certain conditions. According to Spall (2003), this insight can be deduced since the random error in the gradient approximation within the SPSA procedure acts statistically like injecting noise as described by Maryak and Chin (2001). Besides this argument, the increasing run-time of the SPSA approach due to noise injection and the good results achieved by the basic SPSA approach applied to our alliance capacity control problem (compare Section 5.3.2) suggests to deploy the basic SPSA method to the presented application area.

5.3 Computational Study for the Option-Based Procedure with Simultaneous Perturbation Stochastic Approximation

We implemented the simulation-based optimization procedure in C++. Since the introduced SPSA approach takes the booking limits calculated in the option-based procedure as input, we refer to the simulation-based optimization procedure as OBP&SPSA in the following.

5.3.1 Test Bed for OBP&SPSA Procedure Analysis

To compare the OBP&SPSA algorithm with the option-based approach studied in Chapter 4, the same test bed is taken as basis in the computational study of the OBP&SPSA procedure as defined in Section 4.3.1 for the computational study of the option-based approach. To terminate the OBP&SPSA procedure, we set the maximum allowable number of iterations to 300. In each iteration of the OBP&SPSA approach, 5000 booking processes of the airlines were simulated. We conducted the computational study on an AMD Athlon(tm) 64X2 Dual Core Processor 4600+ 2.41 GHz PC with 1,96 GB RAM running Windows XP.

The performance of the OBP&SPSA algorithm depends on the right choice of the parameters needed to calculate the sequences, which were described in Step 1 of the simulation-based procedure. Since Spall (1998a) gives an interval in which the parameters can be defined, we have chosen the parameters in a way that improved the results of the OBP&SPSA approach. Parameter a, which influences the step size of the change of booking limits from iteration to iteration in the OBP&SPSA procedure, cannot be set higher than 0.9 due to the fact that the OBP&SPSA algorithm converges to a low revenue value in the early iterations otherwise. The parameter A also affects the step size of the OBP&SPSA method. Defining parameter A lower than four leads to the same effect. In setting a equal to 0.5 and A equal to 10, the OBP&SPSA procedure gains the best results. To influence the magnitude of the booking limit perturbation in Step 3, parameter R has to be defined. Setting R higher than 70 generates poor results. In that case, the OBP&SPSA approach does not converge to one value since the gap between the iteratively produced results is too large. Setting R equal to five gains the best results applying the OBP&SPSA procedure.

As we will see in the evaluation of the OBP&SPSA procedure in the following section, the performance of the OBP&SPSA approach depends on the proper choice of the strike price and option price as well as the results of the option-based procedure. Again, due to good results achieved by the OBP&SPSA procedure and due to the computational time, which is only up to four minutes to solve one instance, we pass on systematically changing the prices step by step. The optimization of the option price and strike price will be further discussed in Section 7.

5.3.2 Evaluation of the OBP&SPSA Procedure

The revenue generated by the OBP&SPSA approach over all instances is 5.38% higher than the revenue calculated by the option-based procedure, 10.88% higher than the revenue achieved by the FCFS approach, and 10.46% lower than the revenue generated in the ex post optimal solution.

The result of the option-based procedure is the initial solution of the OBP&SPSA algorithm. From this it follows that the solution of the option-based procedure is a lower bound for the OBP&SPSA result. An upper bound for the OBP&SPSA result is the ex post optimal solution.

The run-time of the OBP&SPSA procedure depends on the assumed demand and the defined capacity. To achieve the result for one instance, the OBP&SPSA algorithm needs about two minutes in low demand settings considering the seat capacity to be 100 and up to four minutes in instances with a higher seat capacity and higher total demand.

The percentage gap ($gap3$) between the solution of the OBP&SPSA and the OBP approach is computed by:

$$gap3 = \frac{OBP\&SPSA - OBP}{OBP} * 100.$$

The percentage gap ($gap4$) between the solution of the OBP&SPSA and the FCFS approach is computed by:

$$gap4 = \frac{OBP\&SPSA - FCFS}{FCFS} * 100.$$

The percentage gap ($gap5$) between the ex post optimal solution and the solution of the OBP&SPSA is computed by:

$$gap5 = \frac{ex\ post - OBP\&SPSA}{OBP\&SPSA} * 100.$$

Table 5.1 shows the achieved results aggregated over all instances in one capacity instance. The OBP&SPSA procedure determines better results in all three capacity settings than both the option-based procedure and the FCFS approach. The gap between the OBP&SPSA results and the ex post optimal solutions, however, can still be reduced. It can be noticed that gap3 decreases as the capacity scales up although the performance of the OBP&SPSA procedure improves as the capacity increases compared to the FCFS solutions. As the capacity grows, the results of the option-based method increase faster than the results of the OBP&SPSA procedure, which explains the shrinking of gap3.

Table 5.2 presents the revenue per seat in the capacity instances. Studying the revenue per seat calculated by the OBP&SPSA approach, we identify the same outcome as we identified while analyzing the results of the option-based procedure: The OBP&SPSA approach performs better in instances with higher capacity since the solution space expands when considering a higher seat capacity.

Capacity	$gap3$	$gap4$	$gap5$
100	6.04	8.20	12.60
120	5.31	10.74	10.40
150	4.81	13.59	8.47

Table 5.1: OBP&SPSA – Results Aggregated over Demand, Revenue, and Price Instances

Capacity	$gap3/C$	$gap4/C$	$gap5/C$
100	0.06	0.08	0.13
120	0.04	0.09	0.09
150	0.03	0.09	0.06

Table 5.2: OBP&SPSA – Results Aggregated over Demand, Revenue, and Price Instances Per Seat

We fixed the demand and aggregated the computed results over all revenue and price instances in a first observation in order to evaluate the estimated revenue values according to the demand variations.

Table 5.3 shows the aggregated results for the assumed capacity of 100, 120, and 150. The OBP&SPSA method improves the results of the option-based procedure in all demand settings and performs better than the FCFS approach in the instances with the demand being 120%, 130%, and 140% of the capacity. In low demand settings, the same effect as in the analysis of the option-based procedure appears: The revenue generated by the FCFS method is higher than the revenue achieved by the OBP&SPSA approach, although the gap between the OBP&SPSA method and the FCFS procedure decreased compared to the gap between the option-based method and the FCFS approach. The results of the OBP&SPSA procedure increase as the total demand scales up. Hence, in these cases (identical to the analysis of the option-based approach) the solution space increases and it is advantageous to reserve seat capacity for higher yielding classes through booking limits.

Capacity	Demand in %	$gap3$	$gap4$	$gap5$
100	110	3.49	-6.31	16.29
	120	5.21	1.95	13.98
	130	7.13	12.13	11.36
	140	7.94	22.78	9.33
120	110	3.29	-5.10	13.80
	120	4.85	6.12	10.91
	130	5.87	15.78	9.10
	140	7.23	26.17	7.81
150	110	2.93	-1.78	10.96
	120	4.24	7.66	8.99
	130	5.35	19.17	7.34
	140	6.71	29.30	6.58

Table 5.3: OBP&SPSA – Results Aggregated over Revenue and Price Instances

To show the performance of the OBP&SPSA procedure in a low demand setting, we calculated the expected revenue for 13 demand instances assuming the total demand to be 90% of the capacity.

Capacity	Demand in %	$gap3$	$gap4$	$gap5$
100	90	5.17	-12.12	19.40
120	90	5.00	-11.01	17.27
150	90	4.64	-9.85	14.02

Table 5.4: OBP&SPSA – Results Aggregated over Revenue and Price Instances in Instances with Demand Intensity 0.9

Table 5.4 shows the results for the seat capacity being 100, 120, and 150. The average revenue of the OBP&SPSA approach over all demand, revenue, and price instances is much lower than the revenue generated by the FCFS approach and much lower than the ex post optimal solution. Although, the OBP&SPSA approach performs better than the option-based method in all revenue and price instances in which the demand is lower than the capacity, the results of the OBP&SPSA procedure are lower than the results of the FCFS approach in all these settings. The same effect could already be seen when comparing the results of the option-based procedure to the FCFS approach. Mentionable is the fact that the performance of the OBP&SPSA procedure is particularly bad in price instance d in which the sum of option price plus strike price is higher than the revenue achieved by selling a flight ticket in the lower yielding booking classes of the operating carrier and the ticketing carrier ($x + s > v_{21}$ and $x + s > v_{22}$). In price instance d, the ticketing carrier only operates requests for the higher yielding booking class and the operating carrier rejects all requests for the second booking class as soon as the remaining capacity is equal to the number of options the ticketing carrier owns. If this point is reached in the booking process, the only booking classes in which requests are accepted are the operating carrier's and ticketing carrier's highest booking yielding class. And since the demand is low, especially for the higher yielding booking classes, most of the flight tickets for seats in the aircraft remain unsold which causes the poor performance of the OBP&SPSA procedure in price instance d.

In a second survey, we fixed the revenue and aggregated the computed results over all price and demand instances in order to evaluate the effect of revenue variation among the tested instances.

Table 5.5 contains the results for capacity 100, 120 and 150. The revenue gained from the OBP&SPSA approach is higher than the results gained from the option-based approach and the FCFS procedure in all capacity settings and revenue instances. The performance of the OBP&SPSA approach in the revenue instances 1, 2, and 3 is much better compared to the FCFS method. In the fourth revenue instance, the difference between the revenue gained by selling a flight ticket for the carriers' higher yielding booking class and the revenue that the carriers achieve by selling a flight ticket for the lower yielding booking class is lower than in the other revenue settings. The conclusion is that the OBP&SPSA procedure is also most applicable if the protection of seats for higher yielding booking classes from the access of lower yielding booking classes achieves more revenue since the revenue for one sold flight ticket in the higher yielding booking class is remarkably higher than the revenue for one sold ticket in the lower yielding booking class.

Capacity	Revenue Instance	$gap3$	$gap4$	$gap5$
100	1	5.67	10.80	11.54
	2	1.60	11.49	10.84
	3	8.51	7.78	15.16
	4	7.98	0.48	13.43
120	1	5.03	14.10	9.30
	2	1.32	14.13	8.89
	3	7.97	11.77	11.96
	4	6.92	2.96	11.47
150	1	4.47	16.89	7.58
	2	1.33	17.37	6.99
	3	7.38	14.84	9.63
	4	6.05	5.25	9.67

Table 5.5: OBP&SPSA – Results Aggregated over Demand and Price Instances

We fixed the option price and the strike price and aggregated the computed results over all revenue and demand instances in a third survey in order to evaluate the effect of the price variation among the tested instances.

In Table 5.6, the results for capacity 100, 120, and 150 are presented. The OBP&SPSA procedure accomplished higher revenue results than the option-based approach in all price instances and higher revenue results than the FCFS procedure in the price instances a, b, and c. Similar to the performance of the option-based procedure, the OBP&SPSA approach obtains poor results especially in the price instance d although $gap4$ being not as small as in the option-based procedure analysis since the OBP&SPSA approach enhances the results calculated by the option-based procedure.

Capacity	Price Instance	$gap3$	$gap4$	$gap5$
100	a	2.67	13.30	5.61
	b	9.78	11.79	7.31
	c	9.78	11.79	7.31
	d	1.55	-6.33	30.74
120	a	2.53	15.82	4.46
	b	8.72	14.43	5.94
	c	8.72	14.43	5.94
	d	1.26	-1.72	25.27
150	a	2.13	17.95	3.69
	b	7.86	16.82	4.83
	c	7.86	16.82	4.83
	d	1.39	2.76	20.54

Table 5.6: OBP&SPSA – Results Aggregated over Demand and Revenue Instances

Procedure 1, which assigns the spare seats the ticketing carrier does not buy options for (if they exist) to a class of the operating carrier (described in Section 4.2.2), was also considered in the instances solved by the OBP&SPSA procedure. However, the result of the OBP&SPSA approach considering Procedure 1, averaged over all instances with seat capacity 120, is equal to the revenue gained from using Procedure 2, which solves the model of the operating carrier twice, not considering the additional class of the ticketing carrier in calculating the booking limits for the operating carrier. The simultaneous perturbation stochastic approximation approach compensates in its 300 iterations lasting run the marginal differences in the initial values being the booking limits calculated by the two different procedures mentioned in Section 4.2.2.

We compared the performance of the OBP&SPSA procedure using standard nesting with the performance applying a theft nesting control for the seat capacity being 120. Exercising the two nesting controls results in two similar revenue outcomes aggregated over all instances (standard nesting performs 0.03% better than theft nesting). However, no declaration can be made about the comparative performance of the two nesting controls in general.

The performance of the simulation-based optimization procedure with buy-back opportunity of the operating carrier (OBP&SPSA+BB) is compared to the performance of the same procedure without buy-back option (OBP&SPSA-BB). Compare Section 4.2.1 for the description of the operating carrier's buy-back opportunity. The revenue generated by the OBP&SPSA+BB approach, averaged over all instances considering the capacity to be 120, is 2.04% higher than the revenue calculated by the OBP&SPSA-BB. Similar to the performance of the option-based method with buy-back opportunity, the OBP&SPSA+BB procedure gains exactly the same revenue as the OBP&SPSA-BB approach in the revenue and price setting 4d. Only in 13 of the 832 instances studied, OBP&SPSA-BB performs barely better than OBP&SPSA+BB. This phenomenon occurs most likely in instances of revenue and price scenario 3a, combined with instances which describe a very low demand for the highest yielding booking class and a very high demand for the lowest yielding booking class of the operating carrier. The demand for the ticketing carrier's booking classes is high in these instances. In revenue and price scenario 3a, the return for one sold flight ticket in one of the ticketing carrier's booking classes is much higher than in one of the operating carrier's booking classes and the option price plus the strike price is higher than the revenues gained by selling a flight ticket in the operating carrier's lower yielding booking class. The high demand for the operating carrier's second booking class causes that the state in the booking process is reached very fast in which the remaining seat capacity will be equal to the number of options the ticketing carrier holds. Henceforth, the operating carrier buys back options from the ticketing carrier if a request for the first booking class of the operating carrier occurs. Since the total demand for the first booking class of the operating carrier is very small and since the ticketing carrier cannot fill the capacity the operating carrier took from the ticketing by buying back the options, a part of the capacity remains unsold. In this case, it is possible that the operating carrier buys back the options although the ticketing carrier could most likely sell the tickets and for a much higher price, which explains the inferior performance.

Finally, we evaluate the performance of the OBP&SPSA approach applied with the initial booking limit values coming from the EMSR-a+Options and EMSR-b+Options calculations introduced in Section 4.2.3 (which are referred to as OBP&SPSA+EMSR-a+Options method and OBP&SPSA+EMSR-b+Options procedure). We averaged the expected revenue of all instances with seat capacity 120 and gained an expected revenue from the OBP&SPSA+EMSR-b+Options procedure that is slightly higher than the revenue achieved by the OBP&SPSA+EMSR-a+Options approach. This outcome corresponds to the insight we gained comparing the procedures EMSR-a+Options and EMSR-b+Options not considering the simultaneous perturbation stochastic approximation. The results of the OBP&SPSA+EMSR-a+Options approach is 5.86% lower than the revenue calculated by the OBP&SPSA method with underlying DLP. Considering the OBP&SPSA+EMSR-b+Options approach, we receive an expected revenue that is 4.29% lower than the revenue achieved by the DLP underlying OBP&SPSA method observing all instances of the 120 seat capacity scenario.

Chapter 6

Heuristic Calculation of Booking Limits

In this chapter, we investigate two versions of a genetic algorithm which can be applied to determine booking limits for the partners within a strategic alliance. In Section 6.1, we will begin with a basic description of genetic algorithms in general followed by the illustration of the specific implementation of the genetic algorithm versions applied in this thesis. The chapter will be concluded by a survey of the performance of the genetic algorithm versions using a computational study (Section 6.2).

6.1 Determination of Booking Limits with Genetic Algorithm

April et al. (2003) state that the application of metaheuristics in simulation-based optimization becomes more and more popular especially in commercial simulation software. Thereby, mainly evolutionary approaches such as genetic algorithms are applied. Evolutionary algorithms are more capable in simulation-based optimization than approaches that start with a single solution and search for better solutions within a defined neighborhood like simulated annealing. The dominance of evolutionary approaches can be explained since they need fewer evaluations of the objective function to investigate a larger area of the solution space (compare April et al., 2003). Evolutionary algorithms separate the search for new solutions from the evaluation of the solutions which implies that they do not need to be adjusted for being applied in simulation-based optimization, as pointed out by Klein (2005), Section 5.1.3. Spall (2003), Chapter 9, refers to evolutionary algorithms as stochastic search and optimization methods which are based on a mathematical imitation of natural evolution. In this chapter of his monograph, Spall (2003) characterizes genetic algorithms which are, as he points out in Section 9.1, the most popular approaches in evolutionary computation. This statement is also supported by Ashlock (2006), Section 1.2. Genetic algorithms have been developed by Holland (1975). Many papers and books have been written on genetic algorithms since the topic was introduced. Compare Reeves and Rowe (2002), Section 1.1, for a historical background of genetic algorithm theory. Basic principles as well as specific implementation concepts for genetic algorithms can also be found in their monograph. Genetic algorithms generate a population of possible solutions to the considered problem and move this population iteratively towards a global optimum which shows the difference between genetic algorithms and the stochastic approximation methods described in Chapter 5. The SPSA approach, as described before, calculates one solution candidate and updates this possible solution towards the optimal solution (compare Spall, 2003, Section 9.1). As pointed out by Falkenauer (1998), Section 2.3.2, getting stuck in a local optimum is less probable for genetic algorithms since these procedures search for the optimal solution by searching through a population and, therefore, several points in the search space. Genetic algorithms are iterative algorithms since the optimization process within the genetic algorithm can be iteratively repeated as stated in Falkenauer (1998), Section 2.3.2. According to Spall (2003), Section 9.1, an iteration, which is also called generation, describes the transformation of a solution population to another population of possible solutions. After some iterations, this transformation moves the population towards the optimum if the genetic algorithm runs successfully. The general procedure of a genetic algorithm as well as the terminology around genetic algorithms will be described in the following section when introducing the implementation of the genetic algorithm for our application area. A genetic algorithm is classified as metaheuristic which implies a broad range of application. There are only few publications considering genetic algorithms to solve revenue management capacity control problems for single corporations or airlines, compare, e.g., Pulugurtha and Nambisan (2003).

The implementation of the genetic algorithm applied for determining advanced booking limits to control the capacity within the strategic alliance will be outlined in the following. Following the definitions by Falkenauer (1998), Section 2.3.1 as well as Section 2.3.2, some basic genetic algorithm terms will be clarified prior to the description of the procedure.

As described before, the genetic algorithm iteratively modifies the population of solutions. An individual describes a member of the population and this member defines a possible solution to the problem. However, the term solution needs to be examined more precisely. The actual solution of the problem is called phenotype, following the biological terminology. In our application area, the phenotype of the genetic algorithm displays the nested booking limits which are passed to the simulation to evaluate the solution. A genetic algorithm, however, works with representations of solutions. Such a representation is called genotype in genetic algorithm terminology. A genotype represents a chromosome (also called string) that in turn stands for a point in the solution space. The decision variables of a solution within a chromosome or string are called genes (compare Falkenauer, 1998, Section 2.3.1). By encoding a phenotype, a genotype can be identified. A phenotype, on the other hand, can be clearly determined by decoding the genotype. The term fitness describes the value and, therefore, the quality of a solution. It refers to the objective function of the considered problem. Since an analytical objective function is not available in our setting, the fitness value of an individual is approximated by means of simulation. The simulation of the booking processes, described in Section 4.2.4, is applied to determine the fitness values of the individuals. In comparing the fitness values of the individuals to each other, it can be determined which individual is closer to the optimal solution. In our alliance revenue maximization problem, the individual with the highest fitness represents the solution with the highest alliance revenue and, therefore, the best solution of the problem found so far. For each individual within a population, the fitness value is calculated by simulating the booking processes of the alliance partners applying the determined nested booking limits (which represent the phenotype of the genetic algorithm).

There are several types of representations and encoding mechanisms described in genetic algorithm literature, compare, e.g., Falkenauer (1998), Section 2.3.3, Rothlauf (2006), Section 2.1.3, and Talbi (2009), Section 1.4.1. Ashlock (2006), Section 1.2.1, states that there is no globally adequate representation for all genetic algorithm applications. We adopt two different genetic algorithm versions which are distinguishable by different problem-specific genotypes. Both versions will be described in the following.

Genetic Algorithm 1

In a first genotype version, a chromosome is implemented as a string of booking limits b_{jl} (compare Figure 6.1 for illustration). The number of genes within the chromosome corresponds to the number n of products offered within the alliance. The booking limits in the chromosome are neither partitioned nor nested since it is not assured within the procedure of the genetic algorithm that the sum of booking limits is equal to the total capacity as it is the case with partitioned booking limits. In addition, it is not guaranteed that the highest booking limit is equal to the total capacity and that the booking limit of a higher yielding booking class is higher than the booking limit of a lower yielding booking class which specifies nested booking limits. A repair mechanism could be implemented within the genetic algorithm that converts the booking limits with the above mentioned characteristics into partitioned or nested booking limits. Repair mechanisms are generally applied to repair infeasible solutions that are permitted within the procedure of metaheuristics are described by Reeves and Rowe (2002), Section 2.5.2. We tested the performance of the genetic algorithm including a repair approach with the results of the genetic algorithm without repair mechanism using one revenue and one option price and strike price example. The results of the genetic algorithm including the repair mechanism did not exceed the results of the genetic algorithm without repair procedure but the run-time of the genetic algorithm increases when the booking limits are repaired. An explanation for the similar outcome of the analyzed procedures can be found in the phenotype of the genetic algorithm. In the decoding of the chromosomes, the booking limits stored in the chromosomes' genes are converted to nested booking limits. Therefore, the decoding serves as repair mechanism which ensures the feasibility of the booking limits passed to the simulation. In addition to the decoding, the simulation makes sure that the total capacity is not exceeded. Consider the example introduced in Section 4.2.2 in which the operating carrier and the ticketing carrier offer flight tickets in two booking classes ($n_1 = 2, n_2 = 2$, and, therefore, $n = 4$) for a flight with seat capacity $C = 100$. In Figure 6.1, a possible string of Genetic Algorithm 1 is displayed considering the setting from the example described.

37	52	14	89
b_{11}	b_{21}	b_{12}	b_{22}

Figure 6.1: Genotype Genetic Algorithm 1

Genetic Algorithm 2

The chromosome in a second encoding version of the genetic algorithm is implemented as a string of capacity units. In the example of an airline alliance controlling seat capacity on a single flight leg, the number of genes within the chromosome is equal to the total seat capacity in the considered aircraft. To indicate the different products offered by the partners within the alliance, the products are numbered and each gene within the chromosome uses a product number. Recall the example mentioned in the description of Genetic Algorithm 1 in which both of the alliance partners offer two booking classes and the total seat capacity is set to $C = 100$. Considering this setting, a possible string of Genetic Algorithm 2 is shown in Figure 6.2.

# of Product	1	3	2	3	4	1	$\cdots$	3	2	4	1	4	2
# of Seat/Gene	1	2	3	4	5	6	$\cdots$	95	96	97	98	99	100

Figure 6.2: Genotype Genetic Algorithm 2

In the decoding of the chromosomes, the booking limits stored in the strings of the two different genetic algorithm versions are converted to nested booking limits. Therefore, the booking limit of the operating carriers' highest yielding booking class is set equal to the total capacity ($b_{11} = C$) and the booking limits of all other booking classes offered by the operating carrier are set equal to the booking limit of the considered booking class plus the booking limits of all lower yielding booking classes. This converting mechanism is equal to the procedure of converting partitioned booking limits into nested booking limits described in Section 2.2.2.3. The booking limits of the ticketing carrier are nested by defining the booking limit for the ticketing carrier's highest yielding booking class equal to the number of options the ticketing carrier buys from the operating carrier. This number of options is the sum of all booking limits determined for the ticketing carrier's booking classes. The booking limits for the ticketing carrier's other booking classes are calculated by adding to the considered booking class the booking limits of all lower yielding booking classes of the ticketing carrier.

Before the decoding of the chromosomes deployed by Genetic Algorithm 2 can be applied, the numbers of the products stored in a chromosome need to be counted to achieve booking limits. If, e.g., there are 43 genes using the number 3, the booking limit for the class corresponding to the number 3 is 43.

The procedure of the genetic algorithms established in this work is introduced in five steps, following the descriptions of genetic algorithm components by Talbi (2009), Section 3.3:

Step 1: Initialization
An iteration counter k is set equal to zero. Depending on the chosen genotype, the initial population, represent the population size of our genetic algorithm versions, is generated in the first step of the described genetic algorithms. As pointed out by Falkenauer (1998), Section 2.3.2, the initial population is usually randomly selected. The generation of initial populations is discussed by Talbi (2009) in Section 3.1.1. Initial populations of any metaheuristic need to be diversified in order to secure that a premature convergence towards a local optimum does not occur. In Section 3.1.1.1, Talbi (2009) describes the generation of an initial population that is randomly generated by means of a uniform distribution. We follow the descriptions of Talbi (2009), Section 3.1.1.1, and generate the elements within the chromosomes of our initial population randomly in a given range uniformly distributed.

In Genetic Algorithm 1, the booking limit values stored in the genes of the chromosomes are uniformly distributed between zero and the total capacity ($U[0, C]$), prohibiting that an initial booking limit exceeds the total available capacity.

In Genetic Algorithm 2, the values stored in the genes of the chromosomes representing the number of a product are also selected randomly by means of a uniform distribution. In the example described above, there are four products offered by the alliance partners which leads to the numbers 1, 2, 3, and 4 in numbering the products. Therefore, the numbers within the initial population are uniformly distributed between 1 and 4 ($U[1, 4]$) and converted to discrete values such that all integer values have equal probability.

Step 2: Fitness Evaluation
In the second step of the genetic algorithms, the fitness values for all individuals in the considered population are evaluated. As described above, simulating the booking processes of the alliance partners determines the fitness values of the chromosomes within the population in our application area. In most metaheuristics, the fitness evaluation is the part that needs the most run-time, as pointed out by Talbi (2009), Section 1.4.2.6. To compare the run-time of the genetic algorithms with the run-time of the option-based procedure introduced in Chapter 4 and the OBP&SPSA approach's run-time discussed in Chapter 5, the fitness evaluation of one individual needs 5000 simulation iterations to account for the stochastic demand. An increasing run-time of the genetic algorithm with an increasing population size

can be explained by extensive simulation runs necessary for each additional individual.

Step 3: Selection
In the selection step of the genetic algorithms, a promising set of chromosomes in the actual population candidates is selected which is considered for reproduction. The term reproduction subsumes the following steps: recombination and mutation. There are several selection methods that can be applied, compare, e.g., Talbi (2009), Section 3.3.1. A widespread method is to select the individuals with better fitness values with higher probability. We tested several selection methods and compared the resulting performance and the run-time of the genetic algorithms with diverse selection methods. The results of our genetic algorithm implementations improve with the number of individuals being selected. Therefore, we decided to select all chromosomes for reproduction.

Step 4: Recombination
Several recombination methods can be adopted in the fourth step of the genetic algorithms in which the individuals selected in Step 3 are considered. According to Falkenauer (1998), Section 2.3.4.1, recombination operators consider different chromosomes in the current population (parents) and join together parts of these strings to create new chromosomes (offspring). Recombination operators are also called crossover operators. In Talbi (2009), Section 3.3.2.2, various crossover operators are described in detail by means of examples. According to Leguizamón et al. (2007), the two-point crossover operator is the most common form of a recombination operator. We apply a two-point crossover for reproduction in both genetic algorithm variants using a uniform distribution to select the two crossover positions randomly according to the descriptions made by Talbi (2009), Section 3.3.2.2. In Figure 6.3, two strings of booking limits representing the parent chromosomes of Genetic Algorithm 1 are presented. If, e.g., the randomly chosen crossover positions are between the first and the second as well as between the third and fourth gene, the resulting pieces laying in the center piece of the parent chromosomes are swaped and joint together with the first and third part of the respective other parent chromosome, forming two new chromosomes (the offspring). The two-point crossover operator applied in Genetic Algorithm 2 is implemented in the same way. We tested crossover operators in the Genetic Algorithm 2 with more than two crossover positions. However, even if there are more genes in the string resulting in more possibilities to choose and implement crossover positions in Genetic Algorithm 2 (compared to the short strings implemented in Genetic Algorithm 1), the performance of Genetic Algorithm 2 is inferior when implementing crossover operators with more than two crossover points.

Step 5: Mutation
As pointed out by Talbi (2009), Section 3.3.2.1, mutation operators are so called unary operators since they consider and change only single individuals. Contrary to crossover operators which act on multiple chromosomes to generate new individuals, the mutation operators perform small changes within one considered chromosome of the population to create a new individual. The mutation operator sometimes even mutates only one gene of the chromosome. Mutation operators are adopted to overcome the disadvantage which could be carried out by crossover operators. Falkenauer (1998), Section 2.3.4.3, points out that new chromosomes generated by crossover operators and representing the offspring never contain new values stored in the genes within the chromosomes since the crossover operators only combine the genes already present in the parent chromosomes. If the optimal solution of the considered problem contains a value that is not present in the chromosomes within the population, finding this optimal solution by means of crossover operators is impossible (compare Spall, 2004, Section 6.4.5). However, the random modifications carried out on a chromosome by the mutation operator should be used only with small probability, as pointed out by Falkenauer (1998), Section 2.3.4.3, as well as Talbi (2009), Section

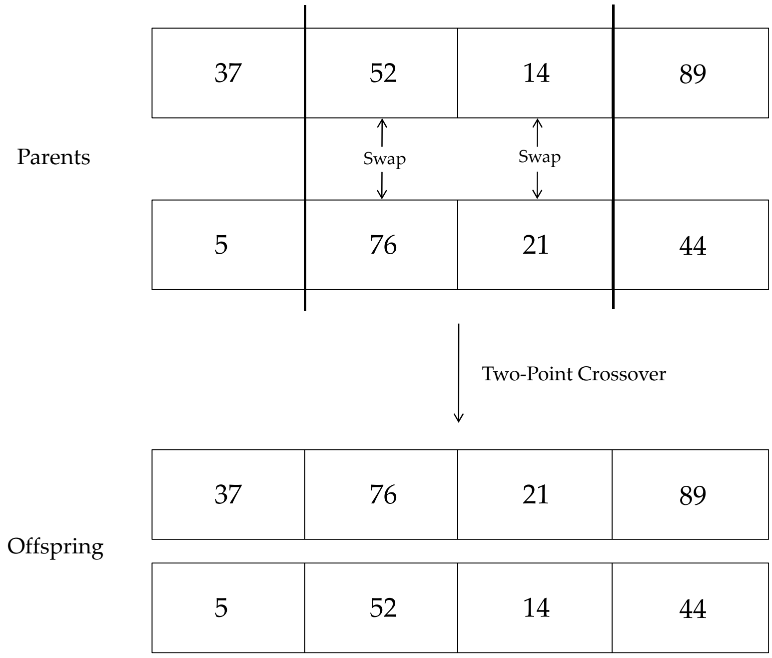

Figure 6.3: Example Two-Point Crossover Genetic Algorithm 1

3.3.2.1. If the mutation operator is applied to too many chromosomes within the population, the positive effects of the crossover operators (converging the solutions towards the optimal solution) could be ruined. Therefore, the mutation operator is applied on maximal one chromosome in each generation of our genetic algorithm versions. The mutated chromosome is chosen randomly by means of a uniform distribution. Additionally, the amount of the random modification of the genes within the selected chromosome is chosen uniformly.

Step 6: Replacement

In the replacement step of the genetic algorithms the individuals compete against each other for getting into the next generation. Individuals need to be eliminated due to a constant population size (compare Talbi, 2009, Section 3.3.2). Many replacing strategies are imaginable, compare Mitchell (1999), Section 5.4. We apply a replacement strategy mentioned in Talbi (2009), Section 3.3.3, and select the individuals holding the best fitness values (in our setting the individuals with the highest fitness values) from the parent and offspring population in the amount of the population size. According to Talbi (2009), Section 3.3.3, a sampling error can be avoided by replacing some individuals with good fitness by individuals holding a poor fitness value. Therefore, some of the individuals holding the worst fitness values are randomly chosen and assigned to the next generation by means of a uniform distribution in our genetic algorithm variants.

Step 7: Iteration or Termination

In the seventh step of the genetic algorithms, the methods return to Step 2 with iteration counter $k + 1$ or are terminated if a predefined stopping criterion is reached. Compare Reeves (2003) for a description of possible termination criteria. The genetic algorithms described in this chapter terminate if a maximum allowable number of iterations has been reached.

During the procedure of the Genetic Algorithm 2, there can be different strings that describe an identical set of booking limits which leads to high redundancy. We allow this redundancy since different strings can emerge from these strings after the recombination which in turn can lead to a broader search through the solution space and to enhanced results.

As stated by Jong (2007), parameter setting in genetic algorithms can be challenging. All decisions concerning the design of the genetic algorithm versions and parameter settings described above are based on the descriptions of the respective topics in literature and/or according to several tested possible characteristics of the genetic algorithms.

6.2 Computational Study for the Genetic Algorithms

The following section provides insights gained by the application of the introduced genetic algorithm versions to the alliance capacity control problem. In the first subsection (Section 6.2.1), the test bed underlying the analysis of the two genetic algorithm variants will be outlined, followed by the evaluation of the proposed procedures in Section 6.2.2.

6.2.1 Test Bed for Genetic Algorithm Analysis

The genetic algorithm variants described in Section 6.1 were implemented in C++. In both genetic algorithm versions, 50 individuals are randomly created. According to Ahn (2006), Section 2.3, it is generally difficult to choose a population size that is adequate for the considered problem. There is a trade-off between a small population size which leads to a fast run-time of the genetic algorithm but lower possibility of finding high quality solutions and a large population size with a longer run-time of the genetic algorithm but higher possibility of finding good solutions. After trading off these arguments, we decided to choose the population size of 50 individuals. Talbi (2009), Section 3.3.3, states that the population size in practice usually lies between 20 and 100 individuals. The amount of the random modification of the genes within the selected chromosome is chosen uniformly distributed between -0.6% and 0.6% since these values lead to a good performance of the established genetic algorithms. Due to an increased run-time of the genetic algorithms compared to the run-time of the previously discussed approaches (namely option-based procedure and OBP&SPSA method), both versions of the genetic algorithm terminate after 15 iterations. In the following section, we will analyze the run-time of the genetic algorithms and the achieved results in more detail.

In the computational study, the performance of the genetic algorithm variants are compared to each other, to the ex post optimal solutions, the first-come-first-served approach performance, and to the results gained by applying the option-based procedure and the OBP&SPSA approach. To ensure comparability, the test bed used in the previous computational studies of the option-based approach and the OBP&SPSA method (in Section 4.3.2 respectively Section 5.3.2) is re-used in the survey discussed in the present section. The revenue of the flight tickets for the partner airlines' booking classes as well as the option price and strike price instances are presented in Table 4.5 in Section 4.3.1. Moreover, the demand instances presented in Table A.1, A.2, A.3, and A.4 in the Appendix A.1 are implied to test the genetic algorithms. The simulation conditions outlined in Section 4.3.1 are adopted in the simulation processes within the genetic algorithms. Since the results of the procedures discussed in the previous sections are better when the simulation is applied with standard nesting control policy and buy-back possibility of the operating carrier, we set the simulations of the booking processes to determine the fitness values in the genetic algorithm variants according to these assumptions.

To create pseudo-random numbers for the uniformly distributed random processes within the genetic algorithm versions, we used the random number generator boost::random::lagged_fibonacci9689 (compare www.boost.org) in the programs. The tests were done on an AMD Athlon(tm) 64X2 Dual Core Processor 4600+ 2.41 GHz PC with 1,96 GB RAM running Windows XP.

To monitor the performance of both genetic algorithm versions in parameter settings that differ from the instances assumed in the present computational study, we calculated the results of the genetic algorithm versions varying three of the given parameters: the number of iterations, the population size, and the crossover version. Table 6.1 shows the different parameter modifications. In each instance modification only one of the given parameters is changed. Therefore, 2+2+3 different modification combinations are considered.

	ParameterComputationalStudy	*ParameterChanged*		
Number of Iterations	15	30	60	
Population Size	50	20	100	
Crossover Version	2-point	1-point	9-point	15-point

Table 6.1: GA – Parameter Modifications

The results of both genetic algorithm versions assuming the parameters to be as described before (*ParameterComputationalStudy*) are compared to the results of both genetic algorithm versions with a changed parameter (*ParameterChanged*). The improvement of the parameter modification is calculated by means of 6.1.

$$improvement = \frac{result(ParameterComputationalStudy) - result(ParameterChanged)}{result(ParameterChanged)} * 100. \tag{6.1}$$

Since the results of the instances behave similarly in all considered instances when changing one of the described parameters, we show the results of capacity instance 100 with demand intensity 1.1, demand instance 6, and revenue/price instance 1a in the following tables.

Table 6.2 presents the results of Genetic Algorithm 1 and Genetic Algorithm 2 with different numbers of iterations compared to the results of GA1 and GA2 with 15 iterations.

Iterations	1	5	10	30	60
GA1	0.27	0.01	0.00	0.00	0.00
GA2	5.34	1.03	0.35	-0.02	-0.03

Table 6.2: GA – Results of GA1 and GA2 with Different Numbers of Iterations

The results of both genetic algorithm versions are considerably improved in the first iterations of the genetic algorithms. After the fifth iteration, the results only improve marginally. The result of GA1 does not change if there are more than 10 iterations (we tested instances with up to 60 iterations). The GA2 result improves marginally if there are more than 15 iterations. The run-time of GA2, however, increases from 3.5 minutes in the instance with 15 iterations up to 7.2 minutes in the instance with 60 iterations. For that reason, we decided to set the number of iterations to 15 in the computational study of GA1 and GA2.

Population Size	20	100
GA1	0.06	0.00
GA2	1.88	-0.01

Table 6.3: GA – Results of GA1 and GA2 with Different Population Sizes

In Table 6.3, the results of GA1 and GA2 with different population sizes compared to the result of GA1 and GA2 with population size 50 are shown.

The results of both genetic algorithm versions in instances with an assumed population size of 20 are inferior to the results with a population of 50 chromosomes. If we assume the population size to be 100 only the result of GA2 marginally improves compared to the result achieved with a population of 50 chromosomes.

Table 6.4 shows the results of GA1 and GA2 with different crossover versions compared to the results of GA1 and GA2 with a two-point crossover. The 9-point crossover and 15-point crossover could only be adopted in Genetic Algorithm 2 since the string implementation in Genetic Algorithm 1 is too short to adopt a crossover with more than two crossover positions.

Crossover Version	1-point	9-point	15-point
GA1	0.00		
GA2	0.02	23.65	24.70

Table 6.4: GA – Results of GA1 and GA2 with Different Crossover Versions

The result of GA1 does not change if a one-point crossover is applied compared to the result of GA1 with the application of a two-point crossover. The result of GA2 with one-point crossover is marginally inferior to the result with two-point crossover. However, the result of GA2 is considerable inferior if more than two crossover positions are applied.

6.2.2 Evaluation of the Genetic Algorithms

The results of the different procedures are compared by computing the percentage gap between the optimal values ($optVal$) of Genetic Algorithm 1 (GA1) and Genetic Algorithm 2 (GA2), the option-based procedure (OBP), the OBP&SPSA method, the first-come-first-served approach (FCFS), and the ex post optimal solution (ex post). The percentage gaps are determined by:

$$gap = \frac{optVal(Procedure1) - optVal(Procedure2)}{optVal(Procedure2)} * 100. \tag{6.2}$$

Table 6.5 shows the procedures which are compared in the computational study of the genetic algorithms and the respective gap assignment.

Depending on the considered instance, the run-time of Genetic Algorithm 1 ranges from two minutes in low capacity and low total demand instances up to 9.2 minutes in high capacity and high total demand instances. Similar to the run-time of Genetic Algorithm 1, to achieve the result for one instance, Genetic Algorithm 2 takes 1.8 minutes in low capacity and low demand settings and up to 8.4 minutes in high capacity and high demand instances. The increased run-time of the genetic algorithm versions, needed

gap	$Procedure1$	$Procedure2$
$gap6$	GA1	GA2
$gap7$	GA1	OBP&SPSA
$gap8$	GA1	OBP
$gap9$	GA1	FCFS
$gap10$	ex post	GA1
$gap11$	GA2	OBP&SPSA
$gap12$	GA2	OBP
$gap13$	GA2	FCFS
$gap14$	ex post	GA2

Table 6.5: Compared Procedures in Computational Study Genetic Algorithm 1 and 2

to achieve a result for one instance, compared to the elapsed time of the option-based procedure (being less than a second) and the OBP&SPSA approach (ranging from two minutes up to four minutes), shows the disadvantage of the genetic algorithm versions.

Averaging the results over all considered instances (capacity, demand, revenue, and price instances), the revenue generated by Genetic Algorithm 1 is 2.26% higher than the revenue achieved by Genetic Algorithm 2. The genotype version holding booking limits (Genetic Algorithm 1) instead of product numbers (Genetic Algorithm 2) performs better considering all established instances.

Table 6.6 presents the gaps between the average revenue of the procedures aggregated over all instances. The Genetic Algorithm 1 performs better than the option-based procedure but the results are inferior to the performance of the OBP&SPSA approach. Similar to the results of the Genetic Algorithm 1, the results of the Genetic Algorithm 2 are superior to the option-based procedure's results but inferior to the performance of the OBP&SPSA approach. Similar results are also noticed by Maryak and Chin (2001). The authors found in their computational study that the results of the SPSA method as a global optimizer are superior to the performance of the genetic algorithm approaches. Both, Genetic Algorithm 1 and Genetic Algorithm 2 outperform the FCFS approach over all instances, but the results of the genetic algorithm versions can still be improved.

	$gap6$	$gap7$	$gap8$	$gap9$	$gap10$	$gap11$	$gap12$	$gap13$	$gap14$
all instances	2.26	-0.16	5.21	10.69	10.67	-0.95	4.18	9.15	12.41

Table 6.6: GA – Results Aggregated over Capacity, Demand, Revenue, and Price Instances

In Table 6.7, the results of the procedures aggregated over all demand, revenue, and price instances are presented. In all capacity instances, the performance of Genetic Algorithm 1 as well as the performance of Genetic Algorithm 2 exceed the results the option-based procedure achieves. Only in capacity instance 100, the Genetic Algorithm 1 performs slightly better than the OBP&SPSA approach. The Genetic Algorithm 2 results are inferior to the results of the OBP&SPSA method in all capacity instances. The genetic algorithm versions overcome the inferior performance of the option-based procedure especially in instances with lower capacity. The results of both genetic algorithm versions approach towards the ex post optimal solution as the capacity in the considered instances increases.

Comparing the results of the procedures aggregated over all revenue and price instances (Table 6.8) reveals that in all capacity instances considering the demand to be 110% of the capacity the results of both genetic algorithm versions are inferior to the FCFS method's results. The same effect could already be observed in the previous computational studies (Section 4.3.2 and Section 5.3.2) analyzing the results

Capacity	$gap6$	$gap7$	$gap8$	$gap9$	$gap10$	$gap11$	$gap12$	$gap13$	$gap14$
100	2.94	0.07	6.10	8.26	12.56	-0.96	4.76	6.30	14.85
120	2.49	-0.18	5.12	10.54	10.63	-1.16	3.91	8.77	12.63
150	1.37	-0.37	4.43	13.18	8.90	-0.74	3.90	12.25	9.85

Table 6.7: GA – Results Aggregated over Demand, Revenue, and Price Instances

of the option-based procedure and the OBP&SPSA approach. Again, the reservation of seat capacity for higher yielding booking classes through booking limits is inferior in low demand instances. In all capacity and demand instances, the genetic algorithm approaches outperform the results of the option-based procedure. However, the results of the Genetic Algorithm 1 exceed the OBP&SPSA procedure's results only slightly in the low demand instances assuming the capacity to be 100 and 120. The results of both genetic algorithm versions improve as the demand increases which confirms the assumption that the reservation of capacity for higher yielding classes is more profitable in instances with higher total demand. Genetic Algorithm 1 performs better than Genetic Algorithm 2 in all demand instances and all capacity scenarios even though the gap between the results of the genetic algorithm approaches ($gap6$) decreases as the total capacity and total demand increase.

Capacity	Demand in %	$gap6$	$gap7$	$gap8$	$gap9$	$gap10$	$gap11$	$gap12$	$gap13$	$gap14$
100	110	4.40	0.63	4.14	-5.68	15.64	-0.57	2.71	-8.25	18.81
	120	3.61	0.08	5.28	2.05	13.94	-1.21	3.67	-0.28	16.81
	130	2.49	-0.07	7.04	12.06	11.48	-1.12	5.61	10.24	13.55
	140	1.48	-0.28	7.65	22.47	9.67	-0.87	6.73	21.26	10.84
120	110	3.68	0.07	3.36	-5.02	13.73	-0.89	2.22	-7.10	16.45
	120	2.60	-0.19	4.66	5.93	11.13	-1.23	3.39	4.13	13.28
	130	2.05	-0.30	5.57	15.46	9.47	-1.31	4.30	13.80	11.22
	140	1.63	-0.31	6.91	25.80	8.18	-1.21	5.72	24.27	9.57
150	110	2.26	-0.14	2.78	-1.91	11.14	-0.63	2.21	-3.21	12.69
	120	1.44	-0.33	3.91	7.33	9.38	-0.71	3.39	6.39	10.39
	130	0.97	-0.47	4.87	18.64	7.90	-0.79	4.38	17.89	8.57
	140	0.78	-0.53	6.17	28.65	7.19	-0.85	5.64	27.92	7.74

Table 6.8: GA – Results Aggregated over Revenue and Price Instances

The next step analyzes the performance of the genetic algorithm versions in scenarios with very low demand. Therefore, instances in which the demand intensity is 0.9 are considered. Table 6.9 shows that both genetic algorithm versions perform worse than the OBP&SPSA approach in all capacity instances assuming the demand to be 90% of the capacity. The results of the option-based procedure, however, can be enhanced in all capacity settings. The same effect can be noticed in the study of the OBP&SPSA procedure's results in Section 5.3.2. Another fact similar to the one identified in Section 4.3.2 and Section 5.3.2 is that the first-come-first-served approach outperforms the results of both genetic algorithm methods since the best strategy in instances with very low demand is to accept all incoming requests in order of occurrence.

In a second survey, we aggregated the averaged revenue results of the procedures over all demand and price instances (Table 6.10). In both genetic algorithm approaches, the performance of the FCFS procedure can be only slightly enhanced in revenue instance 4. Genetic Algorithm 2 performs even worse than the FCFS approach in the fourth price instance assuming the capacity to be 100. In revenue instance 4, the flight ticket revenue of the first booking class is close to the one of the second booking

Capacity	Demand in %	$gap6$	$gap7$	$gap8$	$gap9$	$gap10$	$gap11$	$gap12$	$gap13$	$gap14$
100	90	8.71	-0.20	4.95	-12.34	19.59	-1.94	2.73	-15.92	25.38
120	90	7.35	-0.10	4.89	-11.11	17.38	-1.20	3.39	-14.74	22.16
150	90	4.62	-0.02	6.34	-9.87	14.04	-0.40	4.89	-10.99	16.73

Table 6.9: GA – Results Aggregated over Revenue and Price Instances in Instances with Demand Intensity 0.9

class in the flight ticket revenue structures of both considered carriers. The statement that it is more profitable to reserve seat capacity for higher yielding customer segments if the gap between the flight ticket revenues of the airlines' booking classes is high can be confirmed in this study as well. The performance of the option-based procedure is worse compared to the results of Genetic Algorithm 1 in all revenue instances. Genetic Algorithm 2 performs better than the option-based procedure in all revenue instances apart from revenue instance 2. Revenue instance 2 differs from the other revenue instances since the flight ticket revenues of the ticketing carrier's booking classes are assumed to be lower than the ones in the booking classes of the operating carrier. The results of the option-based procedure and the OBP&SPSA approach (described in Section 4.3.2 and Section 5.3.2) are also better in revenue instances 1, 3, and 4 compared to revenue instance 2.

Capacity	Revenue Instance	$gap6$	$gap7$	$gap8$	$gap9$	$gap10$	$gap11$	$gap12$	$gap13$	$gap14$
100	1	2.38	0.02	5.68	10.80	11.53	0.21	5.52	9.78	12.80
	2	4.79	-0.13	1.47	11.34	10.98	-4.43	-2.91	6.59	16.17
	3	1.07	0.76	9.29	8.56	14.39	-0.28	8.19	7.57	15.70
	4	3.73	-0.30	7.67	0.20	13.83	0.72	7.92	-0.96	15.35
120	1	1.54	-0.26	4.76	13.80	9.59	0.06	4.83	13.23	10.33
	2	4.93	-0.15	1.17	13.95	9.05	-4.67	-3.41	8.85	14.35
	3	0.68	0.03	7.99	11.80	11.96	-0.62	7.31	11.15	12.81
	4	2.80	-0.35	6.57	2.62	11.90	-0.58	6.90	1.87	13.02
150	1	0.76	-0.38	4.08	16.45	8.01	0.04	4.34	16.30	8.20
	2	2.96	-0.28	1.05	17.02	7.29	-3.03	-1.74	13.85	10.42
	3	0.29	-0.28	7.09	14.53	9.97	-0.56	6.79	14.22	10.31
	4	1.45	-0.53	5.51	4.72	10.33	0.59	6.23	4.63	10.47

Table 6.10: GA – Results Aggregated over Demand and Price Instances

Table 6.11 shows the averaged results of the procedures aggregated over all demand and revenue instances. The results of the genetic algorithm versions depend on the chosen price instance similar to the price instance dependent results of the option-based procedure and OBP&SPSA approach. In price instances d, the gap between the results of Genetic Algorithm 1 and the ex post optimal solutions ($gap10$) is much higher compared to the gap in the other price instances. The gap between Genetic Algorithm 2 and the ex post optimal solutions ($gap14$) is high in price instances c and d. The FCFS approach performs better than Genetic Algorithm 1 in price instance d in capacity instances 100 and 120. In price instance d, the sum of option price and strike price is higher than the flight ticket revenue the operating carrier and the ticketing carrier gain by selling a flight ticket in the second booking class. The results of the option-based procedure and the OBP&SPSA approach are also worse in price instance d compared to the performance of the procedures in the other price instances (compare Section 4.3.2 and Section 5.3.2).

Capacity	Price Instance	$gap6$	$gap7$	$gap8$	$gap9$	$gap10$	$gap11$	$gap12$	$gap13$	$gap14$
100	a	3.22	0.34	3.00	13.65	5.25	-2.52	0.07	10.54	8.64
	b	1.40	0.53	10.72	14.31	7.08	-0.81	9.31	12.87	8.59
	c	16.46	0.29	10.07	12.07	7.00	-11.99	-3.49	-1.26	24.32
	d	-9.22	-0.58	0.96	-6.91	31.48	11.89	13.61	3.17	18.40
120	a	2.44	-0.07	2.46	15.73	4.54	-2.25	0.24	13.29	7.09
	b	1.13	0.09	9.32	16.85	5.94	-0.98	8.22	15.63	7.16
	c	14.38	0.02	8.74	14.44	5.92	-11.13	-3.41	2.08	20.97
	d	-8.02	-0.69	0.56	-2.44	26.13	9.82	11.20	6.53	15.28
150	a	1.68	-0.20	1.92	17.70	3.90	-1.74	0.37	15.94	5.65
	b	0.65	-0.08	8.32	19.22	4.90	-0.69	7.68	18.49	5.59
	c	10.86	-0.09	7.76	16.71	4.92	-8.91	-1.76	6.77	16.21
	d	-7.72	-1.10	0.27	1.60	21.88	8.39	9.89	10.30	11.94

Table 6.11: GA – Results Aggregated over Demand and Revenue Instances

Chapter 7

Capacity Control with Real Options and Transfer Price Optimization

In the approaches and surveys introduced and discussed in the previous chapters, the option price and strike price were treated as given parameters. However, the surveys outlined in the previous computational studies revealed that the results of the option-based procedure, the OBP&SPSA method, and the genetic algorithm versions depend on the choice of option price and strike price. As mentioned in Section 4.3.1, the optimal option price and strike price can be determined by systematically searching through the entire solution space. Since this approach is very run-time-intensive, a method to incorporate the optimal option price and strike price in an efficient way as an extension to the previous studies will be introduced in this chapter. At first, the transfer price theory in strategic alliances will be outlined (Section 7.1) before, at second, the booking limit improvement by means of transfer price optimization will be introduced (Section 7.2). At third, in a computational study, the performance of the new procedures including transfer price optimization will be analyzed (Section 7.3). This chapter is based on Graf and Kimms (2010).

7.1 Transfer Prices in Strategic Alliances

The option price and strike price can be subsumed under the generic term transfer price. There are many publications dealing with transfer prices in the field of accounting (compare, e.g., Bierman, 1959; Cook, 1955; Dean, 1955; Eccles, 1985; Kaplan and Atkinson, 1998, Chapter 9; Stone, 1956; Tang, 1993; Verlage, 1975). The main subject in these publications is the description of how to use decentralization as an instrument to control large firms. Dean (1955) defines decentralization as the formation of more or less autonomous divisions within a corporation. Discussing decentralization often brings up the problem of intracompany pricing (compare, e.g., Bierman, 1959; Dean, 1955; Stone, 1956; Verlage, 1975, Section 1.2). For a broad overview, including among other things fundamentals, application requirements, application areas, and classifications of transfer price methods combined with empirical surveys about the implementation of the transfer price methods in companies, consider especially the monographs of Eccles (1985) and Tang (1993).

An early publication which discusses transfer-price policies as instruments for intracompany pricing in the field of accounting was introduced by Hirshleifer (1956). He defines a transfer price to be the price of a good or service that is exchanged between separate autonomous operating divisions within a corporation. According to Tang (1993), Chapter 5, a transfer price is the cost for the division which buys and also the revenue the selling division generates. Establishing a connection between strategic alliances and this definition, an alliance is regarded as a corporation with separate autonomous operating divisions representing the stand-alone partner airlines integrated in the alliance. The option price represents a payment that the ticketing carrier conveys to the operating carrier in exchange for a service, the reservation of seat capacity in the operating carrier's aircraft by means of real options. By paying the strike price to the operating carrier, the ticketing carrier obtains the right to sell a ticket for a seat in the operating carrier's aircraft. The operating carrier can pay back the option price to the ticketing carrier in exchange for an option that the ticketing carrier bought from the operating carrier beforehand. So, as described in our application area, the option price and the strike price are payments that are only authorized among the partners within the alliance. The end customer, which is the airline passenger in our application area, does not pay or even notice these payments.

In a publication which also addresses the transfer price topic, Bierman (1959) discusses the need for transfer prices as an intracompany pricing method to maximize the profits of a decentralized corporation. According to Bierman (1959), the transfer price does not affect the profits of a decentralized corporation as a whole directly. However, Bierman (1959) argues that the profits of the firm as a whole may be affected indirectly since the separate divisions of the corporation make decisions by using the accounting information incorporating the transfer prices. The same effect can be noticed observing strategic alliances. The transfer pricing does not directly influence the expected revenue gained by the strategic alliance as a whole. Nevertheless, the decisions made by the partners within the alliance are affected by the transfer pricing. These changed decision making processes of the partners within the alliance in turn modify the expected revenue of the partners and, therefore, the revenue gained by the strategic alliance. Hirshleifer (1956) raises the question of how the transfer prices should be set in order to incentivize each autonomous division to make their decisions so as to maximize the profit of the corporation as a whole. This corresponds to the question discussed in this chapter: How should the option price and strike price be arranged to induce the partner airlines to maximize the expected revenue of the alliance?

The transfer pricing literature quotes several transfer pricing mechanisms which are sometimes referred to as policies or methods. In the survey by Tang (1979), Chapter 5, the transfer pricing policies are classified into two broad categories, cost-based methods and non-cost-based methods. Cook (1955) discusses five of the most common transfer price policies: cost-based prices, cost-plus return on investment, combination systems, market-based prices, and free negotiation.

In the cost-based method, the transfer prices are calculated on the basis of the costs of the goods or services which should be transferred between the autonomous divisions. The costs of the goods or services are apparent from the cost accounting records of the company (compare Eccles, 1985, Chapter 2). Bierman (1959) subdivided the cost-based method in transfer prices that are established by marginal costs, variable costs, or full costs. In the transfer pricing mechanism applied in the context of capacity control within strategic alliances in the airline industry, the transfer prices cannot be determined by means of the costs apparent from the cost accounting records of the company because of three reasons: First, the marginal costs are very low considering the whole capacity since in the revenue management context it is assumed that there is a lacking operational flexibility of the capacity (compare Klein, 2005, Section 2.1.2.3). In our application area, the operating carrier utilizes an airplane with fixed seat capacity to operate the flight. Second, there are no variable costs implied in our application due to the assumptions made in the revenue management context (compare Section 2.2.1). Third, the considered aircraft is employed by the operating carrier whether or not the ticketing carrier sells tickets for the flight and, therefore, the fixed costs of the flight can be neglected.

The cost-plus return on investment approach introduced by Cook (1955) describes a method to measure the profitability of an investment by means of transfer prices rather than an approach to determine the transfer prices. Since there is no need to valuate the profitability of an investment in our application area, the cost-plus return on investment approach cannot be adopted to calculate the transfer prices in our transfer pricing method.

In the combination systems policy described by Cook (1955), the separated divisions use cost-based transfer prices to charge the transferred goods or services. In contrast to the cost-based method, the combination system policy, however, credits the divisions that sold the transferred goods or services with a portion of the net profit that another division or the firm gains from any further processing and the final sale of the transferred goods or services. This policy could be used in the capacity control for strategic alliances if additional to the assignment of the capacity to the partners in the alliance the allocation of the revenue among the alliance partners should be considered (compare Sections 3.2.1 and 7.2.2). In this scenario, the capacity of the operating carrier could be allocated by means of the transfer prices defined by the operating carrier. A portion of the revenue gained by the ticketing carrier could be payed to the operating carrier to incentivize the operating carrier to set the transfer prices so that the revenue of the alliance will be maximized. Since revenue allocation is a broad topic on its own, it is not considered in this thesis. Therefore, the combination systems policy is not covering the determination of the transfer prices in our application area.

The external market price for a good or service can be used as transfer price if the transferred product can be sold in existing competitive and stable external markets (compare Baldenius et al., 1999). In his early publication, Bierman (1959) describes that the market price could be determined by printed price lists, invoices, or other evidence. According to Bierman (1959), determining the market price could be a problem for the firm especially if the market price is different to the price on the price list, e.g., when purchasing an automobile. In some fields, there could be no market price after all. Consider our application area, the capacity control for strategic alliances in the airline industry: Adopting the revenue management instrument capacity control implies that there are several prices for the same product charged on the market. Since each of the partner airlines (the operating carrier and the ticketing carrier) offers tickets in two different booking classes to sell the seats that are available on the flight operated by the operating carrier, in our example there are four different prices charged on the market by the partner airlines. This raises the question: Which of the market prices should be employed to describe the transfer prices? Since this question cannot be answered easily, there is no possibility to use market-based transfer prices in our application area. However, the combined prices charged by the partners in the strategic alliance give some information which can be used in our transfer price mechanism. This will be described in detail in Section 7.2.

When transfer prices are determined through negotiations, literature refers to the pricing mechanism as negotiated transfer pricing (compare Baldenius et al., 1999). Bierman (1959) suggests to use negotiated transfer prices or a combination of market-based and negotiated transfer prices if the market-based transfer price cannot be easily determined. There are other authors recommending negotiations to determine transfer prices that maximize the revenue of the firm, compare Chalos and Haka (1990), Dean (1955), Haake and Martini (2008), and Kaplan and Atkinson (1998), Chapter 9. However, a negotiation process implicates some disadvantages which is why negotiations cannot be applied in any situation. Cook (1955), e.g., points out that negotiations can be very time-consuming. Eccles (1985), Chapter 2, supports this statement and adds that transfer price negotiations in corporations can be costly if the negotiations take long. There are different reasons why negotiations can be time-consuming. If, for instance, there is a huge amount of different goods or services for which transfer prices should be negotiated, the negotiation process would take too long to be applicable (compare Stone (1956)). Another phenomenon can occur if the transfer prices often need to be revised: Since the transfer prices often have to be modified after a revision, the negotiations could be an endless task (compare Stone, 1956). Considering strategic alliances, the partners within an alliance could negotiate the transfer prices to sell their products to each other in order to maximize the expected revenue of the whole alliance. In our application area, the operating carrier and ticketing carrier could determine the option price and strike price through negotiations. However, the transfer prices need to be revised whenever the parameters, the demand forecasts for the flight and the prices of the tickets in the different booking classes, change. This would often require new negotiations between the operating carrier and the ticketing carrier. Another problem can occur since the number of products could get very large in terms of strategic alliances. If the alliance in the airline industry operates flights on multiple flight legs and the partners within the alliance have to negotiate over all these flights, the negotiation process could take very long, even if there are no flight networks (origin-destination pairs) considered. However, flights with similar parameters (demand and ticket prices) can be pooled and jointly considered in the negotiation process which could speed up the negotiations. Stone (1956) adds that the products for which the transfer prices have to be negotiated can be grouped to overcome the disadvantage in the existence of a large amount of products. If there is still a huge amount of flights or many revisions, negotiations without any other transfer price mechanism that accelerates the negotiation process are not applicable in a strategic alliance, due to the time consumption problem.

Early publications list negotiations to determine transfer prices as a method that is autonomous from the other transfer price mechanisms (compare, e.g., Cook, 1955; Dean, 1955; Hirshleifer, 1956). Cook (1955) assumes that the divisions can negotiate on transfer prices in the absence of any real market conditions and, therefore, in the absence of a market price. However, the absence of any real market conditions is not a necessary requirement to apply negotiations for the determination of the transfer prices. This permits the combination of the negotiation process with other transfer price approaches. Not only Bierman (1959), but also Eccles (1985), Chapter 2, argues that the negotiation mechanism can be combined with a range of other basic transfer price methods. Since, in our application area, the market prices charged by the partner airlines for a ticket in the different booking classes give some evidence about the determination of the transfer prices, we decided to choose a method for determining the optimal transfer prices that is a combination of market-based transfer prices and negotiated transfer prices. This combined mechanism will be described in detail in Section 7.2.

There is another field of research that uses transfer payments: supply chain contracts. As we discussed in Section 3.1, the capacity control problem in strategic alliances can be compared to the coordination in a physical supply chain (compare Shumsky, 2006). As stated by Cachon (2003), the performance of a supply chain depends on actions of the members in the supply chain. Since the supply chain members primary interest is to reach their own objectives, this rational strategy often implicates a poor performance of the overall supply chain. The same effect can be noticed analyzing decisions made by partners within an alliance. For instance, if each partner airline within an alliance tries to maximize their own expected revenue, the optimal alliance performance can suffer from this procedure. The partners within the alliance need to be incentivized to make their decisions in order to optimize the objectives of the whole alliance. An improved alliance performance benefits the alliance partners since the objectives of the alliance partners are enhanced, respectively not declined, after revenue sharing. In the context of supply chain management, the incentives for the partners in the supply chain to support the objectives of the whole alliance can be defined in supply chain contracts. These incentives can be existent, e.g., in terms of transfer payments. Cachon (2003) discusses, among other things, the supply chain coordination on basis of the newsvendor model. In this model, there is one supplier and one retailer. One selling season is considered in which the demand is stochastic. Before the selling period starts, the retailer can only once order inventory from the supplier (compare Silver et al., 1998, Section 10.2, for a discussion of the newsvendor model). If we transfer this newsvendor setting to our alliance example, the operating carrier relates to the supplier and the ticketing carrier to the retailer. We observe a single flight with stochastic demand and the ticketing carrier can only once purchase options for seats before the booking process begins. Cachon (2003) lists several different types of contracts to coordinate the inventory in the newsvendor problem and to divide the profit of the supply chain arbitrarily: buy-back contracts (compare Pasternack, 1985), revenue-sharing contracts (compare Cachon and Lariviere, 2005), quantity-flexibility contracts (compare Tsay, 1999), sales-rebate contracts (compare Taylor, 2002), and quantity-discount contracts (compare Dolan, 1987).

As pointed out in Cachon (2003), the members in the supply chain follow a sequence of steps in a negotiation process in order to draw up the contract: Firstly, the supplier offers a contract to the retailer. Secondly, the retailer decides whether to accept or to reject the contract. If the retailer accepts the contract, the retailer hands the supplier an order quantity. Thirdly, before the selling season begins, the supplier produces the order quantity and delivers it to the retailer. After the selling season, when the season demand occurred, the fourth step takes place: Based upon the agreements as stipulated in the contract, transfer payments are accomplished between the supplier and the retailer. However, if the contract is rejected by the retailer in the second step, the negotiation process ends and each corporation earns a default payoff.

Although the coordination of supply chains for physical goods by means of contracts shows similarities to the capacity control within a strategic alliance, the determination of order quantities and the transfer price calculations cannot be transferred to our application area. First of all, all contract concepts mentioned above assume that all corporations combined in a supply chain possess the same information when making their decisions. That means, the contract concepts assume full and symmetric information. In his publication, Cachon (2003) mentions the problem of asymmetric information since corporations with full information are rare in practice. To overcome this problem, he demonstrates, in addition to the coordination of the actions of the corporations within the supply chain by means of contracts, how the necessary information can be shared. This procedure, however, is not adaptable to our application area. The assumption of asymmetric information still needs to be sustained. The partners within a strategic alliance cannot share their information, for instance, concerning the demand forecasts and flight ticket prices of the airlines, due to antitrust law regulations (compare Section 3.1). According to Shumsky (2006), the idea of supply chain contracts to coordinate the seat capacity within an airline alliance is applicable if the information exchange is technically possible and legal under antitrust law. Since this cannot be ensured in our application area, the seat capacity is controlled without supply chain contracts.

7.2 Determination of Optimal Transfer Prices

In this section, the interaction between the alliance partners to determine the optimal transfer prices (option price and strike price) will be described. As mentioned before, the interaction of the partners within an alliance can be considered as a negotiation process. This negotiation process will be explained using our example from Section 4.2.2. We will consider an alliance with two airlines: one operating carrier and one ticketing carrier.

7.2.1 Interaction Before, During, and After the Booking Process

The interaction between the operating carrier and the ticketing carrier can be divided into the interaction before, during, and after the booking process. The interaction between the two airlines before and during the booking processes does not change compared to the procedures introduced in the previous chapters. However, the airlines start a negotiation process after the simulation of the booking process concerning the option price and the strike price, since these prices are no longer assumed to be given parameters. The negotiation process itself will be described in detail in Section 7.2.2.

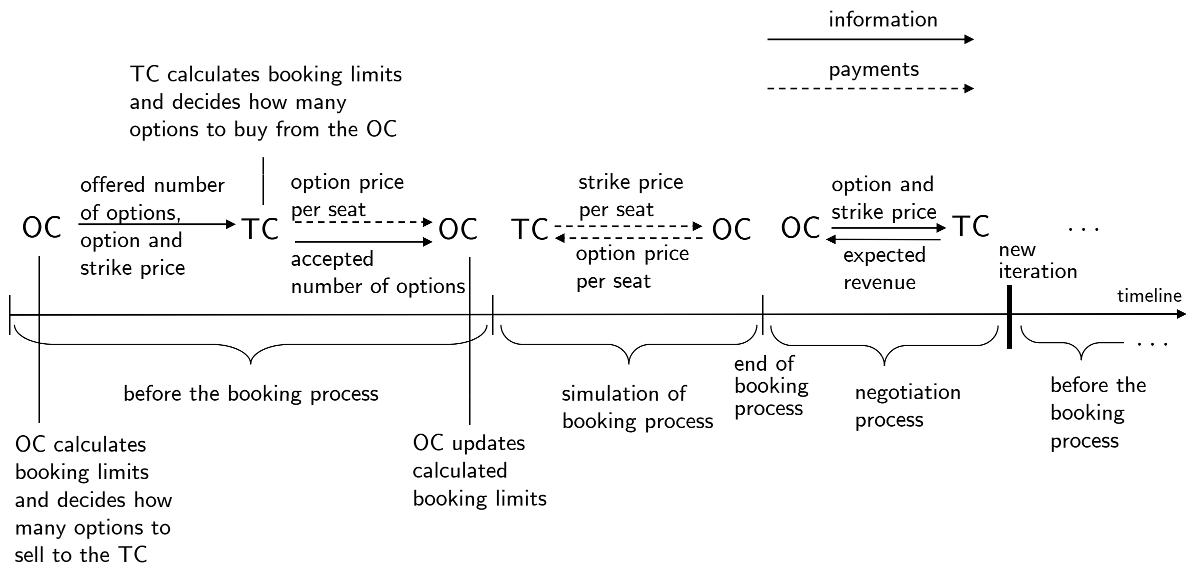

Figure 7.1: Interaction between OC and TC before, during, and after the booking process

Figure 7.1 shows the interaction between the operating carrier and the ticketing carrier.

The interaction before and during the booking process is equal to the interaction of the partner airlines described in Section 4.2.1. To show the whole interaction process, we shortly repeat the interaction between the operating carrier and the ticketing carrier before and during the booking process prior to the detailed discussion of the carriers' interaction after the simulation of the booking processes.

Before the booking process starts for a particular flight operated by the operating carrier, the operating carrier calculates the booking limits for the operating carrier's booking classes according to the deterministic linear model (DLP) described in Section 4.2.2 with arbitrary transfer prices. The operating carrier furthermore decides how many options to sell to the ticketing carrier. After the calculations, the operating carrier communicates the number of options that is available for sale, the option price, and the strike price to the ticketing carrier. Thereafter, the ticketing carrier determines how many options to buy from the operating carrier by means of the deterministic model described in Section 4.2.2. The number of options the ticketing carrier buys ranges from zero to the number of options the operating carrier offers to the ticketing carrier. We decided to calculate the booking limits by means of the DLP models instead of the EMSR heuristics since the performance of the option-based procedure and the OBP&SPSA approach is superior when the booking limits are determined using the DLP models (compare Section 4.3.2 and Section 5.3.2). To consider the total capacity, the calculated booking limits are updated by means of Procedure 1 (compare Section 4.2.2) since the results of the option-based procedure and the OBP&SPSA approach improve using Procedure 1 instead of Procedure 2 (compare Section 4.3.2 and Section 5.3.2). Before the booking process, the ticketing carrier pays the option price per seat to the operating carrier to reserve the seats by using real options. During the booking process, the ticketing carrier can sell a ticket for a seat in the aircraft of the operating carrier by exercising an option and paying the strike price to the operating carrier. If the demand for tickets within one of the ticketing carrier's classes is less than assumed, some of the options the ticketing carrier purchased from the operating carrier before the booking process remain unexercised. To provide a form of re-optimization, the operating carrier has the right to buy back options from the ticketing carrier during the booking process. By paying back the option price to the ticketing carrier, the operating carrier can access the seats reserved for the ticketing carrier. The operating carrier, however, only accesses seats reserved for the ticketing carrier if the revenue that the operating carrier gains for accepting a seat request is greater than or equal to the strike price plus the option price. If the described procedure would not allow the buy-back possibility for the operating carrier, the introduced method would be similar to a blocked seat allotment which holds the drawback of being inflexible. We studied the performance of the option-based procedure and the OBP&SPSA with and without buy-back opportunity in Section 4.3.2 and Section 5.3.2. Since the performance of the procedures with buy-back opportunity was superior to the performance without the operating carrier's opportunity to buy back options, we include the buy-back possibility of the operating carrier during the booking process in the procedures introduced in this chapter. After the booking process, the partner airlines start their negotiation process to determine the optimal transfer prices. Therefore, the operating carrier specifies varying transfer prices and communicates them to the ticketing carrier. Both airlines determine their expected revenues according to the set transfer prices. The highest expected revenue of the alliance specifies the optimal transfer prices. After the optimal transfer prices are determined, the two airlines calculate their booking limits with the optimal transfer prices detected in the negotiation process. The interaction process between the operating carrier and the ticketing carrier then restarts and passes through the same steps as described before until a fixed number of iterations is reached.

To include the search for optimal transfer prices in the booking limit calculations introduced in the previous chapters, the option-based procedure and the OBP&SPSA approach are expanded. We refer to the option-based procedure with transfer price determination as option-based+prices approach and to the OBP&SPSA method with transfer price optimization as OBP&SPSA+Prices procedure.

7.2.2 Negotiation Process

In this section, the negotiation process of the partner airlines within the alliance is described. Another term for negotiation which is often used in literature is bargaining. Nieuwmeijer (1992), Chapter 2, presents the difference in meaning between the two concepts, following the negotiation literature, although many references use the terms as synonym: Negotiation is often described as the complete negotiation process, beginning with the parties' decision to negotiate and ending when the negotiation outcome is implemented. Bargaining, however, is often characterized as the pure communication process taking place within the negotiation process. The negotiation process for transfer price determination, described in this section, covers not only the communication process of the alliance partners, but rather explains the entire negotiation process including the necessary preparations of the operating carrier prior to the communication process. Therefore, the transfer price determination process is referred to as a negotiation process in the following. Beersma and De Dreu (2002) mention the two primary kinds of negotiation distinguished in negotiation theory: distributive negotiations and integrative negotiations. In a distributive negotiation, the parties involved in a negotiation process compete over the allocation of a fixed value. Since the value is fixed, the gain of an additional amount of value made by one of the parties is made at the expense of at least one other party. In an integrative negotiation, the parties seek to achieve maximum joint outcomes by integrative behaviors. These integrative behaviors include the exchange of information about the parties' priorities and preferences and the creation of value by different possible cooperation specifications. Integrative behavior is possible if the gain of one party does not equal the losings of the other parties. The alliance partners do not compete over a fixed revenue rather than negotiate over transfer prices to generate additional revenues for the alliance which classifies the transfer price determination process in our application area as integrative negotiation. For a broader overview of literature on negotiation theory we refer to Lewicki et al. (1999) and Luecke (2003).

The game theory approach is one of the most important theoretical methods applied in negotiation research (compare Nieuwmeijer, 1992, Chapter 3). Fudenberg and Tirole (1991), Section 10.1, describe a bargaining situation as follows: in order to achieve gainings, players must reach an agreement. The problem of how to share a fixed value (often referred to as cake of size 1) describes the standard example of bargaining situations. Popular references describing this allocation problem in game theoretical bargaining theory are Nash (1950), Nash (1953), and Rubinstein (1982). Nash (1950, 1953) describes a combination of cooperative and non-cooperative approach on bargaining. In the bargaining model established by Rubinstein (1982), offers and counteroffers are involved reflecting the dynamic process in bargaining situations. However, as mentioned in Section 3.2.1, the revenue allocation problem is not part of this research. By making use of cooperative game theory, the problem of how partners within a strategic alliance share the alliance revenue realized after the booking process, can be faced. Çetiner and Kimms (2009) present a mechanism which is based on the nucleolus solution concept from cooperative game theory to find fair revenue proportions for airlines in strategic alliances with multiple flight legs. As mentioned before, Wright et al. (2010) concentrate on price and revenue sharing mechanisms to master revenue management decisions across airline alliances operating a flight network. Revenue sharing rules are usually based on negotiated special prorate agreements (SPAs) in this application area as pointed out by Wright et al. (2010). These SPAs involve fixed proration rates or transfer prices for particular ODF combinations which are used to allocate the revenue of a flight to the airlines. By means of the Nash equilibrium, the airline's behavior under different prorate schemes is demonstrated. Non-cooperative game theory tools are applied to satisfy the practical condition that airlines within an alliance cannot jointly coordinate their revenue management systems due to legal and technical reasons. The authors assume that the airlines share full information. Wright et al. (2010) state that the revenue management decisions made by the airlines within an alliance not only depend on the flight ticket price paid by the passenger to the airlines but also depend on transfer prices paid by the alliance partners among each other. The computational studies discussed before show that the results of the option-based procedure, the OBP&SPSA method, and the genetic algorithm approaches depend on the defined transfer prices.

Consider the calculation of the booking limits in the option-based approach and the OBP&SPSA procedure: The booking limits of the operating carrier and the ticketing carrier, calculated by means of the DLPs described in Section 4.2.2, differ depending on the choice of the transfer prices. Since the operating carrier considers the requests coming from the ticketing carrier as an additional booking class with its own revenue, which is equal to the sum of option price and strike price, the order of the revenues gained for a sold ticket in the booking classes of the operating carrier changes depending on the sum of the transfer prices and, therefore, the nesting order of the booking classes of the operating carrier differs. The ticketing carrier decides whether to offer tickets for a booking class or not depending on the sum of the transfer prices. If the sum of the option price and strike price is higher than or equal to the revenue the ticketing carrier gains by selling a ticket in a particular booking class, the ticketing carrier is not selling tickets for that booking class. In that case, the ticketing carrier's costs are higher than the revenue the ticketing carrier gains for one sold ticket. Not only the calculated booking limits depend on the definition of the transfer prices, but also some of the decisions made by the operating carrier and the ticketing carrier during the booking processes. As described in Section 4.2.4, the operating carrier checks if the remaining capacity in the aircraft is greater than the number of unused options the ticketing carrier holds. If the remaining capacity is less than or equal to the number of options, the operating carrier accepts the request if the revenue of the received request is greater than or equal to the option price plus the strike price. The ticketing carrier only accepts requests during the booking process if the revenue the ticketing carrier gains by accepting the request in the booking class is higher than the sum of option price and strike price. Therefore, the decisions of the carriers whether to accept or to reject a request in a particular booking class depend on the transfer prices.

It can be noticed that the revenue of the alliance calculated by means of the option-based procedure and the OBP&SPSA approach does not change if the sum of option price and strike price is assumed to be within a certain interval. The transfer price intervals in which the calculated alliance revenue does not change correspond to the intervals between the different flight ticket revenues of the considered booking classes of the alliance partners.

We explain this statement by means of the following example considering that both carriers offer two booking classes: Assume the revenue for one sold ticket in the operating carrier's highest yielding booking class (v_{11}) to be 350€ and the revenue for a ticket in the operating carrier's second booking class (v_{21}) to be 100€. The ticketing carrier's revenue for a sold ticket in the first booking class (v_{12}) is 400€ and for the ticketing carrier's lowest yielding booking class (v_{22}) 150€. So, the flight ticket revenue sequence of the booking classes of the partner airlines is: $v_{12} > v_{11} > v_{22} > v_{21}$.

In this example, the changing booking limit calculations and decision making in the booking processes of the two partner airlines within the alliance can be divided into five cases. Figure 7.2 shows the different transfer price scenarios and the corresponding nesting order of the booking classes of the partner airlines in the example with four booking classes and five transfer price cases.

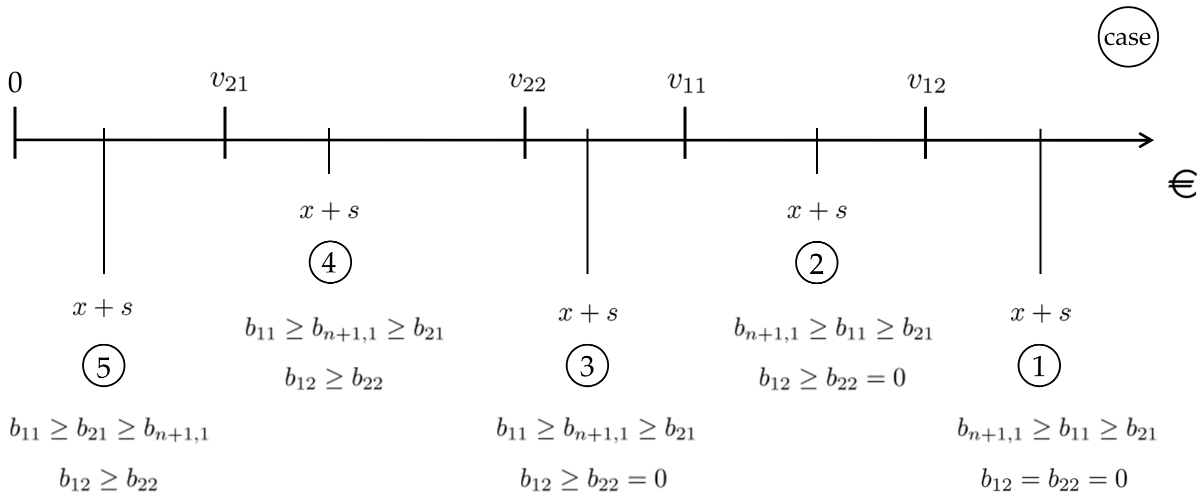

Figure 7.2: Case Differentiation with Four Booking Classes

Consider, for instance, the second case: The operating carrier's nesting order for calculating the booking limits is defined by: $x + s > v_{11} > v_{21}$, i. e. $b_{n+1,1} \geq b_{11} \geq b_{21}$. The operating carrier stops selling tickets for both booking classes once the remaining capacity is equal to or smaller than the number of options the ticketing carrier holds since the revenue the operating carrier gains if the ticketing carrier accepts a request and exercises an option is higher than the flight ticket revenues of the operating carrier's booking classes. The ticketing carrier sells tickets for the higher, but not for the lower yielding booking class since the sum of the transfer prices is lower than the revenue for an accepted request in the higher yielding booking classes but higher than the flight ticket revenue in the lower yielding booking class of the ticketing carrier ($v_{22} < x + s < v_{12}$). This affects the calculation of the booking limits of the ticketing carrier and the decisions made by the ticketing carrier during the booking process. In this case, the booking limit of the first and the second booking class of the ticketing carrier is zero and the ticketing carrier does not accept incoming requests for both booking classes during the booking process.

In our approach, the operating carrier needs to identify the intervals of the flight ticket revenues of the partner airlines within the alliance: First, the flight ticket revenue of the booking classes of the partner airlines is sorted in descending order, in our example: $v_{12} > v_{11} > v_{22} > v_{21}$. And second, the following intervals are arranged:

Interval 1: $]v_{12}, \infty[$

Interval 2: $]v_{11}, v_{12}[$

Interval 3: $]v_{22}, v_{11}[$

Interval 4: $]v_{21}, v_{22}[$

Interval 5: $]v_{21}, 0]$

The endpoints of the intervals are, except for the right endpoint of Interval 5, excluded from the respective sets. The transfer price cases in which the sum of option price and strike price is defined to be equal to one of the flight ticket revenues of the booking classes of the airlines do not have to be considered in addition to the other transfer price cases. This is valid since the booking limit calculations and decision making of the partner airlines corresponding to these transfer price cases are already considered in the other intervals. However, the endpoints need to be excluded since additional cases in the transfer price differentiation would have to be considered if the sum of option price and strike price could be defined equal to the flight ticket revenues of the booking classes of the airlines. The additional cases are necessary since the nesting orders of the booking classes and the decisions made by the alliance partners, which correspond to the transfer price scenario in the interval in which the endpoint is defined equal to the sum of the transfer prices, are not considered otherwise. If this happens, the optimality of the determined transfer prices cannot be assured.

As long as the sum of option price and strike price is within one of the described intervals, neither the nesting order of the booking classes of the airlines and, therefore, the calculated booking limits, nor the decisions during the booking processes made by both of the carriers change. Consequently, the alliance revenue calculated by means of the option-based+prices approach and the OBP&SPSA+Prices procedure does not change.

The insight that the alliance revenue remains constant as long as the sum of the transfer prices is defined within a certain flight ticket revenue interval helps to determine the optimal transfer prices in an efficient way. The partners within the alliance do not have to check their expected revenues and the alliance revenue according to all possible transfer price settings. This means, we do not have to search through the entire solution space to determine the optimal transfer prices. Instead, the partner airlines can calculate their expected revenue step by step each time assuming the sum of the transfer prices within one of the different flight ticket revenue intervals. This procedure requires revenue calculations of the airlines for each revenue interval. After the revenue calculations of the alliance partners, the results can be compared to the determined highest alliance revenue and to the underlying transfer prices.

If the order of the flight ticket revenues of the booking classes of the alliance partners differs from the one illustrated in the example, the described cases in the case differentiation change because the nesting orders of the booking classes and the decisions made in the booking processes of the partner airlines differ from the one discussed above. However, the number of intervals which have to be arranged stays constant even if the flight ticket revenue structure of the booking classes changes. Generally, there are $n + 1$ intervals if the alliance partners offer n booking classes with different flight ticket revenues. If the different partner airlines offer booking classes with identical flight ticket revenues, the number of intervals decreases by the number of booking classes with identical flight ticket revenues plus one.

After the operating carrier identified and declared the intervals for the transfer price scenarios, the partner airlines start their negotiation process. In Figure 7.3 the negotiation process of the alliance partners is displayed considering two airlines within the alliance. In the following, z denotes a transfer price scenario in the case differentiation and $n + 1$ refers to the total number of transfer price scenarios $(z = 1, ..., n + 1)$.

The negotiation process of the partner airlines can be implemented as an iterative process since the operating carrier needs to set the sum of the transfer prices step by step according to all transfer price scenarios. The operating carrier communicates $n + 1$ different option prices and strike prices to the ticketing carrier and the partner airlines need to calculate and communicate their expected revenue in all transfer price scenarios. Since the iterations correspond to the transfer price scenarios, we refer to the iteration index as z just as to the transfer price scenarios.

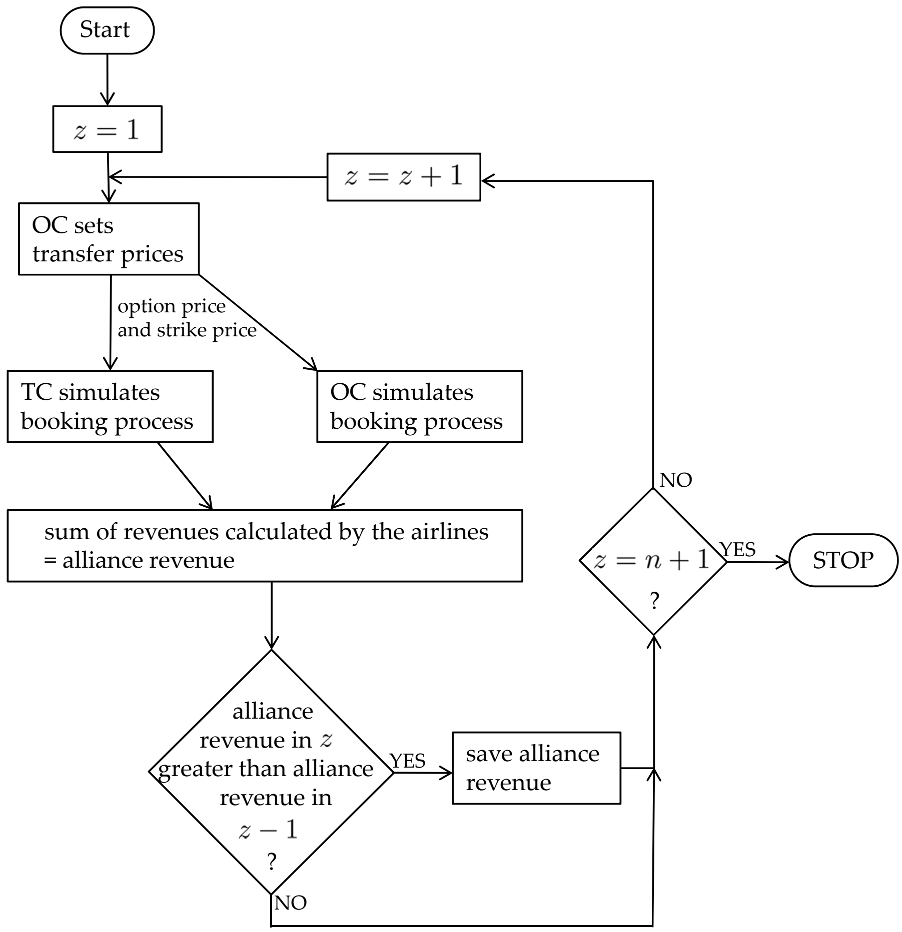

Figure 7.3: Negotiation Process of the Operating Carrier and the Ticketing Carrier

In the first iteration, in the beginning of the negotiation process, the operating carrier sets the transfer prices so that the sum of the transfer prices lies in the interval of transfer price case scenario 1 (displayed in Figure 7.3 as $z = 1$). After the operating carrier sets the transfer prices, they are communicated to the ticketing carrier. The ticketing carrier and the operating carrier simulate their booking process as described in Section 4.2.4 and calculate their respective expected revenue according to the fixed booking limits (calculated before the negotiation process) and to the transfer prices set by the operating carrier. After the ticketing carrier calculated the expected revenue, the ticketing carrier communicates to the operating carrier the revenue that the ticketing carrier expects in this setting. The operating carrier calculates the expected alliance revenue by accumulating the operating carrier's and ticketing carrier's expected revenues. If the expected revenue of the alliance is greater than the expected revenue of the alliance in the previous iteration, the alliance revenue and the corresponding transfer prices are stored. Since there is no previous iteration in the first iteration ($z = 1$) of the negotiation process, the expected alliance revenue is compared to the expected alliance revenue that was calculated with arbitrary transfer prices in the first step of the option-based+prices approach respectively the OBP&SPSA+Prices procedure while determining the booking limits (compare Figure 7.4 respectively Figure 7.5). If the expected alliance revenue is less than the expected alliance revenue in the previous iteration, the alliance revenue of the present iteration is not considered any more. After the results of the iterations are compared, the operating carrier checks if the current iteration index is equal to the total number of iterations ($z = n + 1$). If yes, the negotiation process stops since all transfer price sections are considered. If no, the operating carrier sets the transfer prices so that the sum of the transfer prices lies in the interval of transfer price scenario $z + 1$. After the negotiation process, when the operating carrier sets the sum of the transfer prices according to all transfer price scenarios, the optimal transfer prices which maximize the expected revenue of the alliance are determined. The partner airlines within the alliance recalculate their booking limits with the optimal transfer prices as parameters after the negotiation process.

In a competitive world, the alliance partners normally do not share the information concerning their prices of the tickets in the different booking classes. But, one can argue that the operating carrier can monitor the flight ticket prices that the ticketing carrier requires on the market. Wright et al. (2010) state that the Internet helps the airlines to monitor flight ticket fares offered by their competitors. Moreover, the operating carrier does not have to know the exact flight ticket prices of the ticketing carrier. The operating carrier needs to set the transfer prices so that their sum lies somewhere in the interval between the different revenues for a sold ticket in the different booking classes since the alliance revenue does not change as long as the sum of the transfer prices lies inside the considered interval. There is still an improvement of the expected alliance revenue compared to the results of the option-based procedure and the OBP&SPSA approach even if the operating carrier misses one of the intervals. However, the optimality of the transfer prices can only be guaranteed if the expected alliance revenue is calculated for all transfer price case scenarios.

To include the search for optimal transfer prices in the booking limit calculations, the option-based procedure and the OBP&SPSA approach are expanded. Figure 7.4 shows the control flow of the option-based+prices procedure. Firstly, the booking limits are calculated with arbitrary transfer prices by means of the DLPs introduced in Section 4.2.2. Secondly, the calculated booking limits are fixed and the optimal transfer prices are determined in the negotiation process (compare Figure 7.3). Thirdly, after the transfer price optimization, the booking limits are recalculated using the DLPs with fixed transfer prices. The second and third step are repeated until a predefined number of iterations is reached.

In the first step of the OBP&SPSA+Prices approach, the booking limits of the two alliance partners are calculated with arbitrary transfer prices using the DLP models introduced in Section 4.2.2. In the second step, the determined booking limits are improved by means of the Simultaneous Perturbation Stochastic Approximation method described in Section 5.2. After the booking limits are calculated and improved, the airlines start the transfer price negotiation process. Once the optimal transfer prices are determined, the booking limits are recalculated with the optimal transfer prices as parameters which were determined in the negotiation process. This iterative process stops after a predefined number of iterations. Figure 7.5 presents the control flow of the OBP&SPSA+Prices approach.

It is adequate to consider the sum of the transfer prices in the negotiation process instead of considering the option price and strike price separately since the revenue of the alliance is maximized. There is no difference in the expected revenue of the alliance if the sum of the transfer prices is constant even if the single prices change. This effect occurs since the option price and strike price are payments that are only conducted between partners within the strategic alliance. Every payment between the partner airlines increases the expected revenue of one of the partners but simultaneously decreases the expected

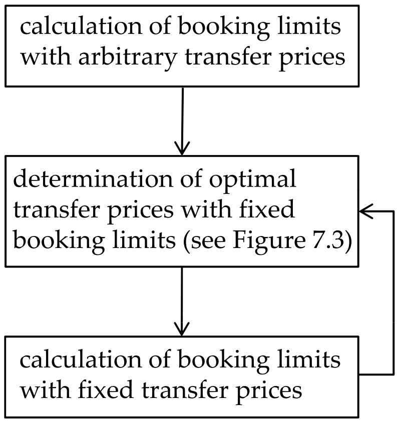

Figure 7.4: Option-Based+Prices Procedure

revenue of another partner airline by the same amount. Therefore, the expected revenue of the alliance is not affected.

Consideration of two prices, the option price and the strike price, is necessary in practice, because the expected revenue of the alliance partners change if the option price and strike price differ although the sum of the transfer prices stays constant. Consider a scenario in which the actual demand of both carriers is much lower compared to the forecasted demand. In this scenario, the operating carrier and the ticketing carrier both hold unsold tickets after the booking process. The ticketing carrier cannot return options to the operating carrier if the seats the ticketing carrier bought options for remain unsold. Therefore, the option price payments of the ticketing carrier before the booking process actually increase the expected revenue of the operating carrier as long as the operating carrier does not buy back the options during the booking process. In a scenario with very low demand a buy back, however, is unlikely. Therefore, the expected demand of the operating carrier is higher if the option price increases compared to a scenario in which the option price is lower, even if the sum of the transfer prices is constant. The transfer prices influence the risk sharing of the alliance partners since the ticketing carrier bears a portion of the risk for unsold tickets for seats in the operating carrier's airplane by paying the option price before the booking process. Due to the option price payments, the loss of profit in case of unsold seats the ticketing carrier bought options for is divided among the alliance partners. So, if the option price is high and the strike price is low, the ticketing carrier bears more risk for unsold seats the ticketing carrier bought options for than in a setting in which the option price is low and the strike price is high. However, the ticketing carrier incorporates the option price and the strike price in the objective function of the DLP to calculate the booking limits by subtracting the sum of the transfer prices from the expected revenue of the ticketing carrier (compare Section 4.2.2). Therefore, the ticketing carrier determines the same booking limits calculated with different option prices and strike prices as long as the sum of both remains constant. This prevents that the ticketing carrier buys more options for seats than the forecasted demand in a low option price setting.

As discussed in this section, the interaction between the partners within an alliance to determine the optimal transfer prices can be considered as negotiation process. Since the operating carrier sets the sum of the transfer prices within the intervals between the respective market prices, the transfer price determination within a strategic alliance can be compared to the determination of negotiated marked-based transfer prices.

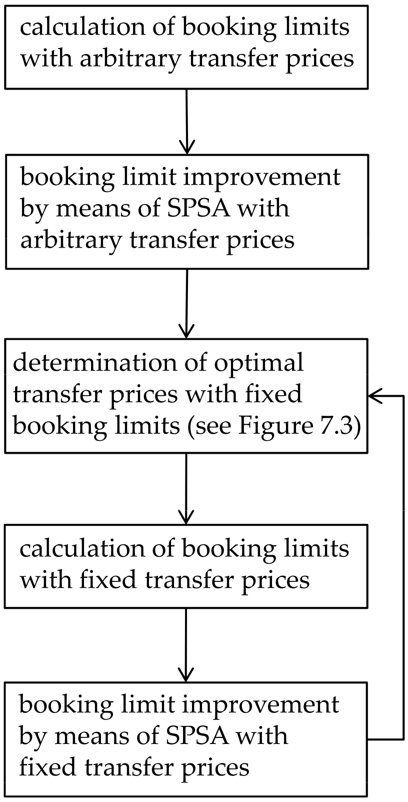

Figure 7.5: OBP&SPSA+Prices Procedure

7.3 Computational Study for the Option-Based Procedures with Transfer Price Optimization

In the previous section, we described the control flow of the option-based+prices approach and the OBP&SPSA+Prices procedure. We implemented both procedures in C++ and compared the results of both approaches in a computational study.

Since the option-based+prices approach and the OBP&SPSA+Prices procedure are extensions of the option-based method and the OBP&SPSA approach introduced in Chapter 4 and Chapter 5, the basic elements, calculating the booking limits and the simulation of the booking process, are identical. The option-based+prices procedure and OBP&SPSA+Prices approach are implemented as follows (compare Figure 7.4 and Figure 7.5): First, the deterministic linear models introduced in Section 4.2.2 are solved in both procedures to calculate the booking limits of the airline partners assuming an arbitrary option price and strike price. We define the option price and the strike price to be 100 in the first iteration of both procedures. The choice of the arbitrary transfer prices in the first iteration of the option-based+prices procedure and OBP&SPSA+Prices approach is not critical to the revenue outcome of the procedures since the booking limits first calculated with arbitrary transfer prices will be improved in the following iterations. However, if the booking limits calculated in the first iteration are good, due to a proper choice of the transfer prices, the iteration, in which the option-based+prices procedure and OBP&SPSA+Prices method generate the highest revenue, is most likely lower than in a setting with poorly chosen transfer prices. The results of our computational study show that the optimal transfer prices are quite low in most of the considered instances. Since we have chosen the transfer prices to be rather high in the first iteration, the promising results of the procedures do not depend on a clever choice of the arbitrary transfer prices. After the calculation of the booking limits, the programs pass the achieved booking limits to the simulation. To determine the revenue obtained with the computed booking limits, the programs simulate the booking processes of the two carriers according to the models outlined in Section 4.2.4. The Simultaneous Perturbation Stochastic Approximation principle discussed in Section 5.2 is implemented in the OBP&SPSA+Prices approach to improve the calculated booking limits. The number of iterations of the SPSA procedure is 100. This implies that the SPSA procedure tries to improve the booking limits 100 times in the OBP&SPSA+Prices method. To determine the best transfer prices corresponding to the best booking limits determined by the option-based+prices approach and the OBP&SPSA+Prices method so far, the programs pass this booking limits to the method which describes the negotiation process of the airline partners (compare Figure 7.3). Before the negotiation process starts, the operating carrier sorts the flight ticket revenues of the booking classes offered by the alliance and determines the revenue intervals as described in Section 7.2.2. In the negotiation process, also described in Section 7.2.2, the partner airlines check their expected revenue in different transfer price scenarios and determine the best transfer prices which are passed to the optimization models introduced in Section 4.2.2. A new iteration starts and the DLPs use the determined transfer prices as parameters to calculate improved booking limits according to the new transfer prices. To terminate the option-based+prices method and the OBP&SPSA+Prices procedure, we set the maximum allowable number of iterations to ten.

The following assumptions were already made in the previous computational studies. They remain constant in the computational study of the option-based+prices approach and the OBP&SPSA+Prices procedure: In the optimization part, the booking limits for the operating carrier were calculated by means of Procedure 1, which assigns the spare seats the ticketing carrier does not buy options for (if they exist) to a class of the operating carrier. Procedure 1 was explicitly described in Section 4.2.2. We have chosen Procedure 1 to calculate the booking limits of the operating carrier since the results of the option-based approach and the OBP&SPSA procedure in the computational studies in Section 4.3.2 and Section 5.3.2 show that Procedure 1 generates the best results. Additionally, we need to make sure that the results of the option-based+prices method and the OBP&SPSA+Prices procedure are comparable to the results of the option-based approach and the OBP&SPSA method. In the simulation part, the booking processes of the airlines were simulated 5000 times in each iteration of the option-based+prices procedure and the OBP&SPSA+Prices approach, taking the stochastic demand into account. The revenue measurements achieved by the 5000 simulation replications are averaged. To approximate a non-stationary Poisson process, the booking process of the alliance partners are divided in three time intervals with different request arrival rates that are constant within a particular time interval. We used the random number generator boost::random::ranlux64_base_01 (compare www.boost.org) to create random numbers for the stochastic request arrivals. In the simulation, we used standard nesting to implement the nested booking limits. The duration of the simulation accounts for 150 periods closing with the departure of the airplane. We conducted the tests on an AMD Athlon(tm) 64X2 Dual Core Processor 4600+ 2.41 GHz PC with 1,96 GB RAM running Windows XP.

As mentioned before, we refer to the alliance revenue in the computational study which is the sum of the revenues of the two airlines since the goal of the introduced procedures is to maximize the combined revenue of the alliance partners.

It can be noticed that the results of the OBP&SPSA+Prices procedure improved the results of the option-based+prices approach in every considered instance. This effect already occurred in the comparison of the option-based procedure and the OBP&SPSA approach in the computational study in Section 5.3.2. To show this effect, the results of the option-based+prices approach are compared to the results of the OBP&SPSA+Prices procedure in the following section. The performance of the introduced OBP&SPSA+Prices procedure is additionally compared to the results of a first-come-first-served approach and the ex post optimal solutions (compare Section 4.3.1 for a description of the implementation of the methods). Moreover, the results of the OBP&SPSA+Prices procedure are compared to the results of the option-based method, the OBP&SPSA approach, a blocked seat allotment method, and a random procedure. The implementation of the blocked seat allotment procedure and the random approach will be described in the following.

Blocked Seat Allotment (BSA)

Boyd (1998) and Talluri and van Ryzin (2004b), Section 3.7, describe the blocked seat allotment as a procedure in which the seat capacity on a considered flight is partitioned among the partner airlines within the alliance. After partitioning the seat capacity, each partner airline is allowed to control the seats which have been assigned to the airline individually. Talluri and van Ryzin (2004b), Section 3.7, state that in a blocked seat allotment procedure the control of the seat capacity for two airlines on the considered flight can be seen as if there were two fictional flights each holding one portion of the partitioned seat capacity. The seat capacity of the different flights is individually controlled by the respective alliance partner. According to Boyd (1998), different variations of blocked seat allotment procedures are conceivable ranging from hard blocks to soft blocks. Considering hard blocks, the seat capacity allocated to the partner airlines persists and does not change once the seat capacity is partitioned. In a blocked seat allotment procedure with soft blocks, the partitioned seat capacity can be updated periodically in the booking process.

We compare the results of the OBP&SPSA+Prices procedure with a blocked seat allotment method that is conceived as follows: The operating carrier forecasts the expected demand for the operating carrier's booking classes. Depending on the sum, the operating carrier decides how many seats will be available to the ticketing carrier. For example, if the expected demand for the operating carrier's first booking class ($E[d_{11}]$) is 20 and the expected number of requests for the operating carrier's second class ($E[d_{21}]$) is 50, the operating carrier reserves a total of 70 ($E[d_{11}] + E[d_{21}]$) seats in the aircraft for the assumed incoming demand for the operating carrier's booking classes. Assuming the total seat capacity in the operating carrier's aircraft (C) to be 100, the operating carrier would make 30 ($C - (E[d_{11}] + E[d_{21}])$) seats available for the ticketing carrier. The ticketing carrier on the other hand forecasts the expected demand for the ticketing carrier's booking classes. According to this forecast, the ticketing carrier decides how many seats to access in the operating carrier's aircraft. If the sum of the expected demand for the ticketing carrier's booking classes is equal to or higher than the seat capacity the operating carrier makes available to the ticketing carrier ($E[d_{12}] + E[d_{22}] \geq C - (E[d_{11}] + E[d_{21}])$), the ticketing carrier can only access the seat capacity the operating carrier allocates to the ticketing carrier ($C - (E[d_{11}] + E[d_{21}])$). If the sum of the expected demand for the ticketing carrier's booking classes is lower than the seat capacity the operating carrier allocates to the ticketing carrier ($E[d_{12}] + E[d_{22}] < C - (E[d_{11}] + E[d_{21}])$), this difference of seat capacity is not offered. After the seat capacity is partitioned and allocated to the carriers, each partner airline individually determines its booking limits by means of the deterministic linear model introduced, for instance, by Williamson (1992), Section 4.1, without underlying real options according to the flight ticket revenues and the expected demand for the booking classes of the airlines. During the booking process, the operating carrier and the ticketing carrier do not transfer seat capacity. The decision whether or not to accept an incoming request is made independently by the considered airlines according to booking limits and remaining seat capacity. The booking processes of the operating carrier and the ticketing carrier are simulated. An incoming request for a flight ticket in a booking class of the airlines is accepted if the respective booking limit and the remaining seat capacity is greater than zero. The remaining capacity and the booking limit of the booking class for which the request occurred is decremented by one after accepting the request. The assumptions behind the simulations in the blocked seat allotment procedure are the same that we defined above for the option-based+prices approach and the OBP&SPSA+Prices method.

Random Approach
To test if an approach, in which the booking limits are chosen randomly, achieves a similar performance as the OBP&SPSA+Prices method, we implemented the random approach as described in the following and compared the performance with the results of the booking limit calculations underlying OBP&SPSA+Prices procedure.

In the random approach, we choose the booking limits of the two airline partners randomly from a defined interval. The booking limits in our random approach are uniformly distributed and can take a random value from zero to the assumed total capacity in the aircraft of the operating carrier depending on which capacity instance is assumed ($U[0, C]$). We simulate the booking process of the two airlines to receive the revenue for the two airlines and the total revenue of the alliance according to randomly chosen booking limits. In the simulations of the booking processes, a request for a flight ticket in a booking class of the airlines is accepted if the respective booking limit and the remaining seat capacity is greater than zero. After accepting the request, the booking limit of the booking class for which the request occurred and the remaining capacity are decremented by one. The assumptions underlying the simulations in the random approach are also the same that we defined above for the option-based+prices approach and the OBP&SPSA+Prices procedure.

The result of the option-based approach is the initial solution of the option-based+prices algorithm and the result of the OBP&SPSA procedure is the initial solution of the OBP&SPSA+Prices algorithm. Consequently, the solution of the option-based approach and the OBP&SPSA procedure is a lower bound for the option-based+prices result and the OBP&SPSA+Prices result, respectively. An upper bound for the option-based+prices algorithm and the OBP&SPSA+Prices result is the ex post optimal solution.

The run-time of the option-based+prices procedure to solve one of the considered instances is very low, ranging from seven to 14 seconds. The OBP&SPSA+Prices procedure's run-time depends on the assumed demand and the defined capacity. To achieve the result for one instance, the OBP&SPSA+Prices algorithm needs about 6.5 minutes in low demand settings considering the seat capacity to be 100 and up to 13 minutes in instances with a higher seat capacity and higher total demand. Since the run-time of the OBP&SPSA+Prices procedure is not critical regardless of which instance is considered, we do not specify the run-time of the OBP&SPSA+Prices method for each single instance in the computational study.

7.3.1 Test Bed for the Analysis of Option-Based Procedures with Transfer Price Optimization

Similar to the computational studies in the previous sections, we systematically varied the parameters to monitor the performance of the option-based+prices approach and the OBP&SPSA+Prices method in different instances. We assumed the total seat capacity C of the operating carrier to be 100, 120, or 150. Table 7.1 shows the different revenue instances (revenue v_{jl} for one ticket in booking class j of airline l) underlying the computational study. As a third variation, the expected value of demand for tickets in booking class j of airline l $E[d_{jl}]$ are varied in the different instances (compare Table A.1, Table A.2, Table A.3, and Table A.4 in the Appendix A.1).

The test bed contains eight different revenue instances. Since the option-based+prices approach and the OBP&SPSA+Prices procedure determine the best option price and strike price for each instance, the computational study no longer contains instances in which the option price and the strike price are

Revenue Instance	v_{11}	v_{21}	v_{12}	v_{22}
1	350	100	400	150
2	400	150	350	100
3	350	100	450	200
4	200	100	250	150
5	500	200	550	250
6	550	250	500	200
7	500	400	200	100
8	200	100	500	400

Table 7.1: Revenue Instances

parameters. The revenue instances still ensure that it is more profitable for the airlines to sell a ticket in their first than in the second class although the gap between the revenues of the different classes of the two airlines changes.

Once more, we assumed the expected value of total demand for flight tickets in all booking classes of both airlines to be 10%, 20%, 30%, and 40% higher than the specified capacity, that means the demand intensity varies between 1.1 and 1.4. In each demand scenario, capturing the total demand for all booking classes, we assumed different demand instances varying in the demand for the booking classes of the airlines. Considering the demand for one airline, the demand for the expensive tickets is lower than the demand for the cheaper ones in every demand instance. We still assumed that there is no revenue management problem if the capacity is equal to or higher than the demand (compare Klein, 2005, Section 6.2.2). However, to test the performance of the introduced option-based+prices procedure and the OBP&SPSA+Prices method in a low demand setting, we analyzed the performence of the approaches in demand instances in which the total demand is 90% of the capacity in Section 7.3.2.1 (Table 7.6).

To compare the results of the option-based procedure and the OBP&SPSA approach with the introduced OBP&SPSA+Prices method, only the revenue instances 1, 2, 3, and 4 can be considered. In the computational studies analyzing the option-based procedure and the OBP&SPSA approach, the instances in the test bed contain the four revenue instances 1, 2, 3, and 4 and each of the revenue instances is varied by means of four price instances since the transfer prices are treated as parameters in both procedures. In the first section of the current computational study (Section 7.3.2.1), the results of the OBP&SPSA+Prices procedure in the different capacity, demand, and revenue instances are compared to the results of the option-based method and the OBP&SPSA approach in the different capacity, demand, and revenue instances aggregated over the price instances. E.g., if the results of the OBP&SPSA+Prices procedure in the instance with seat capacity 100, revenue instance 1, and demand scenario 110 is compared to the results achieved by the option-based method and the OBP&SPSA approach, the solutions of these two approaches in the instance with 100 considered seats, revenue instance 1, and demand scenario 110 have to be aggregated over all price instances (a, b, c, and d).

7.3.2 Evaluation of the Option-Based Procedures with Transfer Price Optimization

In the following analysis of the results of the OBP&SPSA+Prices method, the computational study is split in tree sections: In Section 7.3.2.1, revenue instances 1 through 4 are considered (compare Table 7.1) to be able to analyze the results of the OBP&SPSA+Prices approach compared to the results of the option-based method and the OBP&SPSA approach. Section 7.3.2.2 considers all revenue instances 1 through 8 (compare Table 7.1) to offer a broader test bed for the computational study of the option-based+prices approach and the OBP&SPSA+Prices method. In Section 7.3.2.3, the transfer price optimization is combined with the genetic algorithm versions introduced in Chapter 6. The performance of the OBP&SPSA+Prices approach is compared to the performance of the genetic algorithms approaches also considering transfer price optimization.

The percentage gaps between the optimal values of the OBP&SPSA+Prices procedure and the option-based+prices approach (OBP+Prices), the OBP&SPSA method, the option-based procedure (OBP), the first-come-first-served approach (FCFS), the ex post optimal solution (ex post), the blocked seat allotment procedure (BSA), and the random approach (random) are computed by means of formula 6.2 to compare the different procedures with each other in Section 7.3.2.1 and Section 7.3.2.2.

Table 7.2 shows the procedures which are compared in the following two sections and the respective gap assignment.

gap	$Procedure1$	$Procedure2$
$gap15$	OBP&SPSA+Prices	OBP+Prices
$gap16$	OBP&SPSA+Prices	OBP&SPSA
$gap17$	OBP&SPSA+Prices	OBP
$gap18$	OBP&SPSA+Prices	FCFS
$gap19$	ex post	OBP&SPSA+Prices
$gap20$	OBP&SPSA+Prices	BSA
$gap21$	OBP&SPSA+Prices	Random

Table 7.2: Compared Procedures in Computational Survey Section 7.3.2.1 and Section 7.3.2.2

7.3.2.1 Comparison of Procedures (Revenue Instances 1–4)

Recall that we only consider revenue instances 1 through 4 in this section. If results based on all instances are mentioned in this section, the results are aggregated over all capacity and demand instances and the revenue instances 1 through 4.

The revenue generated by the OBP&SPSA+Prices approach over all capacity, demand, and revenue instances is 5.71 % higher than the results gained by the OBP+Prices method, 4.71% higher than the revenue calculated by the OBP&SPSA procedure, and 10.27% higher than the revenue achieved by the option-based procedure in the considered price instances (compare Table 4.5). The improvement compared to the first-come-first-served method is even more significant: The OBP&SPSA+Prices procedure achieves an expected revenue that is 16.13% higher than the revenue generated by the FCFS approach over all instances. Considering the ex post optimal solution, the results of the OBP&SPSA+Prices approach are closer to the ex post optimal solutions than the results of the option-based procedure or the OBP&SPSA approach. The ex post optimal solution is only 4.33% higher than the result of the OBP&SPSA+Prices approach, aggregated over all capacity, demand, and revenue instances. Over all instances, the expected revenue generated by the OBP&SPSA+Prices procedure is 8.12% higher than the results achieved by means of the blocked seat allotment method and 16.02% higher than the results of the random approach.

Table 7.3 shows the results aggregated over all demand and revenue instances in one capacity instance. The OBP&SPSA+Prices procedure determines better results than the OBP+Prices approach and the OBP&SPSA method in all three capacity settings. The results of the OBP&SPSA+Prices procedure exceed the results of the option-based procedure and the results of the FCFS approach even more in all of the capacity settings. The gap between the ex post optimal solutions and the OBP&SPSA+Prices results ($gap19$) is small, although the results of the OBP&SPSA+Prices procedure still do not reach the ex post optimal solutions. It can be noticed that $gap16$ and $gap17$ decrease as the capacity scales up, although the performance of the OBP&SPSA+Prices procedure improves as the capacity increases compared to the FCFS solutions. The results of the OBP&SPSA procedure and the option-based method increase faster than the results of the OBP&SPSA+Prices procedure as the capacity grows which explains the shrinking of $gap16$ and $gap17$. We identify the same outcome, studying the revenue calculated by the OBP&SPSA+Prices approach, as we recognized while analyzing the results of the OBP&SPSA procedure: Compared to the FCFS method, the OBP&SPSA+Prices approach performs better in instances with higher capacity since the solution space expands if a higher seat capacity is considered.

Comparing the results of the OBP&SPSA+Prices procedure with the results of the blocked seat allotment method shows that the OBP&SPSA+Prices procedure performs considerably better than the blocked seat allotment method in all capacity instances. The same outcome can be noticed in the comparison of the OBP&SPSA+Prices procedure with the random approach. The results of the OBP&SPSA+Prices procedure exceed the results of the random approach even more. In Section 7.3.2.2, the results of the OBP&SPSA+Prices procedure will be compared to the results of the blocked seat allotment procedure and the random approach again with additional underlying revenue instances. This comparison shows that the blocked seat allotment procedure and the random approach perform even worse if other ticket revenues are tested. So, the inferior performance of the blocked seat allotment method and the random approach in the observation in this section is not up to the selection of the revenue instances.

Capacity	$gap15$	$gap16$	$gap17$	$gap18$	$gap19$	$gap20$	$gap21$
100	6.08	5.65	11.91	14.38	5.03	9.36	17.40
120	4.17	4.68	10.19	15.97	4.32	8.17	15.29
150	6.90	3.84	8.78	17.96	3.67	6.88	15.43

Table 7.3: OBP&SPSA+Prices – Results Aggregated over Demand and Revenue Instances

Table 7.4 presents the revenue per seat in the capacity instances. The OBP&SPSA+Prices procedure outperforms the other approaches especially in instances in which the seat capacity is assumed to be low (except for the OBP+Prices approach and the FCFS procedure). The revenue per seat results also show this effect even for the FCFS algorithm (compare Table 7.4).

Capacity	$gap15/C$	$gap16/C$	$gap17/C$	$gap18/C$	$gap19/C$	$gap20/C$	$gap21/C$
100	0.06	0.06	0.12	0.14	0.05	0.09	0.17
120	0.03	0.04	0.08	0.13	0.04	0.07	0.13
150	0.05	0.03	0.06	0.12	0.02	0.05	0.10

Table 7.4: OBP&SPSA+Prices – Results Aggregated over Demand and Revenue Instances Per Seat

To evaluate the estimated revenue according to the demand variations, we fixed the capacity and the demand scenarios and aggregated the computed results over all revenue instances in a first observation. Table 7.5 lists the aggregated results for the seat capacity which is assumed to be 100, 120, and 150. Scenario 110 (demand in %), for instance, shows the average revenue aggregated over the demand instances assuming the total demand to be 110% of the capacity in the considered capacity settings.

The OBP&SPSA+Prices method improves the results of the OBP+Prices approach, the OBP&SPSA procedure, and the option-based approach in all demand settings. Especially in low demand settings, the OBP&SPSA+Prices procedure enhances the results of the OBP&SPSA method and even more the results of the option-based approach. In instances with low demand, the assignment of poor transfer prices causes that the capacity control with booking limits in the OBP&SPSA method and the option-based

Capacity	Demand in %	$gap15$	$gap16$	$gap17$	$gap18$	$gap19$	$gap20$	$gap21$
100	110	5.13	9.60	13.37	2.66	4.10	4.85	22.45
	120	6.81	6.66	12.12	8.83	5.26	7.63	12.56
	130	8.79	4.61	11.70	17.37	5.45	10.78	15.42
	140	6.54	3.29	10.97	26.85	5.17	13.51	19.94
120	110	4.74	8.07	11.65	2.55	3.71	4.33	16.50
	120	4.43	5.08	10.10	11.55	4.61	6.51	9.46
	130	5.22	3.57	9.41	19.97	4.68	9.21	15.18
	140	4.72	2.85	9.88	29.80	4.30	12.63	20.02
150	110	3.02	6.19	9.31	4.34	3.39	2.84	10.04
	120	5.90	4.28	8.67	12.33	3.82	5.41	12.73
	130	8.15	2.94	8.26	22.72	3.80	7.97	17.94
	140	10.75	2.42	8.95	32.46	3.68	11.29	21.00

Table 7.5: OBP&SPSA+Prices – Results Aggregated over Revenue Instances

approach is sometimes inferior to an uncontrolled booking process, e.g., in a first-come-first-served manner. Due to the stochastic demand, the possibility of the demand being less than the capacity is higher in low total demand instances than in demand settings with greater total demand which makes it more profitable to accept all incoming requests than reserve seats for higher yielding requests. Determining the optimal transfer prices in the OBP&SPSA+Prices induces the calculation of superior booking limits which reduces the drawback of the capacity control with booking limits in low demand settings. This effect can also be seen in the comparison of the results of the OBP&SPSA+Prices procedure with the results of the FCFS approach. The OBP&SPSA+Prices procedure performs better than the FCFS approach in all capacity and demand instances even in settings with low total demand. Especially in instances with high demand, the superior performance of the OBP&SPSA+Prices procedure compared to the FCFS approach is noticeable. Due to the inferior performance of the OBP&SPSA approach and particularly the option-based method in the low total demand settings, the results of the OBP&SPSA+Prices procedure exceed the results of the two procedures especially in the instances with the underlying assumption of low total demand. The gap between the ex post optimal solutions and the results of the OBP&SPSA+Prices procedure ($gap19$) is small ranging from 3.39% to 5.45%.

The performance of the OBP&SPSA+Prices procedure is also superior to the performance of the blocked seat allotment method and the random approach in all capacity and demand instances. $Gap18$ and $gap20$ increase as the total demand scales up. In these cases (identical to the analysis of the OBP&SPSA method and the option-based approach), the solution space increases and it is advantageous to reserve seat capacity for higher yielding booking classes through booking limits. The results of the OBP&SPSA+Prices procedure compared to the random approach vary. Only in capacity instance 150, $gap21$ scales up as the demand increases. In the other capacity instances, the results do not follow a pattern. The reason is the random specification of the booking limits in the random approach.

Although the performance of the OBP+Prices method and especially the performance of the OBP&SPSA+Prices approach is satisfying even in instances with low total demand, we want to show the performance of the OBP&SPSA+Prices procedure in a demand setting in which the total demand is 90% of the capacity. We calculated the expected revenue for the 13 demand instances, introduced in Table A.4 in the Appendix A.1.

Table 7.6 shows the results for the seat capacity being 100, 120, and 150. The average revenue of the OBP&SPSA+Prices approach over all 13 demand instances and four revenue instances (compare Table 7.1) is equal to the revenue generated by the FCFS approach in almost all capacity instances. Only in the instances with seat capacity 100, the results of the OBP&SPSA+Prices procedure are slightly inferior to

Capacity	Demand in %	$gap15$	$gap16$	$gap17$	$gap18$	$gap19$	$gap20$	$gap21$
100	90	6.94	13.46	19.74	-0.01	0.41	5.12	26.82
120	90	6.72	12.20	18.14	0.00	0.23	4.54	16.03
150	90	6.22	10.87	16.28	0.00	0.14	3.60	13.94

Table 7.6: OBP&SPSA+Prices – Results Aggregated over Revenue Instances in Instances with Demand Intensity 0.9

the FCFS solutions. The gap between the results of the OBP&SPSA+Prices approach and the ex post optimal solutions ($gap19$) is now very small. Since the solution space of the results of the OBP&SPSA+Prices method expands as the considered capacity increases, the solutions of the OBP&SPSA+Prices procedure and the ex post optimal solutions come close together as the capacity increases. The performance of the OBP&SPSA+Prices procedure is superior to the performance of the OBP+Prices method, the OBP&SPSA procedure, the option-based approach, the blocked seat allotment method, the random approach and nearly equal to the FCFS procedure in all capacity settings. The gaps between the aggregated expected revenue achieved by the OBP&SPSA+Prices approach and the solutions of the other procedures (except for the FCFS approach), however, are higher in the low capacity settings compared to the instances with a higher capacity. This can be reduced to the fact that the performance of the procedures which are compared to the OBP&SPSA+Prices method increases in instances with a higher capacity due to an expanded solution space.

In the results of all capacity, demand, and revenue instances, considered in the instances with the demand being 90% of the capacity, the optimal determined sum of option price and strike price is smaller than the lowest price for a flight ticket charged by the airlines in the considered booking classes. In this computational study, the lowest ticket price is equal to 100 in all revenue instances, only differing whether the operating carrier charges the lowest price in the second booking class or the ticketing carrier charges the lowest price of the alliance in the second booking class. Due to the determined optimal transfer prices, the OBP&SPSA+Prices method proceeds almost like a FCFS procedure in the instances in which we assumed the total demand to be 90% of the capacity. Because of the low expected demand, the alliance partners define the sum of the transfer prices so that as many as possible requests can be accepted. By setting the sum of the transfer prices lower than the smallest price for a flight ticket in the considered booking classes, the ticketing carrier accepts all incoming requests, as long as the booking limit of the respective booking class and the remaining seat capacity is greater than zero. The ticketing carrier does not reject incoming requests because the sum of the transfer prices, the costs of the ticketing carrier, does not exceed the revenue the ticketing carrier gains in selling tickets in a booking class. The same counts for the operating carrier: Since the sum of the transfer prices is lower than the smallest ticket price charged by the operating carrier, the operating carrier accepts all incoming requests, as long as the booking limit and the remaining seat capacity is greater than zero. The operating carrier buys back options from the ticketing carrier once the remaining seat capacity is equal to the number of options the ticketing carrier holds if the operating carrier can sell tickets in either of the booking classes. Differences to the proceeding of the FCFS approach can occur in the OBP&SPSA+Prices method if the booking limit of at least one of the considered booking classes is zero during the booking process and, therefore, incoming requests are declined by the alliance partners. However, the booking limits determined by means of the OBP&SPSA+Prices method are not causing a poor performance of the OBP&SPSA+Prices procedure. The results of the OBP&SPSA+Prices procedure aggregated over all demand and revenue instances are almost equal to the results determined by means of the FCFS approach which was identified in the previous computational studies as the best approach to control the capacity in demand settings with the demand being 90% of the capacity. Comparing the results of the OBP&SPSA+Prices

method to the results of the blocked seat allotment approach and the ones determined by the random approach shows that the OBP&SPSA+Prices approach performs better than the blocked seat allotment and much better than the random method in all capacity settings. Although we assume that capacity control methods are generally applied in scenarios in which the demand exceeds the capacity, the insight of the results achieved by the OBP&SPSA+Prices procedure in the instances in which the demand is only 90% of the capacity shows that the OBP&SPSA+Prices procedure is also applicable if the demand is unexpectedly low.

Figure 7.6 presents the performance of the control procedures evaluated relative to the ex post optimal solution in the different demand scenarios assuming the seat capacity to be 100. The revenues generated by the OBP&SPSA+Prices procedure are almost equal to the ex post optimal solutions if the demand intensity is 0.9 and near the ex post optimal solutions (approximately 95%) in the other demand scenarios. The OBP&SPSA+Prices method constantly produces the highest revenue compared to the other procedures (except for the equal performance compared to the FCFS approach if the demand intensity is 0.9) and outperforms the FCFS method even in instances with demand intensity 1.1. This is a significant enhancement compared to the other methods which trail behind the FCFS approach in low demand instances. The revenues produced by the FCFS method decrease considerably as the demand intensity increases. Figure A.1 and Figure A.2 in the Appendix A.2 show similar revenue outcomes of the procedures if the seat capacity is assumed to be 100 and 150, respectively.

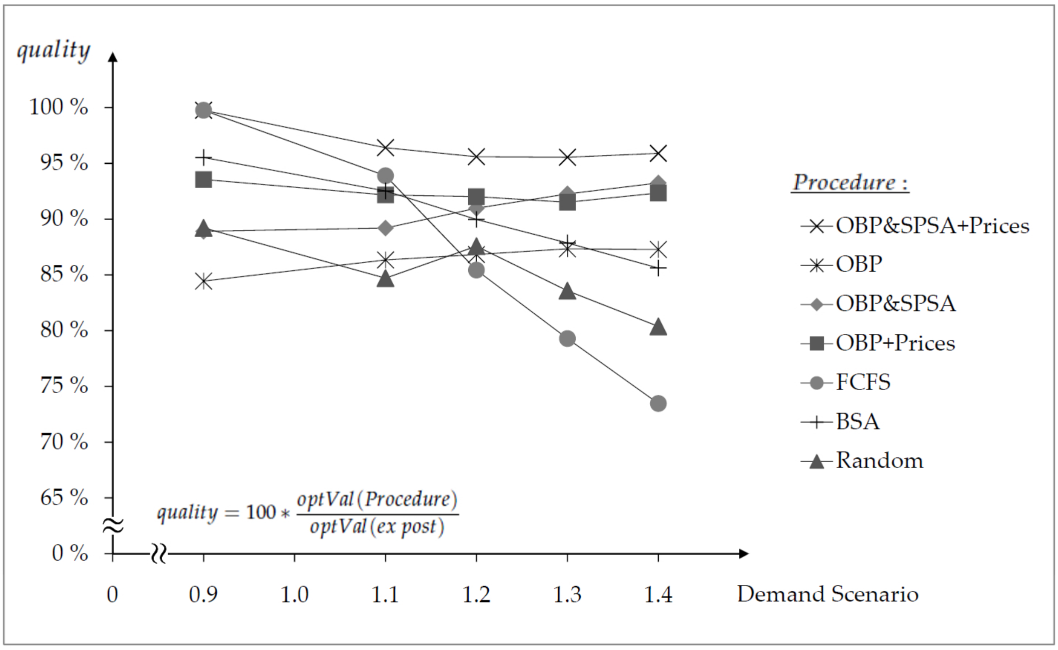

Figure 7.6: OBP&SPSA+Prices (1-4) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=120, Demand Scenarios

We fixed the capacity and revenue settings and aggregated the computed results over all demand instances in a second survey to evaluate the effect of the revenue variation among the tested instances. Table 7.7 presents the results for capacity 100, 120, and 150. The expected revenue gained from the OBP&SPSA+Prices method is higher than the results of the OBP+Prices method, the OBP&SPSA procedure, the option-based approach, the FCFS procedure, the blocked seat allotment method, and the random approach in all considered revenue instances. It is noticeable that especially in the third and in the fourth revenue scenario the OBP&SPSA+Prices approach improved the results of the option-based approach, the OBP&SPSA procedure and the blocked seat allotment method.

The OBP&SPSA+Prices procedure performs much better than the random approach in all revenue instances and capacity scenarios. Compared to the ex post optimal solutions, the OBP&SPSA+Prices method achieves results that are only marginal inferior.

Capacity	Revenue Instance	$gap15$	$gap16$	$gap17$	$gap18$	$gap19$	$gap20$	$gap21$
100	1	5.35	4.68	10.77	16.69	5.23	8.62	18.09
	2	1.94	4.29	5.95	17.19	5.23	1.22	20.40
	3	7.14	7.35	16.79	16.43	4.97	14.99	15.54
	4	13.13	6.33	15.05	7.21	4.67	12.62	15.57
120	1	2.69	3.81	9.13	18.49	4.45	7.49	14.49
	2	1.36	3.67	5.04	18.36	4.42	1.00	15.45
	3	4.17	5.84	14.42	18.34	4.25	13.13	17.80
	4	10.89	5.53	12.97	8.68	4.18	11.05	13.41
150	1	7.00	3.17	7.85	20.60	3.74	6.28	15.48
	2	1.04	2.78	4.15	20.62	3.70	0.53	14.57
	3	11.99	4.82	12.64	20.38	3.56	11.39	17.73
	4	7.79	4.75	11.17	10.25	3.68	9.30	13.92

Table 7.7: OBP&SPSA+Prices – Results Aggregated over Demand Instances

In revenue instance 4, the gap between the results of the OBP&SPSA+Prices procedure and the FCFS approach ($gap18$) is smaller than the gap between the two procedures in the other three revenue instances. This effect can be noticed in all capacity scenarios. The fourth revenue instance differs from the other three instances in the interval of the flight ticket revenues in the first and second booking classes of the two considered airlines. The difference of the revenue in the carriers first and second booking class is equal to 100 ($v_{11} - v_{21}$, respectively $v_{12} - v_{22}$). In the other revenue instances, this difference is 250. The OBP&SPSA+Prices procedure yields better in revenue instances with a larger gap between the flight ticket revenue of the booking classes since it is more profitable to reserve seats in the aircraft for the higher yielding booking classes.

In revenue instance 2, the results of the OBP&SPSA+Prices procedure in all capacity instances are similar to the solutions of the blocked seat allotment approach compared to the other revenue instances. Revenue instance 2 is, compared to the other three revenue scenarios, the only one in which the revenue for one sold flight ticket in the operating carrier's first booking class is higher than the revenue for one sold flight ticket in the ticketing carrier's first booking class ($v_{11} > v_{12}$). The same applies for the revenue for one sold flight ticket in the airlines second booking classes ($v_{21} > v_{22}$). The examination of the optimal transfer prices determined by the OBP&SPSA+Prices procedure shows that the sum of the transfer prices is lower than the smallest revenue charged by the ticketing carrier for a flight ticket in the second booking class in all considered demand instances ($x + s < v_{22}$). This means that the operating carrier allows the ticketing carrier to access only the capacity the operating carrier does not need to fulfill the operating carrier's demand. In other words, the operating carrier does not reserve capacity for the ticketing carrier except for the capacity the operating carrier has to spare which is also not necessary in this revenue instance for maximizing the revenue of the alliance since the operating carrier earns more for a sold ticket in the booking classes compared to the ticketing carrier. Therefore, the booking limits determined by the OBP&SPSA+Prices procedure are similar to the ones calculated by the blocked seat allotment which explains the similar performance of the two procedures. In the revenue instances in which the revenues for the flight tickets in the operating carrier's booking classes are lower than the ones achieved by the ticketing carrier ($v_{11} < v_{12}$ and $v_{21} < v_{22}$), the negotiations of the alliance partners lead to a sum of the transfer prices which is at least higher than the revenue the operating carrier gains in the second booking class in most of the demand and capacity instances. This choice of the transfer prices affects the calculation of the booking limits. Since the operating carrier receives the sum of the transfer prices from the ticketing carrier which is often higher than at least one of the operating carrier's booking class revenues, the operating carrier does now reserve seat capacity for the ticketing carrier's demand beyond the capacity the operating carrier has to spare. This reservation of seat capacity is advantageous to the blocked seat allotment method in which the operating carrier has no incentive to reserve capacity for the ticketing carrier beyond the capacity the operating carrier has to spare even if this increases the revenue of the alliance. Of course, in this discussion the expected demand also plays a role. If the demand for the ticketing carrier's booking classes is very low, the ticketing carrier does not ask for many seat capacity of the operating carrier which is why the sum of the transfer prices is less than the operating carrier's flight ticket revenue in the second booking class in these instances. In the computational study of revenue instances 1 through 8 (compare Section 7.3.2.2), we will see that a different gap between the revenue charged by the operating carrier and the revenue charged by the ticketing carrier does not strongly affect the outcome of the blocked seat allotment approach and the OBP&SPSA+Prices procedure in the revenue instances in which the operating carrier gains more than the ticketing carrier for a sold flight ticket in the booking classes of the operating carrier. Although the performance of the OBP&SPSA+Prices procedure compared to the blocked seat allotment method depends on the revenue instance, it can be noticed that the results of the OBP&SPSA+Prices procedure are always higher than the results of the blocked seat allotment method in all considered instances. The superior performance of the OBP&SPSA+Prices procedure even in revenue instance 2 can be explained due to the fact that the booking limits are always filled up to the seat capacity. That means that the sum of the partitioned booking limits calculated for the partner airlines is not unequal to the total seat capacity. In the blocked seat allotment procedure, however, the sum of the calculated booking limits of the alliance partners can be less than the seat capacity which generates a lower alliance revenue due to unused seat capacity in the aircraft after the booking process. Moreover, the buy back possibility is advantageous in the OBP&SPSA+Prices procedure compared to the static blocked seat allotment method.

In Figure 7.7, the performance of the control procedures evaluated relative to the ex post optimal solution in the different revenue scenarios assuming the seat capacity to be 120 is presented. The revenues achieved by the OBP&SPSA+Prices procedure and the OBP&SPSA method are less sensitive to the different revenue scenarios than the other procedures. In all revenue instances, the OBP&SPSA+Prices approach produces the highest revenue compared to the other methods. Figure A.3 and Figure A.4 in the Appendix A.2 show similar revenue outcomes of the procedures with seat capacity assumed to be 100 and 150, respectively.

In an additional study, we analyze in which transfer price instance (a, b, c, or d) the solutions of the option-based method and the OBP&SPSA approach differ most and least from the results of the OBP&SPSA+Prices procedure in the different capacity, demand, revenue, and price instances. As mentioned before, the results of the option-based procedure and the OBP&SPSA approach discussed in the study presented in this section are aggregated over all transfer price scenarios. The above-mentioned analysis of the results verifies that the OBP&SPSA+Prices procedure improved the aggregated results of the option-based procedure and the OBP&SPSA approach in all capacity, demand, and revenue instances. Comparing the results of the OBP&SPSA+Prices procedure in one capacity, demand, and revenue instance with the results of the option-based procedure and the OBP&SPSA approach in one capacity, demand, revenue, and a particular transfer price instance shows that the gaps between the results of the procedures are very different in the single transfer price instances which are considered (compare Table 7.8). Observe, e.g., the results in capacity instance 100, revenue instance 3, and de-

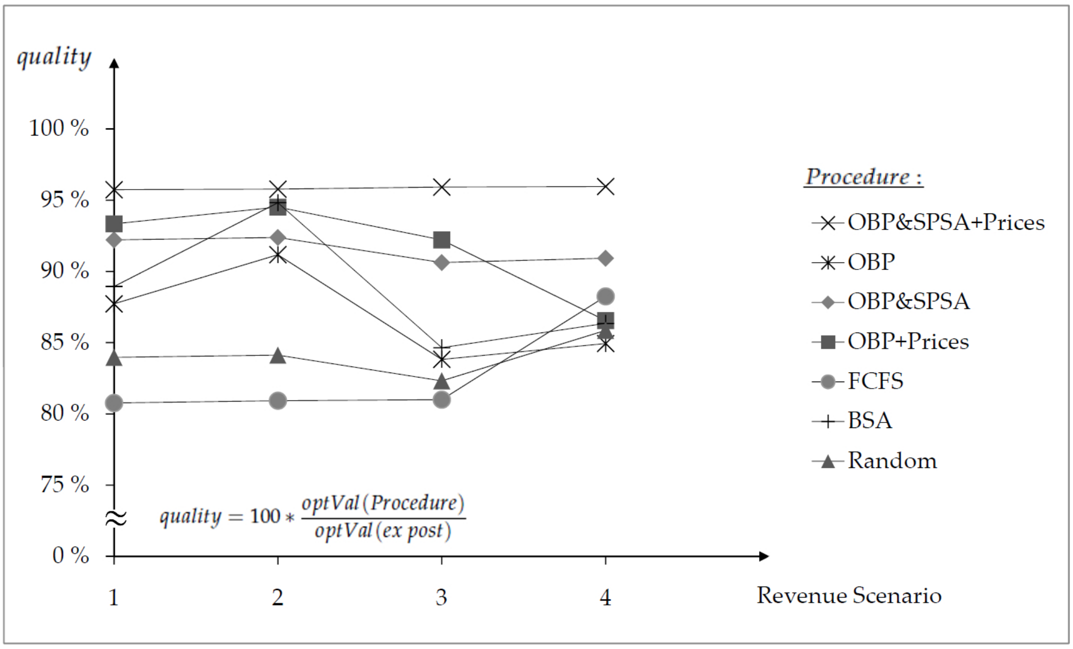

Figure 7.7: OBP&SPSA+Prices (1-4) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=120, Revenue Scenarios

mand instance 110: In transfer price scenario a, the gap between the OBP&SPSA+Prices approach and the OBP&SPSA procedure ($gap16$) is 2.33% whereas $gap16$ is 46.72% in transfer price scenario d. In revenue instance 3 and price instance a, the sum of the transfer prices equals 190. So, the sum of the transfer prices lies within the interval between the flight ticket revenue of the ticketing carrier's second booking class and the revenue for one sold flight ticket in the operating carrier's second booking class ($v_{22} > x + s > v_{21}$). The OBP&SPSA+Prices procedure determined the optimal sum of the transfer prices to lie in the interval between the flight ticket revenue of the operating carrier's second booking class and zero ($v_{21} > x + s > 0$) or in the interval between the revenue for one flight ticket in the ticketing carrier's second booking class and the flight ticket revenue in the lowest yielding booking class of the operating carrier ($v_{22} > x + s > v_{21}$), depending on the respective demand instance in revenue scenario 3 and demand scenario 110. In most instances, the sum of the transfer prices is equal to 199 which is in the same interval ($v_{22} > 199 > v_{21}$) as the sum of the transfer prices in price instance a. This explains that the compared procedures perform similarly in capacity instance 100, demand scenario 110, revenue instance 3, and price instance a. The exceptions in which the optimal sum of transfer prices is between v_{21} and zero in the OBP&SPSA+Prices procedure in revenue scenario 3 and demand scenario 110 explain why the results of the OBP&SPSA+Prices procedure are not equal to the results of the OBP&SPSA approach. In revenue instance 3, the sum of the transfer prices is equal to 270 in price scenario d. This means that the sum of the transfer prices lies in the interval between the revenue of one flight ticket in the operating carrier's highest yielding booking class and the flight ticket revenue in the ticketing carrier's second booking class ($v_{11} > 270 > v_{22}$). In this case, the ticketing carrier rejects all requests for flight tickets in the second booking class. This seems to be inferior in capacity instance 100, revenue instance 3, and demand instance 110 which explains the inferior performance of the procedures without transfer price optimization in price instance d compared to price instance a. The comparison of the OBP&SPSA+Prices approach results with the results of the option-based procedure ($gap17$) shows that $gap17$ is higher than $gap16$ in all price instances since the results of the option-based procedure are inferior to the results of the option-based procedure with booking limit improvement by means of SPSA. In price instance d, $gap17$ is very high compared to the other price instances. This supports the argumentation mentioned already in the consideration of $gap16$: In capacity instance 100, revenue instance 3, and demand scenario 110, the results of the option-based procedure and OBP&SPSA approach in price instance a, b, and c are inferior to the performance of the OBP&SPSA+Prices approach, however, the results are not that poor compared to the results of the procedures in price instance d.

In other settings, compare, e.g., capacity instance 120, revenue instance 2, and demand scenario 110, $gap16$ and $gap17$ are high in three of four price instances. This means that there is only a small possibility that the airlines within the alliance choose transfer prices which improve the performance of the option-based procedure and the OBP&SPSA approach without transfer price optimization. In capacity instance 120, revenue instance 2, demand scenario 110, and price instance a, the performance of the OBP&SPSA approach is equivalent to the results of the OBP&SPSA+Prices procedure. In revenue instance 2 and price instance a, the sum of the transfer prices is 90. The OBP&SPSA+Prices procedure determined the optimal sum of the transfer prices in this setting to lie in the interval between the flight ticket revenue of the ticketing carriers's second booking class and zero ($v_{22} > x + s > 0$) in all demand instances. Therefore, the results of the two procedures are identical.

Table A.5, Table A.6, and Table A.7 in the Appendix A.2 show the performance of the OBP&SPSA+Prices approach compared to the results of the option-based procedure and OBP&SPSA approach in all capacity, revenue, demand, and price instances.

Capacity	Revenue	Demand	Price	$gap16$	$gap17$
100	3	110	a	2.33	4.38
			b	3.06	8.07
			c	3.06	8.07
			d	46.72	50.16
120	2	110	a	0.00	1.66
			b	13.22	14.42
			c	13.22	14.42
			d	13.23	14.42

Table 7.8: OBP&SPSA+Prices (1-4) – Results in Specific Price Scenario Compared to Results with Transfer Price Optimization

In the following section, the performance of the option-based+prices approach and the OBP&SPSA+Prices procedure considering all revenue instances (1 through 8) introduced in Section 7.3.1 will be analyzed.

7.3.2.2 Comparison of Procedures (Revenue Instances 1–8)

In this section, we consider revenue instances 1 through 8 to analyze the outcome of the option-based+prices approach and the performance of the OBP&SPSA+Prices procedure in a broader way. The results of the OBP&SPSA+Prices approach are now compared to the results of the option-based+prices method ($gap15$), the FCFS algorithm ($gap18$), the ex post optimal solutions ($gap19$), the blocked seat allotment method ($gap20$), and the random approach ($gap21$). Recall that the performance of the option-based+prices approach and the OBP&SPSA+Prices method is not compared to the results of the option-based procedure and the OBP&SPSA approach since revenue instances 5 through 8 are considered which are not included in the computational study of the option-based procedure and the

OBP&SPSA approach. If we mention in this section that the results are based on all instances, the results are aggregated over all capacity and demand instances and all revenue instances (1 through 8).

The revenue generated by the OBP&SPSA+Prices approach over all capacity, demand, and revenue instances is 7.28% higher than the performance of the option-based+prices procedure, 14.45% higher than the revenue calculated by the FCFS procedure and only 4.03% lower than outcome achieved by the ex post optimal solutions. Over all instances, the expected revenue according to the OBP&SPSA+Prices procedure is 10.16% higher than the results achieved by means of the blocked seat allotment method. The improvement according to the random approach is even more significant: The OBP&SPSA+Prices procedure achieves an expected revenue that is 18.27% higher than the revenue generated by the random approach over all instances.

Table 7.9 shows the achieved results aggregated over all demand and revenue instances for each capacity instance. The results determined by the OBP&SPSA+Prices procedure are higher than the results of the option-based+prices approach, the FCFS method, the blocked seat allotment procedure, and the random approach in all capacity settings if all revenue instances (1 through 8) are considered. This shows that the good performance of the OBP&SPSA+Prices procedure discussed in the previous section (Section 7.3.2.1) is not an output of cleverly chosen revenue instances. The performance of the OBP&SPSA+Prices procedure is also good if other revenue instances are considered as it is the case in the computational study discussed in this section.

The gap between the OBP&SPSA+Prices procedure and the FCFS approach ($gap18$) is still very high, but not as high as if only revenue instances 1 through 4 are considered (compare Table 7.3) like in the analysis shown in the previous section (compare Section 7.3.2.1). In the computational study in the present section, the same effect can be identified, studying the revenue calculated by the OBP&SPSA+Prices approach, as we noticed while discussing the results of the OBP&SPSA+Prices procedure in revenue instances 1 through 4: Since the solution space expands if a higher seat capacity is considered, the gap between the results of the ex post optimal solutions and the performance of the OBP&SPSA+Prices approach ($gap19$) decreases with higher total capacity. The aggregated revenue in the ex post optimal solutions is only slightly superior to the aggregated expected revenue gained by the OBP&SPSA+Prices procedure in all capacity instances.

Capacity	$gap15$	$gap18$	$gap19$	$gap20$	$gap21$
100	8.34	12.92	4.64	11.62	20.38
120	5.04	14.27	4.01	10.21	17.57
150	8.50	16.10	3.47	8.70	16.96

Table 7.9: OBP&SPSA+Prices (1-8) – Results Aggregated over Demand and Revenue Instances

Table 7.10 presents the revenue per seat aggregated over all demand and revenue instances for each capacity instance. The revenue per seat of the OBP&SPSA+Prices procedure is, compared to the other approaches, higher in instances in which the seat capacity is assumed to be low, except for the revenue comparison of the option-based+price approach with the OBP&SPSA+Prices procedure ($gap15$).

In a first observation, we fixed the demand and aggregated the computed results over all revenue instances to see how the estimated revenue values behave according to demand variations. Table 7.11 shows the results aggregated over all revenue instances for the seat capacity assumed to be 100, 120, and 150.

Considering all revenue instances, the OBP&SPSA+Prices procedure still performs better than the FCFS approach in all demand and capacity instances even in the low demand settings. The superior per-

Capacity	$gap15/C$	$gap18/C$	$gap19/C$	$gap20/C$	$gap21/C$
100	0.08	0.13	0.05	0.12	0.20
120	0.04	0.12	0.03	0.09	0.15
150	0.06	0.11	0.02	0.06	0.11

Table 7.10: OBP&SPSA+Prices (1-8) – Results Aggregated over Demand and Revenue Instances Per Seat

formance of the OBP&SPSA+Prices procedure compared to the FCFS approach, especially in instances with high demand, is noticeable. However, the gap between the OBP&SPSA+Prices procedure and the FCFS approach ($gap18$) is slightly smaller than $gap18$ calculated in the previous section. In some of the revenue instances that are additionally considered in this section (revenue instances 5 through 8), the FCFS method performance is superior to the performance of the FCFS approach in revenue instances 1 through 4. Nevertheless, considering only revenue instances 5 through 8, the results of the OBP&SPSA+Prices procedure still exceed the FCFS results ($gap18$=12.78%) over all capacity and demand instances. The gap between the ex post optimal solutions and the results of the OBP&SPSA+Prices procedure ($gap19$) is smaller than in the analysis of revenue instances 1 through 4, ranging from 3.31 to 5.05.

The performance of the OBP&SPSA+Prices procedure is superior to the results of the blocked seat allotment method and the random approach in all capacity and demand settings considering revenue instances 1 through 8 in contrast to the analysis of revenue settings 1 through 4. Since the solution space increases as the total demand scales up, it is advantageous to reserve seat capacity for higher yielding booking classes through booking limits especially in the high total demand settings. The increase of $gap18$ and $gap20$ supports this insight. There is no trend of the performance of the OBP&SPSA+Prices procedure compared to the random approach ($gap21$) while the considered demand increases recognizable. Due to the random specification of the booking limits in the random approach, the results do not follow a pattern.

Capacity	Demand in %	$gap15$	$gap18$	$gap19$	$gap20$	$gap21$
100	110	5.70	2.36	3.80	5.62	24.48
	120	8.52	7.89	4.89	9.17	16.57
	130	11.34	15.59	5.05	13.45	23.31
	140	7.40	24.20	4.69	17.31	17.79
120	110	5.43	2.19	3.46	5.09	17.21
	120	5.18	10.29	4.34	8.06	13.25
	130	5.55	17.82	4.37	11.68	17.42
	140	3.99	26.78	3.88	16.02	22.37
150	110	3.34	3.74	3.36	3.43	11.00
	120	6.73	11.12	3.63	6.77	15.37
	130	10.29	20.45	3.56	10.25	18.37
	140	13.64	29.11	3.31	14.35	23.09

Table 7.11: OBP&SPSA+Prices (1-8) – Results Aggregated over Revenue Instances

The performance of the OBP&SPSA+Prices approach is additionally analyzed in a demand setting in which the total demand is 90% of the capacity. Therefore, we calculated the expected revenue for the demand instances, introduced in Table A.4 in the Appendix A.1, for each capacity and revenue scenario.

Table 7.12 shows the results for the seat capacity being 100, 120, and 150. In all capacity instances, the

Capacity	Demand in %	$gap15$	$gap18$	$gap19$	$gap20$	$gap21$
100	90	6.77	0.00	0.37	5.37	24.49
120	90	6.58	0.00	0.21	4.80	19.14
150	90	6.16	0.00	0.13	3.86	19.15

Table 7.12: OBP&SPSA+Prices (1-8) – Results Aggregated over Revenue Instances in Instances with Demand Intensity 0.9

average revenue of the OBP&SPSA+Prices approach over all demand and revenue instances is equal to the revenue generated by the FCFS approach. The results of the OBP&SPSA+Prices approach and the ex post optimal results are close to each other in all capacity instances. Similar to the results of the analysis of revenue instances 1 through 4, the performance of the OBP&SPSA+Prices procedure is superior to the performance of the option-based+prices approach, the blocked seat allotment method, and the random approach in all capacity settings.

Also in the evaluation of revenue instances 1 through 8, considering instances with the demand being 90% of the capacity, the optimal determined sum of option price and strike price is smaller than the lowest price for a flight ticket charged by the airlines in the considered booking classes. Since the expected total demand is very low, the alliance partners define the sum of the transfer prices so that as many requests as possible can be accepted. In instances in which the total demand is assumed to be 90% of the capacity, the OBP&SPSA+Prices method proceeds similarly to a FCFS procedure, due to the determined optimal transfer prices. This effect could already be noticed in the analysis of revenue instances 1 through 4. Compare Section 7.3.2.1 for a detailed survey discussing this effect.

The performance of the OBP&SPSA+Prices procedure, the option-based+prices approach, the FCFS algorithm, the blocked seat allotment method, and the random approach is evaluated relatively to the ex post optimal solution. Figure 7.8 shows the performance of the control procedures in the different demand scenarios assuming the seat capacity to be 120. The revenue results of the different procedures are similar to the ones discussed in the previous section even though more revenue instances are considered. The revenue achieved by the OBP&SPSA+Prices approach is almost equal to the ex post optimal solution if the demand intensity is 0.9. In the other demand scenarios, the performance of the OBP&SPSA+Prices procedure is near the ex post optimal solutions. Even in the present study in with revenue instances 5 through 8 are additionally considered, the OBP&SPSA+Prices procedure achieves the highest revenue in all demand instances compared to the other procedures. We present Figure A.5 and Figure A.6 in the Appendix A.2 which show that the performance of the approaches in capacity settings 100 and 150 is similar to the one presented in Figure 7.8, except for the results of the random approach.

To evaluate the effect of the revenue variation among the tested instances, we fixed the revenue and aggregated the computed results over all demand instances in a second survey. In Table 7.13, the results for the capacity being 100, 120, and 150 are presented. The results of the procedures in revenue instances 1 through 4 are equal to the results in the previous computational study and were already presented in Section 7.3.2.1. However, we quote them again to compare and discuss the different results belonging to all considered revenue instances. The expected revenue gained from the OBP&SPSA+Prices method is higher than the results of the option-based+prices algorithm, the blocked seat allotment method, the random approach, and the FCFS procedure in all considered revenue instances.

Considering all eight revenue instances, revenue instance 4 in all capacity scenarios is still the revenue instance in which the gap between the results of the OBP&SPSA+Prices procedure and the FCFS approach ($gap18$) is smaller than the gap between the two procedures in all other revenue instances. In revenue instance 4, 7, and 8, the interval of the flight ticket revenues in the first and second booking

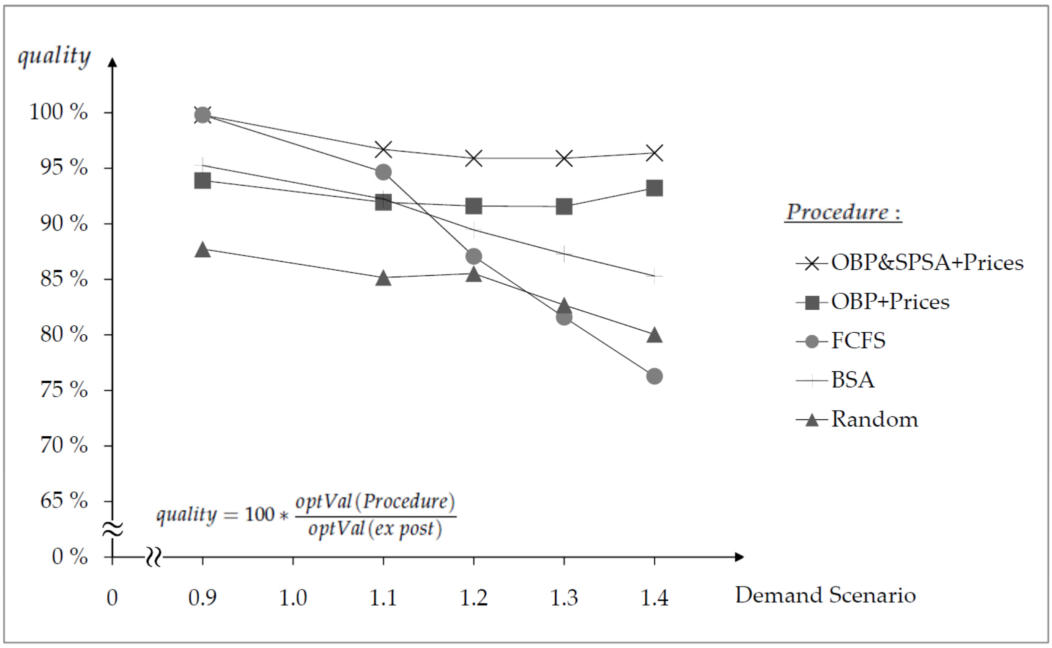

Figure 7.8: OBP&SPSA+Prices (1-8) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=120, Demand Scenarios

classes of the two considered airlines is equal to 100 ($v_{11} - v_{21}$, respectively $v_{12} - v_{22}$). In the other revenue instances, this difference is 250 or 300. The good performance of the OBP&SPSA+Prices procedure compared to the FCFS approach in revenue instances with a larger gap between the ticket revenue of the classes is explainable since in these instances it is more profitable to reserve seats in the aircraft for the higher yielding booking classes. However, the results of the OBP&SPSA+Prices procedure compared to the FCFS approach performance in revenue instances 7 and 8 show that the interval of the flight ticket revenues in the first and second booking classes of the two considered airlines is not the only effect that affects the outcome of the methods. As mentioned before, the difference of the flight ticket revenues in the first and second booking classes of the operating carrier and the ticketing carrier is equal to 100, identical to the difference in revenue instance 4. The gap between the results of the OBP&SPSA+Prices procedure compared to the FCFS approach results, however, is in revenue instances 7 and 8 not noticeably smaller than in the other revenue instances. An explanation is that in revenue instances 7 and 8 the gap between the flight ticket revenues in the booking classes of the operating carrier and the booking classes of the ticketing carrier ($v_{11} - v_{12}$, respectively $v_{21} - v_{22}$) are very high compared to the gap in revenue instance 4. Although the difference of the flight ticket revenues in the first and second booking classes of the airlines is small, the reservation of seat capacity by means of booking limits in the OBP&SPSA+Prices procedure pays off compared to the control without control variables in the FCFS method since the flight ticket revenues of the airlines lie far apart.

It is noticeable that especially in revenue scenarios 3 and 4, the OBP&SPSA+Prices approach improved the results of the blocked seat allotment method. Only in revenue instance 8, the gap between the results of the OBP&SPSA+Prices procedure and the results of the blocked seat allotment approach ($gap20$) is even higher. This is, however, significant in all capacity instances. In revenue instance 8, the flight ticket revenues of the ticketing carrier's booking classes are much higher than the revenues of the booking classes of the operating carrier. In this case, the booking limits calculated by the blocked seat allotment procedure are inferior compared to the ones calculated by the OBP&SPSA+Prices procedure since the

Capacity	Revenue Instance	$gap15$	$gap18$	$gap19$	$gap20$	$gap21$
100	1	5.35	16.69	5.23	8.62	18.09
	2	1.94	17.19	5.23	1.22	20.40
	3	7.14	16.43	4.97	14.99	15.54
	4	13.13	7.21	4.69	12.62	15.57
	5	6.25	10.35	5.06	6.93	12.02
	6	2.92	10.72	5.13	2.21	12.08
	7	2.69	13.95	3.20	2.57	41.51
	8	27.32	10.80	3.60	43.78	27.83
120	1	2.69	18.49	4.45	7.49	14.49
	2	1.36	18.36	4.42	1.00	15.45
	3	4.17	18.34	4.25	13.13	17.80
	4	10.89	8.68	4.18	11.05	13.41
	5	4.17	11.93	4.43	5.89	10.94
	6	2.10	11.99	4.43	1.73	15.28
	7	2.23	13.71	2.67	2.20	32.56
	8	12.68	12.66	3.28	39.19	20.60
150	1	7.00	20.60	3.74	6.28	15.48
	2	1.04	20.62	3.70	0.53	14.57
	3	11.99	20.38	3.56	11.39	17.73
	4	7.79	10.25	3.68	9.30	13.92
	5	3.19	13.86	3.80	4.65	9.88
	6	1.54	13.95	3.80	0.90	17.80
	7	1.70	15.31	2.33	1.67	24.75
	8	32.23	13.87	3.11	34.87	21.51

Table 7.13: OBP&SPSA+Prices (1-8) – Results Aggregated over Demand Instances

blocked seat allotment procedure does not take the much higher revenue the ticketing carrier gains by selling a flight ticket in one of the ticketing carrier's booking classes into account. In revenue scenarios 2, 6, and 7, the results of the OBP&SPSA+Prices procedure are superior to the results of the blocked seat allotment procedure but similar to the solutions of the blocked seat allotment approach compared to the other revenue instances. This applies for all capacity instances. Compared to the other revenue scenarios, revenue scenarios 2, 6, and 7 are the revenue settings in which the flight ticket revenue for one sold ticket in the operating carrier's first booking class is higher than the revenue for one sold ticket in the ticketing carrier's first booking class ($v_{11} > v_{12}$). The same applies for the revenue for one sold flight ticket in the alliance partner airline's second booking classes ($v_{21} > v_{22}$).

The analysis of the optimal transfer prices determined by the OBP&SPSA+Prices procedure shows that apart from a few exceptions, the optimal option prices and strike prices remain constant in revenue instances 2, 6, and 7 in all capacity and demand instances while in revenue instances 1, 3, 4, 5, and 8, the optimal option prices and strike prices differ depending on the capacity and demand setting. In revenue instances 2, 6, and 7, the sum of the transfer prices is lower than the smallest revenue charged by the partner airlines for a flight ticket in all considered capacity and demand instances, apart from very few exceptions. Therefore, the operating carrier does not reserve capacity for the ticketing carrier in the OBP&SPSA+Prices procedure except for the capacity the operating carrier has to spare. For maximizing the revenue of the alliance this is not necessary in revenue instance 2, 6, and 7 since the operating carrier earns more from a sold ticket in one of the booking classes compared to the ticketing carrier. Due to this effect, the booking limits determined by the OBP&SPSA+Prices procedure are similar to the ones calculated by the blocked seat allotment which explains the similar performance of the two procedures in revenue instances 2, 6, and 7. The superior performance of the OBP&SPSA+Prices procedure compared to the results of the blocked seat allotment approach in revenue instances in which the revenues for the flight tickets in the operating carrier's booking classes are lower than the ones achieved by the ticketing carrier ($v_{11} < v_{12}$ and $v_{21} < v_{22}$) can be explained as follows: The negotiations of the alliance partners concerning the definition of the optimal transfer prices lead to a sum of transfer prices which is at least higher than the revenue the operating carrier gains in the second booking class in most of the demand and capacity instances. The operating carrier, therefore, reserves seat capacity for the ticketing carrier's demand beyond the capacity the operating carrier has to spare since the operating carrier receives the sum of the transfer prices from the ticketing carrier which is often higher than at least one of the operating carrier's booking class revenues. This reservation of seat capacity is advantageous to the blocked seat allotment method in the respective revenue instances.

The gap between the results of the OBP&SPSA+Prices procedure and the results of the blocked seat allotment approach is only slightly higher in revenue instance 7 than in revenue instances 2 and 6. This leads to the conjecture that the gap between the flight ticket revenue charged by the operating carrier and the flight ticket revenue charged by the ticketing carrier only marginally affects the outcome of the OBP&SPSA+Prices procedure compared to the blocked seat allotment method. In revenue instance 7, the gap between the flight ticket revenue charged by the operating carrier and the flight ticket revenue gained by the ticketing carrier for a sold ticket in the booking classes is higher than in revenue instances 2 and 6. Concluding this discussion, it can be observed that the results of the OBP&SPSA+Prices procedure are always higher than the results of the blocked seat allotment method even in revenue instances 2, 6, and 7. The booking limits are always filled up to the seat capacity in the OBP&SPSA+Prices procedure which explains the superior performance of the OBP&SPSA+Prices approach compared to the blocked seat allotment method. In the blocked seat allotment procedure, the sum of the calculated booking limits of the alliance partners can be less than the seat capacity. This generates a lower alliance revenue due to unused seat capacity in the aircraft after the booking process. Moreover, compared to the static blocked seat allotment method, the buy back possibility is advantageous in the OBP&SPSA+Prices procedure.

In all revenue instances and capacity scenarios, the OBP&SPSA+Prices procedure performs a lot better than the random approach. The OBP&SPSA+Prices method achieves results that are only marginally inferior compared to the ex post optimal solutions. Due to an expanded solution space, the results of the OBP&SPSA+Prices method approach towards the ex post optimal solutions as the seat capacity increases. This effect was already recognizable in the previous computational studies.

Figure 7.9 shows the control procedures and their performance evaluated relatively to the ex post optimal solution in the different revenue scenarios in seat capacity instance 120. The performance of the OBP&SPSA+Prices procedure is less sensitive to the different revenue scenarios and is superior to the performance of the other procedures in all eight revenue instances. Especially the outcome of the blocked seat allotment approach which is extremely sensitive according to the respective revenue instance can be noticed in Figure 7.9. In the Appendix A.2, Figure A.7 and Figure A.8 show the revenue outcome of the procedures in seat capacity instances 100 and 150 which are similar to the ones shown in Figure 7.9. As the considered seat capacity increases, the performance of the OBP&SPSA+Prices procedure and the blocked seat allotment method improve slightly towards the ex post optimal solutions.

7.3.2.3 Comparison of Procedures to Genetic Algorithm Procedures (Revenue Instances 1–8)

The genetic algorithm versions, introduced in Section 6.1, are enlarged by the transfer price optimization presented in Section 7.2 to compare the results of the OBP&SPSA+Prices approach to an heuristic approach combined with transfer price optimization. In the following, we refer to Genetic Algorithm 1 and Genetic Algorithm 2 with included transfer price optimization as GA1+Prices approach and GA2+Prices

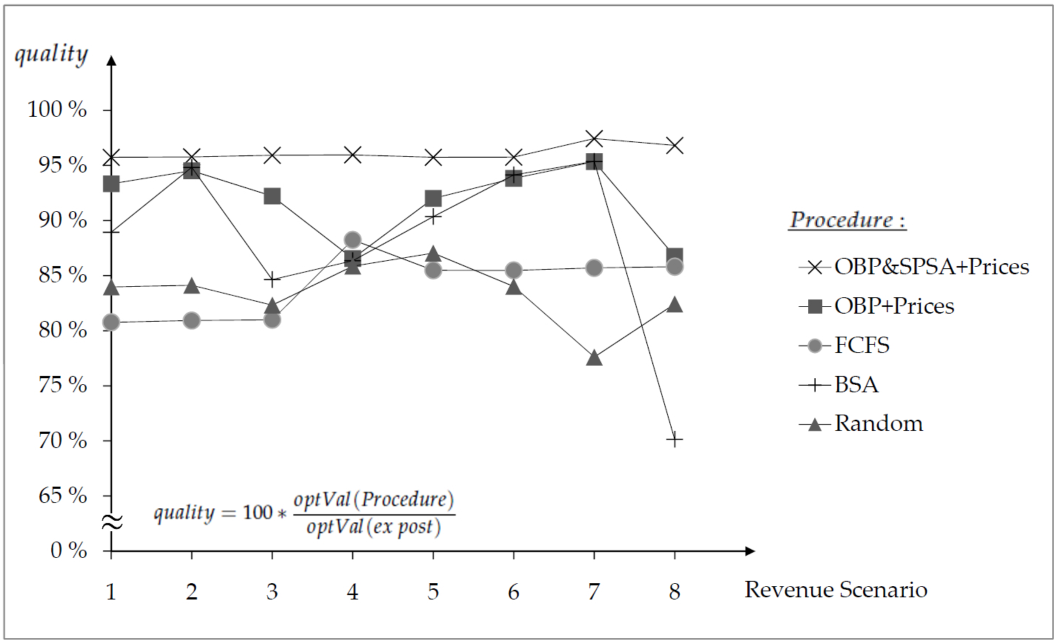

Figure 7.9: OBP&SPSA+Prices (1-8) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=120, Revenue Scenarios

procedure, respectively. The procedure of GA1+Prices and GA2+Prices only differs in the varying genotypes. Compare Section 6.1 for a description of these genotypes. In the first step of the GA1+Prices method and the GA2+Prices procedure, the genetic algorithm approaches determine the best booking limit set with arbitrary transfer prices according to the procedure outlined in Section 6.1. In the second step, the best determined booking limits are fixed and the optimal transfer prices are calculated by means of the procedure shown in Figure 7.3. In the third step, the optimal transfer prices are fixed and the booking limits are calculated with the fixed transfer prices by means of the procedure of Genetic Algorithm 1 and Genetic Algorithm 2 described in Section 6.1. This process is iteratively repeated until a predefined number of iterations is reached. With regard to the run-time of the procedures, the GA1+Prices method and the GA2+Prices approach terminate after ten transfer price optimization iterations. The number of iterations applied for the booking limit improvement within the genetic algorithm part of the procedure are 15 iterations and, therefore, remains the same as described in Section 6.2.1.

In the present section, the percentage gap between the optimal values of the GA1+Prices procedure and the GA2+Prices approach, the option-based+prices procedure (OBP+Prices), the OBP&SPSA+Prices method, the first-come-first-served approach (FCFS), and the ex post optimal solution (ex post) is computed by Formula 6.2. Table 7.14 shows the procedures which are compared in the computational study of the genetic algorithms with transfer price optimization and the respective gap assignment.

In the computational study presented in this section, the revenue results of the considered procedures are calculated for all revenue instances (1-8), introduced in Section 7.3.1. The run-times of the genetic algorithm approaches with transfer price optimization are high compared to the run-time of the OBP&SPSA+Prices approach. To calculate the best solution for a specific instance, the GA1+Prices procedure needs 17.6 minutes in low capacity/low demand instances and up to 37.4 minutes in high capacity/high demand scenarios. Similar to this, the run-time of the GA2+Prices method ranges from 17.7 minutes to 49.2 minutes for solving a considered instance. The GA2+Prices approach needs to handle strings that are larger compared to the strings in the GA1+Prices approach. This different definition

gap	$Procedure1$	$Procedure2$
$gap22$	GA1+Prices	GA2+Prices
$gap23$	GA1+Prices	OBP&SPSA+Prices
$gap24$	GA1+Prices	OBP+Prices
$gap25$	GA1+Prices	FCFS
$gap26$	ex post	GA1+Prices
$gap27$	GA1+Prices	BSA
$gap28$	GA1+Prices	Random
$gap29$	GA2+Prices	OBP&SPSA+Prices
$gap30$	GA2+Prices	OBP+Prices
$gap31$	GA2+Prices	FCFS
$gap32$	ex post	GA2+Prices
$gap33$	GA2+Prices	BSA
$gap34$	GA2+Prices	Random

Table 7.14: Compared Procedures in Computational Study GA1+Prices and GA2+Prices

of the individuals in the genetic algorithm part of the procedures explains the run-time increase of the GA2+Prices approach compared to the run-time of the GA1+Prices algorithm.

The results of the procedures aggregated over all capacity, demand, and revenue instances are presented in Table 7.15 and Table 7.16. Similarly to the performance of Genetic Algorithm 1 that is better than the performance of Genetic Algorithm 2 (compare Section 6.2.2), the results of the GA1+Prices method exceed the results of the GA2+Prices approach. However, aggregated over all considered instances, both genetic approaches with transfer price optimization perform better than all compared procedures except for the OBP&SPSA+Prices approach.

	$gap22$	$gap23$	$gap24$	$gap25$	$gap26$	$gap27$	$gap28$
all instances	0.84	-0.03	7.25	14.41	4.07	10.12	18.24

Table 7.15: GA1+Prices – Results Aggregated over Capacity, Demand, and Revenue Instances

	$gap29$	$gap30$	$gap31$	$gap32$	$gap33$	$gap34$
all instances	-0.83	6.39	13.50	4.93	9.26	17.18

Table 7.16: GA2+Prices – Results Aggregated over Capacity, Demand, and Revenue Instances

In Table 7.17 and Table 7.18, the results of the procedures aggregated over all demand and revenue instances are presented. The results of the GA1+Prices method and the GA2+Prices procedure approach as the capacity increases. The expanded solution space one again causes that the gaps between the ex post optimal solutions and the results of the genetic algorithm methods with transfer price optimization decrease when the total capacity increases.

The effect of total demand variation on the compared procedures can be identified in Table 7.19 and Table 7.20. In all demand instances assuming the capacity to be 100 and in demand instances 100 and 120 in capacity instance 150, the GA1+Prices approach performs slightly better than the OBP&SPSA+Prices method. The results of the GA2+Prices approach, however, are inferior to the results of the OBP&SPSA+Prices procedure in all considered instances. Especially in the instances with higher total demand, both genetic algorithms with transfer price optimization outperform the FCFS approach

Capacity	$gap22$	$gap23$	$gap24$	$gap25$	$gap26$	$gap27$	$gap28$
100	1.23	-0.04	8.29	12.87	4.68	11.57	20.33
120	0.74	-0.04	4.99	14.22	4.06	10.17	17.52
150	0.54	-0.01	8.49	16.09	3.48	8.69	16.94

Table 7.17: GA1+Prices – Results Aggregated over Demand and Revenue Instances

Capacity	$gap29$	$gap30$	$gap31$	$gap32$	$gap33$	$gap34$
100	-1.22	7.03	11.56	5.97	10.30	18.73
120	-0.76	4.25	13.40	4.83	9.40	16.60
150	-0.54	7.93	15.45	4.03	8.13	16.27

Table 7.18: GA2+Prices – Results Aggregated over Demand and Revenue Instances

and the blocked seat allotment procedure. As mentioned before, the reservation of seat capacity for higher yielding booking classes by means of promising booking limits pays off, particularly in scenarios with high total demand.

Capacity	Demand in %	$gap22$	$gap23$	$gap24$	$gap25$	$gap26$	$gap27$	$gap28$
100	110	1.54	0.04	5.66	2.32	3.84	5.58	24.43
	120	1.26	0.07	8.45	7.82	4.97	9.10	16.49
	130	1.06	0.03	11.30	15.55	5.08	13.41	23.27
	140	1.12	0.03	7.37	24.16	4.72	17.28	17.75
120	110	0.75	-0.03	5.39	2.15	3.50	5.05	17.18
	120	0.50	-0.06	5.24	9.33	4.32	6.10	14.16
	130	0.70	-0.04	5.51	17.78	4.41	11.64	17.38
	140	1.10	-0.04	3.95	26.74	3.92	15.98	22.33
150	110	0.32	0.09	3.43	3.82	3.27	3.52	11.11
	120	0.27	0.08	5.05	10.30	3.65	4.98	15.64
	130	0.56	-0.02	10.26	20.42	3.59	10.22	18.34
	140	1.06	-0.06	13.59	29.04	3.37	14.29	23.02

Table 7.19: GA1+Prices – Results Aggregated over Revenue Instances

Comparing the procedures in the demand setting in which the total demand is 90% of the capacity reveals that the results of the GA1+Prices approach are almost equal to the results of the OBP&SPSA+Prices method ($gap23 = 0.007$) and the FCFS procedure results ($gap25 = 0.006$). In the analysis of the performance of the OBP&SPSA+Prices approach, we already noticed that the OBP&SPSA+Prices procedure and the FCFS approach perform almost equally in demand instances in which the total demand is 90% of the capacity (compare Section 7.3.2.1). Since the simulation, introduced in Section 4.2.4, is applied in the OBP&SPSA+Prices approach as well as in both genetic algorithm versions with transfer price optimization, the decision processes of the carriers only differ in the booking limits which are applied after their determination by means of the DLPs and the SPSA approach and the genetic algorithm versions, respectively. However, the booking limits determined by the GA1+Prices approach are superior to the ones established by the GA2+Prices procedure which is expressed by the inferior performance of the GA2+Prices approach compared to the GA1+Prices method and the FCFS algorithm. Both genetic algorithm versions with transfer price optimization approach towards the ex post optimal solutions as the total capacity increases.

Capacity	Demand in %	$gap29$	$gap30$	$gap31$	$gap32$	$gap33$	$gap34$
100	110	-1.53	4.06	0.80	5.43	3.99	22.35
	120	-1.27	7.15	6.54	6.28	7.80	14.84
	130	-1.04	10.19	14.40	6.19	12.31	21.81
	140	-1.09	6.25	22.85	5.88	16.13	16.48
120	110	-0.76	4.62	1.41	4.27	4.28	16.30
	120	-0 54	4.73	8.81	4.83	5.59	13.56
	130	-0 71	4.81	16.99	5.14	10.93	16.56
	140	-1.08	2.88	25.42	5.05	14.83	20.83
150	110	-0.22	3.10	3.50	3.59	3.20	10.76
	120	-0.18	4.78	10.01	3.93	4.70	15.30
	130	-0.56	9.70	19.78	4.16	9.66	17.63
	140	-1.07	12.46	27.75	4.45	13.17	21.68

Table 7.20: GA2+Prices – Results Aggregated over Revenue Instances

Capacity	Demand in %	$gap22$	$gap23$	$gap24$	$gap25$	$gap26$	$gap27$	$gap28$
100	90	4.34	0.00	6.78	0.00	0.36	5.38	24.50
120	90	3.08	0.00	6.59	0.00	0.20	4.81	19.14
150	90	1.28	0.00	6.16	0.00	0.13	3.86	19.15

Table 7.21: GA1+Prices – Results Aggregated over Revenue Instances in Instances with Demand Intensity 0.9

After analyzing the effect of demand variations on the results of the considered approaches, the effect of different revenue instances is surveyed in the present computational study. The GA2+Prices results are inferior to the ones achieved by the GA1+Prices procedure and to the results of the OBP&SPSA method in all capacity and revenue instances. In capacity instance 100, the GA1+Prices method performs slightly better than the OBP&SPSA+Prices approach in all revenue instances. This also applies for revenue instance 8 in capacity instance 150. Especially in revenue instances 8, the GA1+Prices approach and the GA2+Prices procedure clearly outperform the blocked seat allotment method. The results of the OBP&SPSA+Prices procedure also exceed the results of the blocked seat allotment method especially in revenue scenario 8 as displayed in Section 7.3.2.2. The same argument, as discussed while explaining the better performance of the OBP&SPSA+Prices approach compared to the blocked seat allotment algorithm, can be stated discussing the results of the genetic algorithms with transfer price optimization: The blocked seat allotment ignores the flight ticket revenue of the ticketing carrier that is much higher than the revenue the operating carrier achieves in revenue instance 8.

Capacity	Demand in %	$gap29$	$gap30$	$gap31$	$gap32$	$gap33$	$gap34$
100	90	-4.07	2.43	-4.07	4.72	1.07	19.41
120	90	-2.93	3.46	-2.93	3.28	1.72	15.56
150	90	-1.26	4.82	-1.26	1.41	2.55	17.62

Table 7.22: GA2+Prices – Results Aggregated over Revenue Instances in Instances with Demand Intensity 0.9

Capacity	Revenue Instance	$gap22$	$gap23$	$gap24$	$gap25$	$gap26$	$gap27$	$gap28$
100	1	0.36	0.08	5.26	16.60	5.32	8.53	17.99
	2	1.36	0.03	1.90	17.15	5.26	1.19	20.37
	3	0.47	0.06	7.08	16.37	5.03	14.93	15.48
	4	0.90	0.07	13.05	7.14	4.76	12.55	15.49
	5	0.45	0.07	6.17	10.27	5.14	6.85	11.93
	6	1.13	0.01	2.91	10.70	5.14	2.20	12.07
	7	4.21	0.02	2.68	13.93	3.22	2.56	41.49
	8	0.98	0.01	27.30	10.79	3.61	43.77	27.82
120	1	0.12	-0.09	2.59	18.39	4.54	7.39	14.39
	2	0.82	-0.03	1.33	18.33	4.45	0.97	15.42
	3	0.22	-0.06	4.11	18.27	4.31	13.06	17.73
	4	0.38	-0.06	10.82	8.62	4.24	10.99	13.35
	5	0.13	-0.05	4.12	11.88	4.49	5.84	10.88
	6	0.62	-0.02	2.08	11.97	4.44	1.71	15.26
	7	3.11	-0.02	2.21	13.68	2.69	2.18	32.53
	8	0.54	-0.01	12.67	12.66	3.29	39.18	20.59
150	1	0.08	-0.06	6.94	20.53	3.80	6.21	15.42
	2	0.53	-0.06	0.99	20.54	3.76	0.48	14.50
	3	0.15	-0.05	11.93	20.32	3.62	11.34	17.67
	4	0.10	-0.04	7.74	10.20	3.73	9.25	13.87
	5	0.04	-0.06	2.50	13.79	3.87	4.58	9.81
	6	0.36	-0.02	1.42	13.93	3.82	0.88	17.78
	7	2.61	-0.05	1.65	15.24	2.38	1.62	24.69
	8	0.47	0.26	34.76	14.13	2.84	35.14	21.82

Table 7.23: GA1+Prices – Results Aggregated over Demand Instances

Capacity	Revenue Instance	$gap29$	$gap30$	$gap31$	$gap32$	$gap33$	$gap34$
100	1	-0.43	4.89	16.23	5.69	8.15	17.54
	2	-1.35	0.55	15.64	6.70	-0.15	18.78
	3	-0.52	6.57	15.86	5.53	14.40	14.94
	4	-0.94	12.07	6.24	5.70	11.57	14.38
	5	-0.51	5.70	9.81	5.60	6.38	11.44
	6	-1.11	1.77	9.52	6.33	1.07	10.78
	7	-3.92	-1.34	9.45	7.55	-1.46	35.48
	8	-0.97	26.02	9.76	4.63	42.46	26.50
120	1	-0.21	2.47	18.25	4.67	7.26	14.25
	2	-0.83	0.52	17.35	5.31	0.16	14.46
	3	-0.28	3.88	18.02	4.55	12.81	17.48
	4	-0.43	10.42	8.23	4.64	10.59	12.90
	5	-0.18	3.98	11.74	4.63	5.70	10.74
	6	-0.63	1.45	11.29	5.09	1.09	14.54
	7	-2.96	-0.80	10.25	5.88	-0.83	28.50
	8	-0.54	12.08	12.06	3.85	38.44	19.90
150	1	-0.14	6.85	20.42	3.89	6.12	15.35
	2	-0.58	0.46	19.89	4.31	-0.05	13.88
	3	-0.20	11.75	20.12	3.78	11.16	17.49
	4	-0.14	7.63	10.10	3.83	9.15	13.76
	5	-0.10	2.46	13.75	3.91	4.55	9.77
	6	-0.38	1.05	13.50	4.20	0.51	17.36
	7	-2.53	-0.87	12.28	5.04	-0.90	21.39
	8	-0.20	34.08	13.58	3.32	34.48	21.22

Table 7.24: GA2+Prices – Results Aggregated over Demand Instances

Chapter 8

Conclusions and Future Research

The present work has concentrated on situations in which multiple corporations build a strategic alliance in sectors in which revenue management concepts are adopted. There are many problems that arise when dealing with strategic alliances, however, the question of how to distribute the capacity among the alliance partners plays an important role. In the present work, we have analyzed this practical problem and have developed capacity control methods to maximize the combined revenue of the alliance partners. Although, strategic alliances arise in many sectors in which revenue management concepts are adopted, we have focused on the passenger airline industry being the most important sector in theory and practice in which revenue management is applied.

In Chapter 2, we have started with providing the theoretical background of revenue management. Especially topics that were essential for the understanding of the revenue management problems, discussed in this thesis, have been outlined. After the description of the historical development of revenue management, the requirements to enable an effective revenue management application have been presented. Additionally, we have discussed revenue management instruments focusing on the capacity control instrument. The deterministic linear program and the EMSR heuristics, being two of the most important concepts for the determination of control variables in capacity control, have been described in detail in Chapter 2. Capacity control problems that arise within strategic alliances are complex since not only the capacity needs to be allocated to the different customer segments, but also needs to be divided among the alliance partners. Therefore, we have chosen the deterministic linear program and EMSR heuristics to calculate the booking limits in our approaches.

We have presented definitions and basic information concerning strategic alliances in Chapter 3. To bring together the topics revenue management and strategic alliances, we have provided an overview of sectors in which revenue management instruments can be applied and the influence strategic alliances have on capacity control decisions when strategic alliances arise in the specific sectors. Practical examples of strategic alliances in the different industries have been mentioned in Chapter 3 as well.

The capacity control concepts for single corporations need to be enhanced to solve the complex decision problems within strategic alliances arising in practice. In Chapter 4, we have introduced a real option approach that helps to determine booking limits for the alliance partners. We have formulated an option-based procedure to solve the capacity control problem which addresses the question of how many seats should be available on a single flight leg to the booking classes of two partner airlines within an alliance. Using real options, the partners within the alliance can reserve seats in a considered aircraft. The new option-based approach helps the airlines to distribute the seat capacity before and during the booking process in an effective way. This procedure overcomes the drawbacks of the capacity control methods applied so far for strategic alliances by calculating booking limits for the alliance partners to reserve seat capacity for higher yielding booking classes and by allowing the partner airlines to switch their assigned capacity during the booking process. To calculate the booking limits for the fare classes of the two airlines, deterministic option-based models as well as EMSR-heuristics with underlying real option idea have been proposed. We have presented simulation models, which account for the option-based approach, to simulate the booking processes of the airlines. The results of the option-based procedure have been compared to a first-come-first-served approach and to ex post optimal solutions. The computational study shows that the option-based approach overcomes the drawback of a first-come-first-served scenario (not reserving capacity for higher yielding classes and, therefore, accepting to many lower yielding requests) in most of the considered instances.

To include the benefits of simulation-based optimization in the booking limit determination for strategic alliances, we have implemented a stochastic approximation procedure in combination with our DLP underlying option-based approach in Chapter 5 which improved the results of the option-based procedures with DLPs, described in Chapter 4, towards the ex post optimal solutions.

In Chapter 6, we have introduced two problem specific genetic algorithm approaches to compare the promising results of the option-based approach with booking limit determination by means of the DLPs and combined stochastic approximation with the performance of an evolutionary heuristic with underlying real option idea. The results of the genetic algorithm approaches are slightly inferior to the results achieved by the option-based stochastic approximation, introduced in Chapter 5.

The DLP underlying option-based approach combined with stochastic approximation, which has been presented in Chapter 5, is a promising procedure for the distribution of the capacity among the customer segments of the partners within an alliance. Unfortunately, the results of the proposed procedure highly depend on the choice of the transfer prices which are treated as given parameters. In order to improve the performance of the option- and DLP-based approach combined with stochastic approximation, we have presented an extension of the procedure which optimizes the transfer prices in addition to the booking limit optimization in Chapter 7. The negotiation process between the two partner airlines has been outlined, describing the determination of the optimal transfer prices. Furthermore, the problem specific genetic algorithm versions, introduced in Chapter 6, have been extended by the transfer price optimization in Chapter 7. In a computational study, the performance of the discussed procedures has been analyzed. The survey showed, that the results of the option-based approach with booking limit calculation by means of DLPs and booking limit improvement by stochastic approximation and transfer price optimization are very promising. Only in a few considered instances, one of the option-based genetic algorithm approaches with transfer price optimization slightly enhanced the results of the DLP underlying option-based procedure with stochastic approximation and transfer price optimization. However, due to the run-time that is considerably higher for the genetic algorithm approaches than for the option-based procedure with underlying DLPs and stochastic approximation, we recommend the application of the option- and DLP-based procedure with booking limit improvement by stochastic approximation and transfer price optimization to solve capacity control problems within strategic alliances. Due to its short run-time, the presented approach is applicable in revenue management systems of airlines and can be easily adopted for real-world problems.

Since many real-world problems appear in a network revenue management setting, future work may adjust the proposed procedures for the single-leg case to network revenue management problems. Furthermore, our option approach for alliances could be extended to integrate customer-choice behavior in future work. In this way, the more realistic case of the demand being dependent among the classes of the alliance partners could be included within the analysis. The described alliance revenue management capacity control problem could also be regarded as a multi-objective optimization problem. The expected revenues of the single airlines within the alliance could be considered as a vector of revenues, whereas a capacity control decision can increase the expected revenue of one airline while simultaneously decreasing the expected revenue of the other airline. Moreover, future research may discuss the adoption of the option-based concept to solve capacity control problems in non-airline service sectors. Additionally, the option-based capacity control mechanism may be generalized to allow the consideration of more than two partners within the alliance.

Appendix A

Computational Studies

A.1 Computational Study: Demand Input Data

The tables in Appendix A.1 show the λ values for booking class j of airline l (described in Section 4.2.4) in the different simulation sectors, demand instances, and capacity settings.

Demand Instance		Sector 1				Sector 2				Sector 3			
booking class j, airline l		1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2
1.1	1a	0.05	0.6	0.01	0.5	0.05	0.3	0.08	0.16	0.2	0.1	0.11	0.04
	1b	0.01	0.8	0.01	0.6	0.09	0.14	0.03	0.08	0.2	0.06	0.16	0.02
	1c	0.1	0.6	0.1	0.5	0.1	0.3	0.06	0.16	0.1	0.1	0.04	0.04
	2	0.04	0.6	0.02	0.52	0.1	0.3	0.02	0.14	0.26	0.1	0.06	0.04
	3	0.02	0.6	0.04	0.52	0.04	0.3	0.08	0.14	0.14	0.1	0.18	0.04
	4	0.02	0.64	0.02	0.46	0.06	0.34	0.06	0.12	0.22	0.12	0.12	0.02
	5	0.02	0.56	0.02	0.58	0.06	0.26	0.06	0.16	0.22	0.08	0.12	0.06
	6	0.04	0.56	0.02	0.52	0.1	0.26	0.06	0.14	0.26	0.08	0.12	0.04
	7	0.02	0.64	0.02	0.52	0.04	0.34	0.06	0.14	0.14	0.12	0.12	0.04
	8	0.02	0.6	0.04	0.46	0.06	0.3	0.08	0.12	0.22	0.1	0.18	0.02
1.2	1	0.04	0.62	0.03	0.53	0.08	0.32	0.08	0.16	0.23	0.11	0.14	0.06
	2	0.04	0.6	0.04	0.52	0.1	0.3	0.08	0.14	0.26	0.1	0.18	0.04
	3	0.06	0.6	0.02	0.52	0.14	0.3	0.02	0.14	0.4	0.1	0.06	0.04
	4	0.02	0.6	0.08	0.52	0.04	0.3	0.14	0.14	0.14	0.1	0.28	0.04
	5	0.02	0.64	0.02	0.58	0.06	0.34	0.06	0.16	0.22	0.12	0.12	0.06
	6	0.02	0.74	0.02	0.46	0.06	0.4	0.06	0.12	0.22	0.16	0.12	0.02
	7	0.02	0.56	0.02	0.7	0.06	0.26	0.06	0.22	0.22	0.08	0.12	0.08
	8	0.04	0.64	0.02	0.52	0.1	0.34	0.06	0.14	0.26	0.12	0.12	0.04
	9	0.06	0.56	0.02	0.52	0.14	0.26	0.06	0.14	0.4	0.08	0.12	0.04
	10	0.02	0.74	0.02	0.52	0.04	0.4	0.06	0.14	0.14	0.16	0.12	0.04
	11	0.02	0.6	0.04	0.58	0.06	0.3	0.08	0.16	0.22	0.1	0.18	0.06
	12	0.02	0.6	0.08	0.46	0.06	0.3	0.14	0.12	0.22	0.1	0.28	0.02
	13	0.02	0.6	0.02	0.7	0.06	0.3	0.02	0.22	0.22	0.1	0.06	0.08
1.3	1	0.04	0.64	0.04	0.58	0.1	0.34	0.08	0.16	0.26	0.12	0.18	0.06
	2	0.05	0.62	0.05	0.56	0.12	0.32	0.1	0.14	0.28	0.11	0.2	0.05
	3	0.07	0.62	0.03	0.56	0.16	0.32	0.04	0.14	0.42	0.11	0.08	0.05
	4	0.01	0.62	0.07	0.56	0.04	0.32	0.16	0.14	0.2	0.11	0.32	0.05
	5	0.03	0.66	0.03	0.6	0.08	0.36	0.06	0.18	0.24	0.13	0.16	0.07
	6	0.03	0.76	0.03	0.5	0.08	0.42	0.06	0.12	0.24	0.17	0.16	0.03
	7	0.03	0.56	0.03	0.72	0.08	0.3	0.06	0.24	0.24	0.09	0.16	0.09
	8	0.05	0.66	0.03	0.56	0.12	0.36	0.06	0.14	0.28	0.13	0.16	0.05

Demand Instance		Sector 1				Sector 2				Sector 3			
booking class j, airline l		1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2
	9	0.07	0.56	0.03	0.56	0.16	0.3	0.06	0.14	0.42	0.09	0.16	0.05
	10	0.01	0.76	0.03	0.56	0.04	0.42	0.06	0.14	0.2	0.17	0.16	0.05
	11	0.03	0.62	0.05	0.6	0.08	0.32	0.1	0.18	0.24	0.11	0.2	0.07
	12	0.03	0.62	0.07	0.5	0.08	0.32	0.16	0.12	0.24	0.11	0.32	0.03
	13	0.03	0.62	0.03	0.72	0.08	0.32	0.04	0.24	0.24	0.11	0.08	0.09
1.4	1	0.06	0.66	0.04	0.6	0.12	0.36	0.1	0.18	0.28	0.14	0.22	0.08
	2	0.06	0.64	0.06	0.58	0.14	0.34	0.1	0.16	0.3	0.12	0.24	0.06
	3	0.08	0.64	0.02	0.58	0.22	0.34	0.06	0.16	0.4	0.12	0.12	0.06
	4	0.02	0.64	0.08	0.58	0.06	0.34	0.16	0.16	0.22	0.12	0.36	0.06
	5	0.04	0.68	0.04	0.64	0.1	0.38	0.08	0.18	0.26	0.14	0.18	0.08
	6	0.04	0.8	0.04	0.52	0.1	0.42	0.08	0.14	0.26	0.18	0.18	0.04
	7	0.04	0.6	0.04	0.76	0.1	0.3	0.08	0.24	0.26	0.1	0.18	0.1
	8	0.06	0.68	0.04	0.58	0.14	0.38	0.08	0.16	0.3	0.14	0.18	0.06
	9	0.08	0.6	0.04	0.58	0.22	0.3	0.08	0.16	0.4	0.1	0.18	0.06
	10	0.02	0.8	0.04	0.58	0.06	0.42	0.08	0.16	0.22	0.18	0.18	0.06
	11	0.04	0.64	0.06	0.64	0.1	0.34	0.1	0.18	0.26	0.12	0.24	0.08
	12	0.04	0.64	0.08	0.52	0.1	0.34	0.16	0.14	0.26	0.12	0.36	0.04
	13	0.04	0.64	0.02	0.76	0.1	0.34	0.06	0.24	0.26	0.12	0.12	0.1

Table A.1: Demand Instances - Seat Capacity 100

Demand Instance		Sector 1				Sector 2				Sector 3			
booking class j, airline l		1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2
1.1	1	0.04	0.65	0.04	0.59	0.1	0.34	0.08	0.16	0.27	0.12	0.19	0.06
	2	0.04	0.64	0.02	0.58	0.1	0.34	0.06	0.16	0.28	0.12	0.24	0.06
	3	0.06	0.64	0.02	0.58	0.14	0.34	0.04	0.16	0.32	0.12	0.16	0.06
	4	0.02	0.64	0.04	0.58	0.06	0.34	0.1	0.16	0.24	0.12	0.28	0.06
	5	0.04	0.66	0.02	0.6	0.1	0.34	0.06	0.16	0.26	0.12	0.22	0.06
	6	0.04	0.7	0.02	0.54	0.1	0.38	0.06	0.14	0.26	0.14	0.22	0.04
	7	0.04	0.62	0.02	0.66	0.1	0.3	0.06	0.18	0.26	0.1	0.22	0.08
	8	0.04	0.66	0.02	0.58	0.1	0.34	0.06	0.16	0.28	0.12	0.22	0.06
	9	0.06	0.62	0.02	0.58	0.14	0.3	0.06	0.16	0.32	0.1	0.22	0.06
	10	0.02	0.7	0.02	0.58	0.06	0.38	0.06	0.16	0.24	0.14	0.22	0.06
	11	0.04	0.64	0.02	0.6	0.1	0.34	0.06	0.16	0.26	0.12	0.24	0.06
	12	0.04	0.64	0.04	0.54	0.1	0.34	0.1	0.14	0.26	0.12	0.28	0.04
	13	0.04	0.64	0.02	0.66	0.1	0.34	0.04	0.18	0.26	0.12	0.16	0.08
1.2	1	0.06	0.67	0.04	0.61	0.12	0.36	0.1	0.18	0.29	0.14	0.23	0.08
	2	0.06	0.66	0.04	0.6	0.14	0.36	0.1	0.18	0.3	0.14	0.26	0.08
	3	0.1	0.66	0.02	0.6	0.18	0.36	0.04	0.18	0.38	0.14	0.18	0.08
	4	0.02	0.66	0.08	0.6	0.06	0.36	0.16	0.18	0.26	0.14	0.32	0.08
	5	0.06	0.68	0.04	0.64	0.12	0.38	0.08	0.18	0.28	0.14	0.24	0.08
	6	0.06	0.76	0.04	0.56	0.12	0.42	0.08	0.14	0.28	0.18	0.24	0.04
	7	0.06	0.6	0.04	0.72	0.12	0.32	0.08	0.22	0.28	0.12	0.24	0.12
	8	0.06	0.68	0.04	0.6	0.14	0.38	0.08	0.18	0.3	0.14	0.24	0.08
	9	0.1	0.6	0.04	0.6	0.18	0.32	0.08	0.18	0.38	0.12	0.24	0.08
	10	0.02	0.76	0.04	0.6	0.06	0.42	0.08	0.18	0.26	0.18	0.24	0.08
	11	0.06	0.66	0.04	0.64	0.12	0.36	0.1	0.18	0.28	0.14	0.26	0.08
	12	0.06	0.66	0.08	0.56	0.12	0.36	0.16	0.14	0.28	0.14	0.32	0.04
	13	0.06	0.66	0.02	0.72	0.12	0.36	0.04	0.22	0.28	0.14	0.18	0.12

Demand Instance		Sector 1				Sector 2				Sector 3			
booking class j, airline l		1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2
	1	0.06	0.72	0.04	0.68	0.16	0.38	0.1	0.18	0.32	0.14	0.3	0.08
	2	0.08	0.68	0.06	0.64	0.16	0.38	0.12	0.18	0.32	0.14	0.28	0.08
	3	0.1	0.68	0.02	0.64	0.22	0.38	0.08	0.18	0.46	0.14	0.14	0.08
	4	0.02	0.68	0.08	0.64	0.06	0.38	0.18	0.18	0.26	0.14	0.42	0.08
	5	0.06	0.74	0.04	0.66	0.14	0.38	0.1	0.2	0.3	0.14	0.26	0.1
	6	0.06	0.84	0.04	0.56	0.14	0.46	0.1	0.14	0.3	0.18	0.26	0.04
1.3	7	0.06	0.6	0.04	0.8	0.14	0.32	0.1	0.26	0.3	0.12	0.26	0.12
	8	0.08	0.74	0.04	0.64	0.16	0.38	0.1	0.18	0.32	0.14	0.26	0.08
	9	0.1	0.6	0.04	0.64	0.22	0.32	0.1	0.18	0.46	0.12	0.26	0.08
	10	0.02	0.84	0.04	0.64	0.06	0.46	0.1	0.18	0.26	0.18	0.26	0.08
	11	0.06	0.68	0.06	0.66	0.14	0.38	0.12	0.2	0.3	0.14	0.28	0.1
	12	0.06	0.68	0.08	0.56	0.14	0.38	0.18	0.14	0.3	0.14	0.42	0.04
	13	0.06	0.68	0.02	0.8	0.14	0.38	0.08	0.26	0.3	0.14	0.14	0.12
	1	0.06	0.74	0.06	0.7	0.14	0.4	0.14	0.2	0.4	0.16	0.3	0.1
	2	0.06	0.74	0.08	0.66	0.14	0.38	0.16	0.2	0.44	0.14	0.3	0.1
	3	0.1	0.74	0.04	0.66	0.24	0.38	0.08	0.2	0.58	0.14	0.14	0.1
	4	0.04	0.74	0.1	0.66	0.08	0.38	0.2	0.2	0.24	0.14	0.52	0.1
	5	0.08	0.76	0.06	0.74	0.16	0.42	0.12	0.2	0.32	0.16	0.28	0.1
	6	0.08	0.94	0.06	0.54	0.16	0.48	0.12	0.16	0.32	0.2	0.28	0.06
1.4	7	0.08	0.72	0.06	0.9	0.16	0.22	0.12	0.28	0.32	0.12	0.28	0.14
	8	0.06	0.76	0.06	0.66	0.14	0.42	0.12	0.2	0.44	0.16	0.28	0.1
	9	0.1	0.72	0.06	0.66	0.24	0.22	0.12	0.2	0.58	0.12	0.28	0.1
	10	0.04	0.94	0.06	0.66	0.08	0.48	0.12	0.2	0.24	0.2	0.28	0.1
	11	0.08	0.74	0.08	0.74	0.16	0.38	0.16	0.2	0.32	0.14	0.3	0.1
	12	0.08	0.74	0.1	0.54	0.16	0.38	0.2	0.16	0.32	0.14	0.52	0.06
	13	0.08	0.74	0.04	0.9	0.16	0.38	0.08	0.28	0.32	0.14	0.14	0.14

Table A.2: Demand Instances - Seat Capacity 120

Demand Scenario		Sector 1				Sector 2				Sector 3			
booking class j, airline l		1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2
	1	0.06	0.72	0.06	0.68	0.16	0.4	0.14	0.2	0.355	0.175	0.295	0.115
	2	0.06	0.74	0.06	0.66	0.14	0.38	0.14	0.2	0.4	0.14	0.3	0.1
	3	0.1	0.74	0.04	0.66	0.22	0.38	0.08	0.2	0.54	0.14	0.14	0.1
	4	0.04	0.74	0.1	0.66	0.08	0.38	0.22	0.2	0.24	0.14	0.44	0.1
	5	0.08	0.74	0.06	0.7	0.16	0.4	0.12	0.2	0.32	0.16	0.28	0.1
	6	0.08	0.88	0.06	0.54	0.16	0.48	0.12	0.16	0.32	0.2	0.28	0.06
1.1	7	0.08	0.72	0.06	0.84	0.16	0.22	0.12	0.28	0.32	0.12	0.28	0.14
	8	0.06	0.74	0.06	0.66	0.14	0.4	0.12	0.2	0.4	0.16	0.28	0.1
	9	0.1	0.72	0.06	0.66	0.22	0.22	0.12	0.2	0.54	0.12	0.28	0.1
	10	0.04	0.88	0.06	0.66	0.08	0.48	0.12	0.2	0.24	0.2	0.28	0.1
	11	0.08	0.74	0.06	0.7	0.16	0.38	0.14	0.2	0.32	0.14	0.3	0.1
	12	0.08	0.74	0.1	0.54	0.16	0.38	0.22	0.16	0.32	0.14	0.44	0.06
	13	0.08	0.74	0.04	0.84	0.16	0.38	0.08	0.28	0.32	0.14	0.14	0.14
	1	0.08	0.76	0.08	0.72	0.16	0.42	0.16	0.22	0.41	0.17	0.31	0.11
	2	0.08	0.74	0.08	0.7	0.18	0.4	0.16	0.2	0.44	0.16	0.36	0.1
	3	0.1	0.74	0.06	0.7	0.24	0.4	0.1	0.2	0.56	0.16	0.24	0.1
	4	0.06	0.74	0.1	0.7	0.14	0.4	0.22	0.2	0.3	0.16	0.48	0.1
	5	0.06	0.8	0.08	0.76	0.14	0.42	0.14	0.22	0.4	0.18	0.28	0.12
	6	0.06	0.92	0.08	0.64	0.14	0.48	0.14	0.18	0.4	0.2	0.28	0.08

Demand Scenario		Sector 1				Sector 2				Sector 3			
booking class j, airline l		1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2
1.2	7	0.06	0.68	0.08	0.88	0.14	0.38	0.14	0.28	0.4	0.14	0.28	0.14
	8	0.08	0.8	0.08	0.7	0.18	0.42	0.14	0.2	0.44	0.18	0.28	0.1
	9	0.1	0.68	0.08	0.7	0.24	0.38	0.14	0.2	0.56	0.14	0.28	0.1
	10	0.06	0.92	0.08	0.7	0.14	0.48	0.14	0.2	0.3	0.2	0.28	0.1
	11	0.06	0.74	0.08	0.76	0.14	0.4	0.16	0.22	0.4	0.16	0.36	0.12
	12	0.06	0.74	0.1	0.64	0.14	0.4	0.22	0.18	0.4	0.16	0.48	0.08
	13	0.06	0.74	0.06	0.88	0.14	0.4	0.1	0.28	0.4	0.16	0.24	0.14
	1	0.08	0.82	0.08	0.78	0.18	0.42	0.16	0.22	0.465	0.185	0.385	0.125
	2	0.1	0.8	0.1	0.76	0.2	0.42	0.18	0.22	0.45	0.18	0.37	0.12
	3	0.12	0.8	0.06	0.76	0.26	0.42	0.1	0.22	0.62	0.18	0.24	0.12
	4	0.06	0.8	0.1	0.76	0.14	0.42	0.24	0.22	0.3	0.18	0.56	0.12
	5	0.08	0.84	0.08	0.78	0.18	0.44	0.16	0.26	0.44	0.17	0.36	0.11
	6	0.08	1	0.08	0.64	0.18	0.5	0.16	0.18	0.44	0.2	0.36	0.08
1.3	7	0.08	0.68	0.08	0.94	0.18	0.38	0.16	0.32	0.44	0.14	0.36	0.14
	8	0.1	0.84	0.08	0.76	0.2	0.44	0.16	0.22	0.45	0.17	0.36	0.12
	9	0.12	0.68	0.08	0.76	0.26	0.38	0.16	0.22	0.62	0.14	0.36	0.12
	10	0.06	1	0.08	0.76	0.14	0.5	0.16	0.22	0.3	0.2	0.36	0.12
	11	0.08	0.8	0.1	0.78	0.18	0.42	0.18	0.26	0.44	0.18	0.37	0.11
	12	0.08	0.8	0.1	0.64	0.18	0.42	0.24	0.18	0.44	0.18	0.56	0.08
	13	0.08	0.8	0.06	0.94	0.18	0.42	0.1	0.32	0.44	0.18	0.24	0.14
	1	0.08	0.9	0.08	0.84	0.2	0.42	0.18	0.24	0.52	0.18	0.44	0.12
	2	0.1	0.825	0.1	0.785	0.22	0.42	0.22	0.22	0.555	0.18	0.455	0.12
	3	0.14	0.825	0.08	0.785	0.3	0.42	0.14	0.22	0.68	0.18	0.3	0.12
	4	0.06	0.825	0.12	0.785	0.14	0.42	0.26	0.22	0.42	0.18	0.64	0.12
	5	0.08	0.915	0.08	0.855	0.18	0.46	0.16	0.28	0.465	0.2	0.385	0.14
	6	0.08	1.08	0.08	0.72	0.18	0.52	0.16	0.2	0.465	0.22	0.385	0.1
1.4	7	0.08	0.76	0.08	1	0.18	0.4	0.16	0.36	0.465	0.16	0.385	0.16
	8	0.1	0.915	0.08	0.785	0.22	0.46	0.16	0.22	0.555	0.2	0.385	0.12
	9	0.14	0.76	0.08	0.785	0.3	0.4	0.16	0.22	0.68	0.16	0.385	0.12
	10	0.06	1.08	0.08	0.785	0.14	0.52	0.16	0.22	0.42	0.22	0.385	0.12
	11	0.08	0.825	0.1	0.855	0.18	0.42	0.22	0.28	0.465	0.18	0.455	0.14
	12	0.08	0.825	0.12	0.72	0.18	0.42	0.26	0.2	0.465	0.18	0.64	0.1
	13	0.08	0.825	0.08	1	0.18	0.42	0.14	0.36	0.465	0.18	0.3	0.16

Table A.3: Demand Instances - Seat Capacity 150

Demand Scenario		Sector 1				Sector 2				Sector 3			
booking class j, airline l		1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2
Capacity 100													
	1	0.02	0.54	0.02	0.46	0.04	0.26	0.04	0.1	0.14	0.1	0.04	0.04
	2	0.02	0.5	0.02	0.42	0.06	0.26	0.04	0.1	0.18	0.08	0.1	0.02
	3	0.02	0.5	0.001	0.42	0.08	0.26	0.001	0.1	0.32	0.08	0.001	0.02
	4	0.01	0.5	0.02	0.42	0.02	0.26	0.1	0.1	0.07	0.08	0.2	0.02
	5	0.01	0.58	0.01	0.5	0.03	0.3	0.01	0.12	0.1	0.08	0.02	0.04
	6	0.01	0.64	0.01	0.4	0.03	0.36	0.01	0.09	0.1	0.12	0.02	0.01
0.9	7	0.01	0.52	0.01	0.6	0.03	0.22	0.01	0.18	0.1	0.06	0.02	0.04
	8	0.02	0.58	0.01	0.42	0.06	0.3	0.01	0.1	0.18	0.08	0.02	0.02
	9	0.01	0.52	0.01	0.42	0.08	0.22	0.01	0.1	0.32	0.06	0.02	0.02
	10	0.01	0.64	0.01	0.42	0.02	0.36	0.01	0.1	0.07	0.12	0.02	0.02
	11	0.01	0.5	0.02	0.5	0.03	0.26	0.04	0.12	0.1	0.08	0.1	0.04

Demand Scenario		Sector 1				Sector 2				Sector 3			
booking class j, airline l		1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2	1,1	2,1	1,2	2,2
	12	0.01	0.5	0.02	0.4	0.03	0.26	0.1	0.09	0.1	0.08	0.2	0.01
	13	0.01	0.5	0.001	0.6	0.03	0.26	0.001	0.18	0.1	0.08	0.001	0.04
Capacity 120													
	1	0.02	0.59	0.02	0.51	0.06	0.3	0.06	0.14	0.21	0.1	0.11	0.04
	2	0.02	0.58	0.02	0.5	0.08	0.28	0.06	0.12	0.24	0.08	0.16	0.02
	3	0.04	0.58	0.01	0.5	0.12	0.28	0.01	0.12	0.38	0.08	0.02	0.02
	4	0.01	0.58	0.06	0.5	0.02	0.28	0.12	0.12	0.11	0.08	0.26	0.02
	5	0.01	0.62	0.01	0.56	0.03	0.32	0.03	0.14	0.2	0.1	0.1	0.04
	6	0.01	0.72	0.01	0.43	0.03	0.38	0.03	0.1	0.2	0.14	0.1	0.01
0.9	7	0.01	0.54	0.01	0.68	0.03	0.24	0.03	0.2	0.2	0.06	0.1	0.06
	8	0.02	0.62	0.01	0.5	0.08	0.32	0.03	0.12	0.24	0.1	0.1	0.02
	9	0.04	0.54	0.01	0.5	0.12	0.24	0.03	0.12	0.38	0.06	0.1	0.02
	10	0.01	0.72	0.01	0.5	0.02	0.38	0.03	0.12	0.11	0.14	0.1	0.02
	11	0.01	0.58	0.02	0.56	0.03	0.28	0.06	0.14	0.2	0.08	0.16	0.04
	12	0.01	0.58	0.06	0.43	0.03	0.28	0.12	0.1	0.2	0.08	0.26	0.01
	13	0.01	0.58	0.01	0.68	0.03	0.28	0.01	0.2	0.2	0.08	0.02	0.06
Capacity 150													
	1	0.046	0.68	0.046	0.6	0.1	0.32	0.08	0.16	0.28	0.126	0.2	0.066
	2	0.02	0.7	0.03	0.62	0.11	0.34	0.08	0.18	0.28	0.1	0.2	0.04
	3	0.04	0.7	0.02	0.62	0.1	0.34	0.02	0.18	0.38	0.1	0.16	0.04
	4	0.02	0.7	0.06	0.62	0.04	0.34	0.12	0.18	0.24	0.1	0.24	0.04
	5	0.02	0.68	0.02	0.64	0.06	0.34	0.06	0.18	0.32	0.12	0.22	0.04
	6	0.02	0.72	0.02	0.56	0.06	0.38	0.06	0.16	0.32	0.16	0.22	0.02
0.9	7	0.02	0.66	0.02	0.7	0.06	0.3	0.06	0.2	0.32	0.08	0.22	0.06
	8	0.02	0.68	0.02	0.62	0.12	0.36	0.06	0.16	0.3	0.1	0.22	0.04
	9	0.04	0.66	0.02	0.62	0.12	0.3	0.06	0.16	0.38	0.08	0.22	0.04
	10	0.02	0.72	0.02	0.62	0.06	0.38	0.06	0.16	0.26	0.14	0.22	0.04
	11	0.02	0.68	0.02	0.62	0.06	0.34	0.1	0.18	0.32	0.1	0.22	0.04
	12	0.02	0.68	0.06	0.54	0.06	0.34	0.12	0.18	0.32	0.1	0.26	0.02
	13	0.02	0.68	0.04	0.68	0.06	0.34	0.04	0.2	0.32	0.1	0.16	0.06

Table A.4: Demand Instances with Demand Intensity 0.9 - Seat Capacity 100, 120, and 150

A.2 Computational Study: Computational Study OBP&SPSA+Prices

Capacity	Revenue	Demand in %	Price	$gap16$	$gap17$
		110	a	0.00	3.25
			b	1.69	5.63
			c	1.69	5.63
			d	33.68	36.55
		120	a	0.51	2.59
			b	0.10	8.35
			c	0.10	8.35
			d	23.87	26.22
100	1	130	a	0.71	2.77

Capacity	Revenue	Demand in %	Price	$gap16$	$gap17$
			b	0.03	11.41
			c	0.03	11.41
			d	17.08	18.98
		140	a	0.01	2.11
			b	0.03	12.93
			c	0.03	12.93
			d	12.84	14.60
100	2	110	a	0.00	2.17
			b	14.51	16.27
			c	14.51	16.27
			d	14.54	16.27
		120	a	0.00	1.92
			b	7.98	9.54
			c	7.98	9.54
			d	8.08	9.55
		130	a	0.01	2.03
			b	3.45	4.89
			c	3.45	4.89
			d	3.58	4.89
		140	a	0.02	1.83
			b	1.02	2.71
			c	1.02	2.71
			d	1.03	2.37
100	3	110	a	2.33	4.38
			b	3.06	8.07
			c	3.06	8.07
			d	46.72	50.16
		120	a	2.26	3.78
			b	1.15	13.46
			c	1.15	13.46
			d	35.73	38.54
		130	a	1.74	4.01
			b	0.04	19.43
			c	0.04	19.43
			d	28.20	30.45
		140	a	0.60	3.31
			b	0.02	22.81
			c	0.02	22.81
			d	23.40	25.48
100	4	110	a	0.04	4.80
			b	0.30	7.65
			c	0.30	7.65
			d	46.39	48.84
		120	a	0.41	4.27
			b	0.11	11.67
			c	0.11	11.67
			d	34.81	36.53
		130	a	0.57	4.69
			b	0.07	16.33
			c	0.07	16.33
			d	26.41	27.43
		140	a	0.01	3.51
			b	0.04	18.08
			c	0.04	18.08

Capacity	Revenue	Demand in %	Price	$gap16$	$gap17$
			d	20.90	21.57

Table A.5: OBP&SPSA+Prices (1-4) – Results in Specific Price Scenario Compared to Results with Transfer Price Optimization, C=100

Capacity	Revenue	Demand in %	Price	$gap16$	$gap17$
120	1	110	a	0.02	2.76
			b	0.13	4.54
			c	0.13	4.54
			d	29.16	31.03
		120	a	0.06	2.14
			b	0.09	7.31
			c	0.09	7.31
			d	18.59	20.55
		130	a	0.03	2.03
			b	0.05	9.23
			c	0.05	9.23
			d	13.36	14.99
		140	a	0.00	1.85
			b	0.04	11.99
			c	0.04	11.99
			d	10.97	12.47
120	2	110	a	0.00	1.66
			b	13.22	14.42
			c	13.22	14.42
			d	13.23	14.42
		120	a	0.01	1.36
			b	5.81	7.18
			c	5.81	7.18
			d	5.90	7.18
		130	a	0.02	1.31
			b	2.27	3.53
			c	2.27	3.53
			d	2.40	3.52
		140	a	0.02	1.87
			b	0.98	2.61
			c	0.98	2.61
			d	0.72	1.82
120	3	110	a	0.37	3.88
			b	1.26	6.71
			c	1.26	6.71
			d	40.22	42.43
		120	a	0.69	3.29
			b	0.07	12.21
			c	0.07	12.21
			d	28.40	30.71
		130	a	0.63	3.15
			b	0.04	16.11
			c	0.04	16.11
			d	22.54	24.45

Capacity	Revenue	Demand in %	Price	$gap16$	$gap17$
		140	a	0.08	2.97
			b	0.01	20.83
			c	0.01	20.83
			d	20.19	21.97
120	4	110	a	0.02	4.41
			b	0.01	6.63
			c	0.01	6.63
			d	41.75	43.43
		120	a	0.01	3.50
			b	0.10	10.43
			c	0.10	10.43
			d	28.26	29.70
		130	a	0.04	3.38
			b	0.07	13.39
			c	0.07	13.39
			d	21.52	22.30
		140	a	0.01	2.92
			b	0.05	16.26
			c	0.05	16.26
			d	18.20	18.69

Table A.6: OBP&SPSA+Prices (1-4) – Results in Specific Price Scenario Compared to Results with Transfer Price Optimization, C=120

Capacity	Revenue	Demand in %	Price	$gap16$	$gap17$
150	1	110	a	0.01	1.87
			b	0.10	3.72
			c	0.10	3.72
			d	21.71	24.01
		120	a	0.01	1.73
			b	0.05	6.12
			c	0.05	6.12
			d	15.43	17.59
		130	a	0.00	1.73
			b	0.03	8.32
			c	0.03	8.32
			d	11.12	12.70
		140	a	0.11	1.81
			b	0.04	11.07
			c	0.04	11.07
			d	9.33	10.57
150	2	110	a	0.01	1.01
			b	9.64	11.23
			c	9.64	11.23
			d	9.67	11.24
		120	a	0.01	1.08
			b	4.82	6.37
			c	4.82	6.37
			d	4.89	6.37
		130	a	0.01	1.01

Capacity	Revenue	Demand in %	Price	$gap16$	$gap17$
			b	1.52	2.73
			c	1.52	2.73
			d	1.62	2.70
		140	a	0.04	1.74
			b	0.40	2.10
			c	0.40	2.10
			d	0.38	1.33
150	3	110	a	0.01	2.93
			b	0.49	5.87
			c	0.49	5.87
			d	30.36	33.02
		120	a	0.00	2.81
			b	0.06	10.38
			c	0.06	10.38
			d	23.71	26.22
		130	a	0.00	2.85
			b	0.03	14.77
			c	0.03	14.77
			d	19.26	21.10
		140	a	0.01	2.94
			b	0.01	19.30
			c	0.01	19.30
			d	17.50	18.96
150	4	110	a	0.01	2.75
			b	0.05	5.19
			c	0.05	5.19
			d	32.53	34.67
		120	a	0.02	2.56
			b	0.08	8.67
			c	0.08	8.67
			d	24.11	25.87
		130	a	0.00	2.66
			b	0.03	12.06
			c	0.03	12.06
			d	18.28	19.07
		140	a	0.00	2.81
			b	0.03	15.24
			c	0.03	15.24
			d	15.76	16.12

Table A.7: OBP&SPSA+Prices (1-4) – Results in Specific Price Scenario Compared to Results with Transfer Price Optimization, C=150

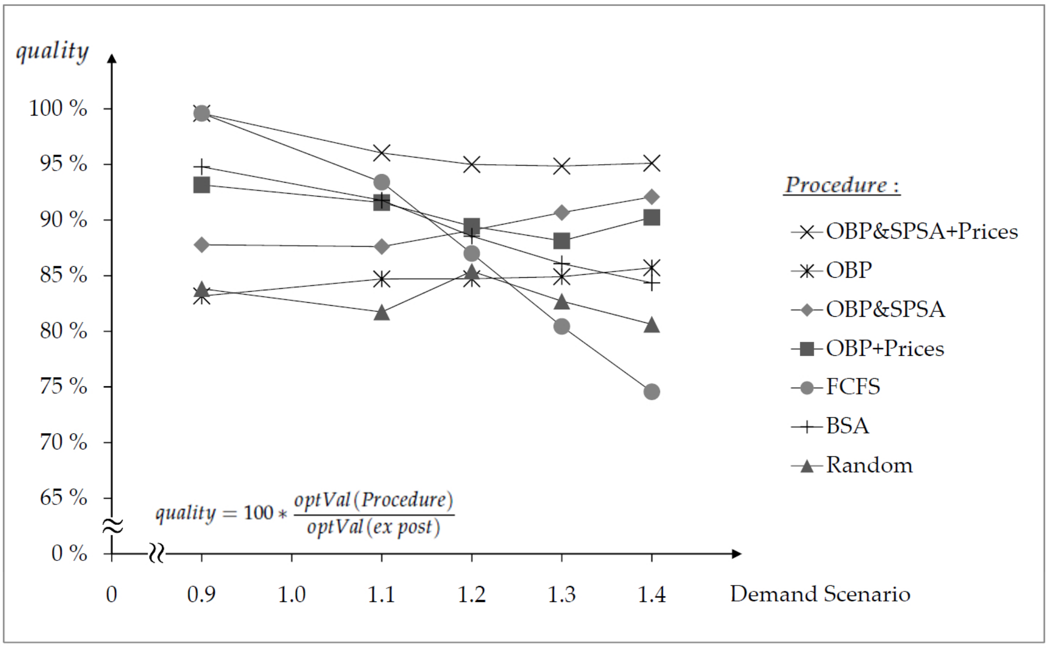

Figure A.1: OBP&SPSA+Prices (1-4) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=100, Demand Scenarios

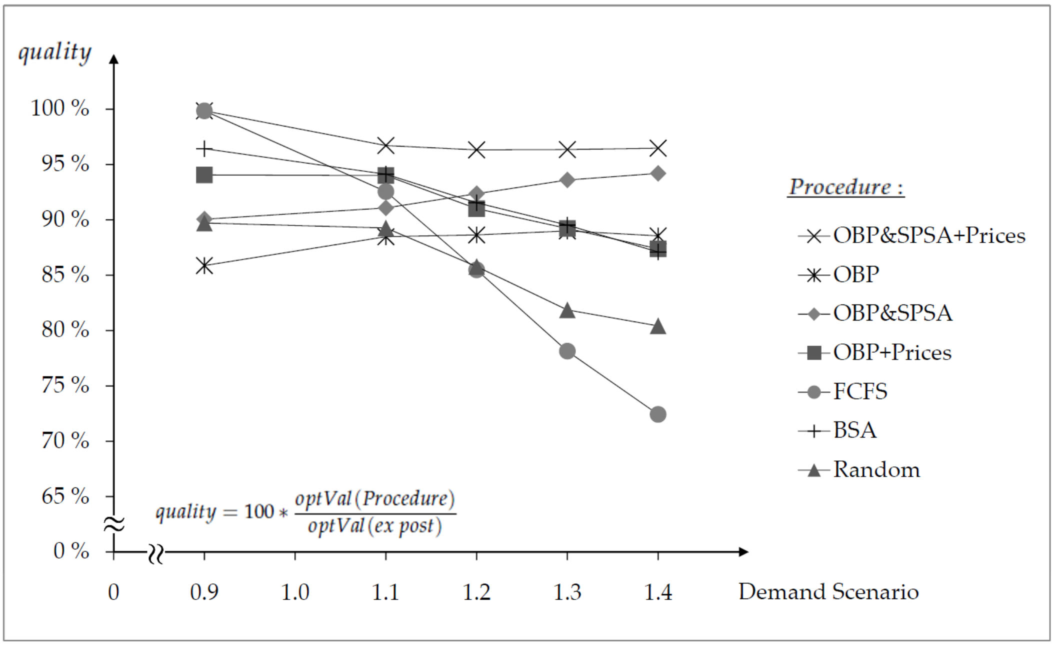

Figure A.2: OBP&SPSA+Prices (1-4) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=150, Demand Scenarios

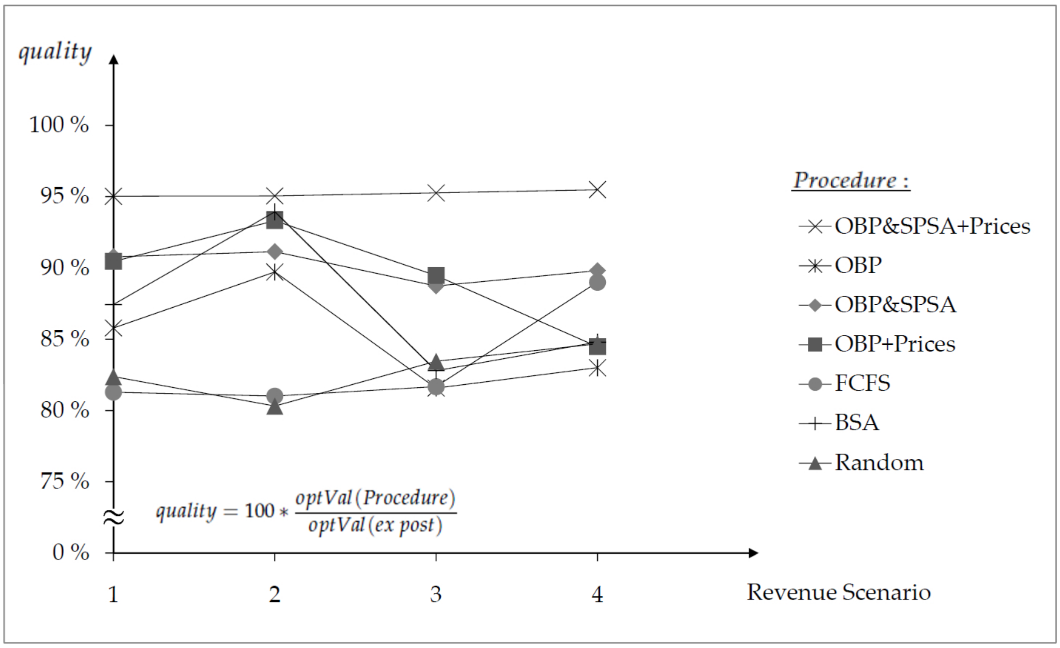

Figure A.3: OBP&SPSA+Prices (1-4) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=100, Revenue Scenarios

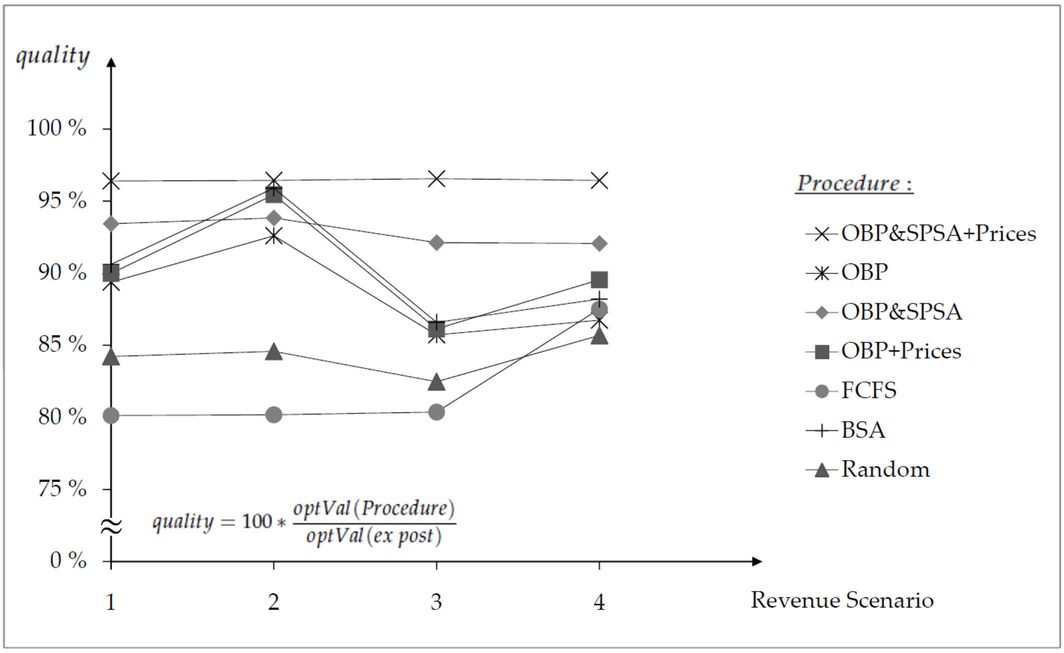

Figure A.4: OBP&SPSA+Prices (1-4) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=150, Revenue Scenarios

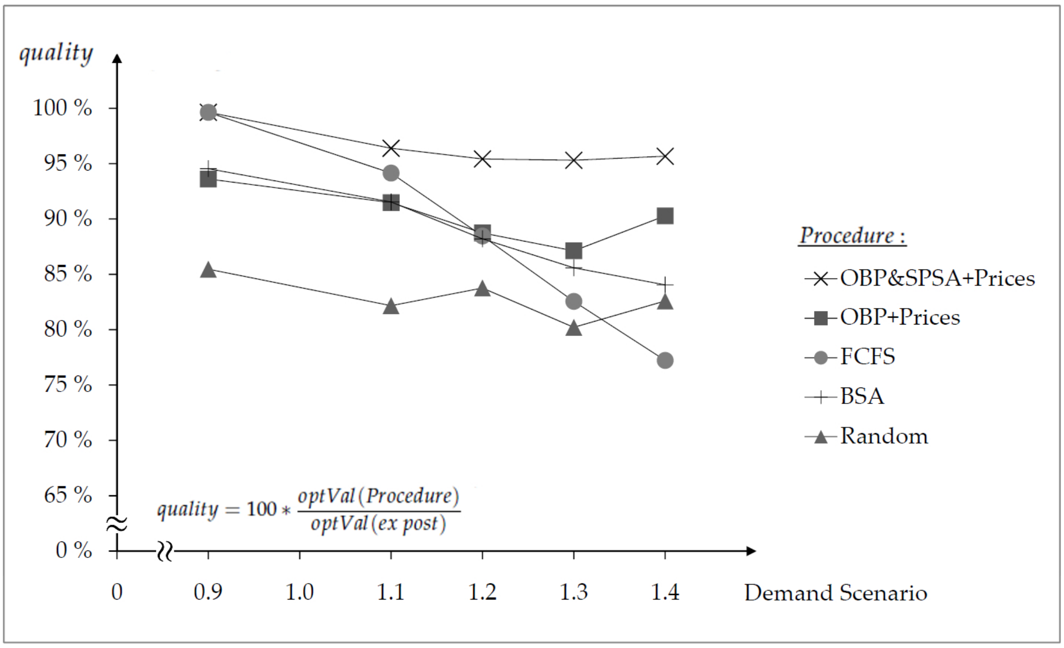

Figure A.5: OBP&SPSA+Prices (1-8) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=100, Demand Scenarios

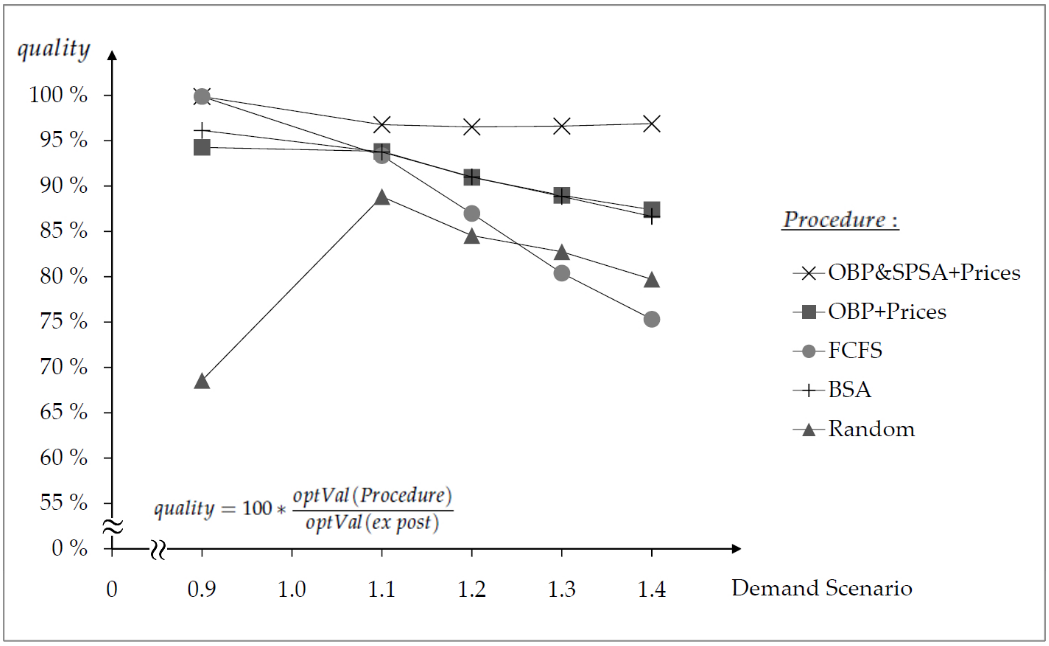

Figure A.6: OBP&SPSA+Prices (1-8) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=150, Demand Scenarios

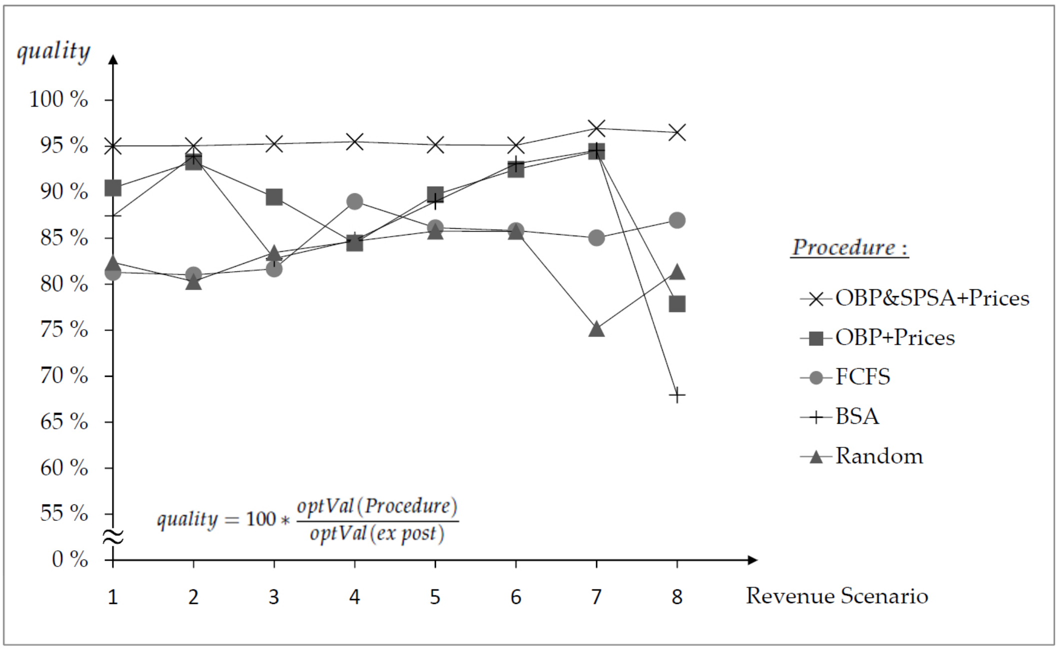

Figure A.7: OBP&SPSA+Prices (1-8) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=100, Revenue Scenarios

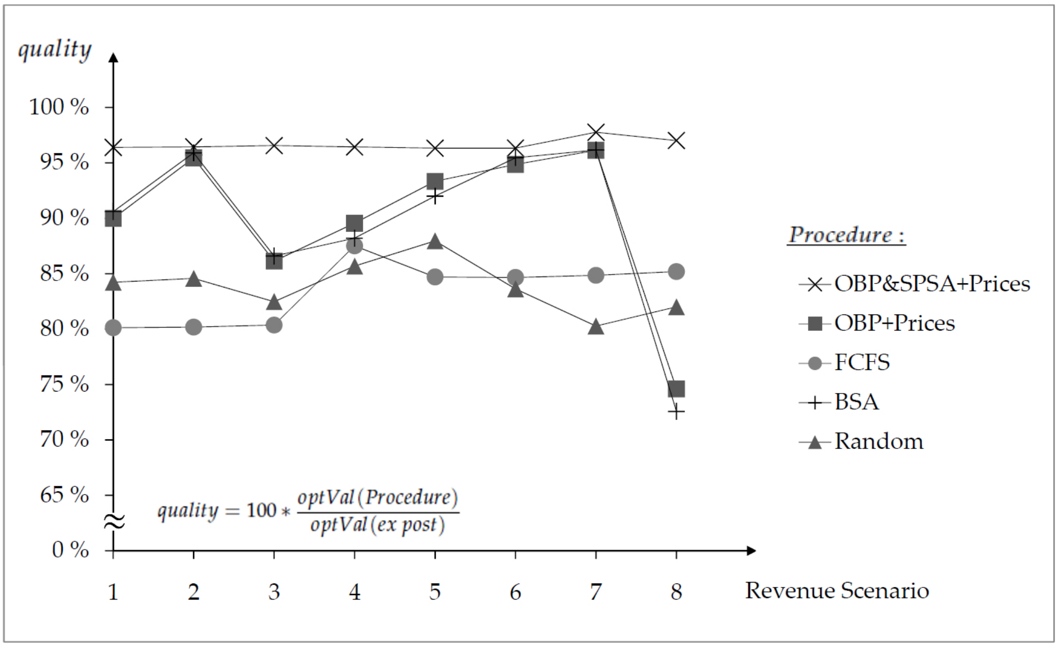

Figure A.8: OBP&SPSA+Prices (1-8) – Performance of Procedures Relative to Ex Post Optimal Solutions, C=150, Revenue Scenarios

Bibliography

Abdulla, M. S. and Bhatnagar, S., (2006), SPSA Algorithms with Measurement Reuse, in: Perrone, L. F., Wieland, F. P., Liu, J., Lawson, B. G., Nicol, D. M., and Fujimoto, R. M., eds., *Proceedings of the 2006 Winter Simulation Conference*, pp. 320–328. (Cited on page 54.)

Ahn, C. W., (2006), *Advances in Evolutionary Algorithms: Theory, Design and Practice*, Springer, Berlin. (Cited on page 69.)

Amaruchkul, K., Cooper, W. L., and Gupta, D., (2007), Single-Leg Air-Cargo Revenue Management, *Transportation Science*, **41** (4), pp. 457–469. (Cited on page 28.)

Amram, M. and Kulatilaka, N., (1999), *Real Options: Managing Strategic Investment in an Uncertain World*, Harvard Business School Press, Boston. (Cited on page 31.)

Anderson, C. K., Davidson, M., and Rasmussen, H., (2004), Revenue Management: A Real Options Approach, *Naval Research Logistics*, **51** (5), pp. 686–703. (Cited on page 31.)

Andersson, S. E., (1998), Passenger Choice Analysis for Seat Capacity Control: A Pilot Project in Scandinavian Airlines, *International Transactions in Operational Research*, **5** (6), pp. 474–486. (Cited on page 13.)

Anjos, M. F., Cheng, R. C. H., and Currie, C. S. M., (2004), Maximizing Revenue in the Airline Industry under One-Way Pricing, *Journal of the Operational Research Society*, **55** (5), pp. 535–541. (Cited on page 12.)

April, J., Glover, F., Kelly, J., and Laguna, M., (2003), Practical Introduction to Simulation Optimization, in: Chick, S., Sanchez, J., Ferrin, D., and Morrice, D., eds., *Proceedings of the 2003 Winter Simulation Conference*, pp. 71–78. (Cited on pages 53, 54, and 63.)

Ashlock, D., (2006), *Evolutionary Computation for Modeling and Optimization*, Springer, Berlin. (Cited on pages 63 and 64.)

Aydin, N., Birbil, S. I., Frenk, J. B. G., and Noyan, N., (2010), Single-Leg Airline Revenue Management with Overbooking, URL: http://www.optimization-online.org/DB_FILE/2010/04/2603.pdf. (Cited on page 13.)

Azadivar, F., (1999), Simulation Optimization Methodologies, in: Farrington, P., Nembhard, H., Sturrock, D., and Evans, G., eds., *Proceedings of the 1999 Winter Simulation Conference*, pp. 93–100. (Cited on page 53.)

Backhaus, K. and Piltz, K., (1990), Strategische Allianzen – eine neue Form kooperativen Wettbewerbs?, in: Backhaus, K. and Piltz, K., eds., *Strategische Allianzen*, Zeitschrift für betriebswirtschaftliche Forschung, Sonderheft 27, pp. 1–10. (Cited on page 23.)

Badinelli, R. D., (2000), An Optimal, Dynamic Policy for Hotel Yield Management, *European Journal of Operational Research*, **121**, pp. 476–503. (Cited on page 29.)

Bailey, E. E., Graham, D. R., and Kaplan, D. P., (1985), *Deregulating the Airlines*, MIT Press, Cambridge. (Cited on page 3.)

Baldenius, T., Reichelstein, S., and Sahay, S. A., (1999), Negotiated versus Cost-Based Transfer Pricing, *Review of Accounting Studies*, **4**, pp. 67–91. (Cited on page 79.)

Barlow, G. L., (2002), Capacity Management in the Football Insdustry, in: Ingold, A., McMahon-Beattie, U., and Yeoman, I., eds., *Yield Management: Strategies for the Service Industries*, vol. 2, Continuum, London, pp. 303–314. (Cited on page 30.)

Barnes-Schuster, D., Bassok, Y., and Anupindi, R., (2002), Coordination and Flexibility in Supply Contracts with Options, *Manufacturing & Service Operations Management*, **4** (3), pp. 171–207. (Cited on page 32.)

Barringer, B. R. and Harrison, J. S., (2000), Walking a Tightrope: Creating Vaiue Through Interorganizational Relationships, *Journal of Management*, **26** (3), pp. 367–403. (Cited on page 26.)

Bartodziej, P., Derigs, U., and Zils, M., (2007), O&D Revenue Management in Cargo Airlines — A Mathematical Programming Approach, *OR Spectrum*, **29**, pp. 105–121. (Cited on page 28.)

Basedow, J. and Jung, C., (1993), *Strategische Allianzen: Die Vernetzung der Weltwirtschaft durch projektbezogene Kooperation im deutschen und europäischen Wettbewerbsrecht*, C. H. Beck, München. (Cited on page 24.)

Beckmann, M. J. and Bobkoski, F., (1958), Airline Demand: An Analysis of Some Frequency Distributions, *Naval Research Logistics Quarterly*, **5** (1), pp. 43–51. (Cited on page 10.)

Beersma, B. and De Dreu, C. K. W., (2002), Integrative and Distributive Negotiation in Small Groups: Effects of Task Structure, Decision Rule, and Social Motive, *Organizational Behavior and Human Decision Processes*, **87** (2), pp. 227–252. (Cited on page 83.)

Belobaba, P., (1987), Air Travel Demand and Airline Seat Inventory Management, Ph.D. thesis, Flight Transportation Laboratory, Massachusetts Institute of Technology, Cambridge, MA. (Cited on pages 1, 5, 20, and 38.)

Belobaba, P., (1989), Application of a Probabilistic Decision Model to Airline Seat Inventory Control, *Operations Research*, **37**, pp. 183–197. (Cited on pages 1, 19, 20, and 38.)

Belobaba, P., (1992), Optimal vs. Heuristic Methods for Nested Seat Allocation, Presentation to the AGIFORS Yield Management Study Group. (Cited on pages 40 and 52.)

Bertsimas, D. and de Boer, S., (2005), Simulation-Based Booking Limits for Airline Revenue Management, *Operations Research*, **53** (1), pp. 90–106. (Cited on pages 18, 22, and 54.)

Bertsimas, D. and Popescu, I., (2003), Revenue Management in a Dynamic Network Environment, *Transportation Science*, **37** (3), pp. 257–277. (Cited on pages 16 and 19.)

Bertsimas, D. and Shioda, R., (2003), Restaurant Revenue Management, *Operations Research*, **51** (3), pp. 472–486. (Cited on page 29.)

Bierman, H. J., (1959), Pricing Intracompany Transfers, *The Accounting Review*, **34** (3), pp. 429–432. (Cited on pages 77, 78, 79, and 80.)

Billings, J. S., Diener, A. G., and Yuen, B. B., (2003), Cargo Revenue Optimisation, *Journal of Revenue and Pricing Management*, **2** (1), pp. 69–79. (Cited on page 28.)

Bitran, G. and Caldentey, R., (2003), An Overview of Pricing Models for Revenue Management, *Manufacturing & Service Operations Management*, **5**, pp. 203–230. (Cited on pages 5 and 6.)

Bitran, G. R. and Gilbert, S. M., (1996), Managing Hotel Reservations with Uncertain Arrivals, *Operations Research*, **44** (1), pp. 35–49. (Cited on page 29.)

Bitran, G. R. and Mondschein, S. V., (1995), An Application of Yield Management to the Hotel Industry Considering Multiple Day Stays, *Operations Research*, **43** (3), pp. 427–443. (Cited on page 29.)

de Boer, S. V., Freling, R., and Piersma, N., (2002), Mathematical Programming for Network Revenue Management Revisited, *European Journal of Operational Research*, **137**, pp. 72–92. (Cited on pages 16 and 41.)

Botimer, T., (1996), Efficiency Considerations in Airline Pricing and Yield Management, *Transportation Research Part A*, **30** (4), pp. 307–317. (Cited on page 12.)

Botimer, T. C. and Belobaba, P. P., (1999), Airline Pricing and Fare Product Differentiation: A New Theoretical Framework, *Journal of the Operational Research Society*, **50** (11), pp. 1085–1097. (Cited on page 12.)

Boyd, E. and Bilegan, I., (2003), Revenue Management and E-Commerce, *Management Science*, **49**, pp. 1363–1386. (Cited on pages 4, 5, 6, 10, 11, 19, and 22.)

Boyd, E. A., (1998), Airline Alliances, *OR/MS Today*, **25** (10), pp. 28–31. (Cited on pages 24, 26, 27, and 92.)

Bratley, P., Fox, B. L., and Schrage, L. E., (1987), *A Guide to Simulation*, Springer, New York. (Cited on page 40.)

Brealey, R. A., Myers, S. C., and Allen, F., (2006), *Corporate Finance*, 8 ed., McGraw-Hill, New York. (Cited on page 31.)

Bront, J. J. M., Méndez-Díaz, I., and Vulcano, G., (2009), A Column Generation Algorithm for Choice-Based Network Revenue Management, *Operations Research*, **57** (3), pp. 769–784. (Cited on page 22.)

Brueckner, J. K., (2001), The Economics of International Codesharing: an Analysis of Airline Alliances, *International Journal of Industrial Organization*, **19**, pp. 1475–1498. (Cited on page 27.)

Brueckner, J. K., (2003), International Airfares in the Age of Alliances: The Effects of Codesharing and Antitrust Immunity, *The Review of Economics and Statistics*, **85** (1), pp. 105–118. (Cited on pages 27 and 32.)

Brueckner, J. K. and Whalen, W. T., (2000), The Price Effects of International Airline Alliances, *Journal of Law & Economics*, **XLII** (2), pp. 503–545. (Cited on page 27.)

Brumelle, S. and McGill, J. I., (1993), Airline Seat Allocation with Multiple Nested Fare Classes, *Operations Research*, **41** (1), pp. 127–137. (Cited on pages 13 and 20.)

Brumelle, S. and Walczak, D., (2003), Dynamic Airline Revenue Management with Multiple Semi-Markov Demand, *Operations Research*, **51** (1), pp. 137–148. (Cited on page 21.)

Cachon, G. P., (2003), Supply Chain Coordination with Contracts, in: Graves, S. C. and de Kok, A. G., eds., *Handbooks in Operations Research and Management Science: Supply Chain Management*, chap. 6, North-Holland, Amsterdam, pp. 229–332. (Cited on pages 25, 80, and 81.)

Cachon, G. P. and Lariviere, M. A., (2005), Supply Chain Coordination with Revenue-Sharing Contracts: Strengths and Limitations, *Management Science*, **51** (1), pp. 30–44. (Cited on page 81.)

Caldentey, R. and Vulcano, G., (2007), Online Auction and List Price Revenue Management, *Management Science*, **53** (5), pp. 795–813. (Cited on page 8.)

Carroll, W. J. and Grimes, R. C., (1995), Ecolutionary Changes in Product Management: Experiences in the Car Rental Industry, *Interfaces*, **25** (5), pp. 84–104. (Cited on page 29.)

Carson, Y. and Maria, A., (1997), Simulation Optimization: Methods and Applications, in: Andradóttir, S., Healy, K. J., Withers, D. H., and Nelson, B. L., eds., *Proceedings of the 1997 Winter Simulation Conference*, pp. 118–126. (Cited on page 53.)

Casson, M. and Mol, M. J., (2006), Strategic Aliances: A Survey of Issues From an Entrepreneurial Perspective, in: Shenkar, O. and Reuer, J. J., eds., *Handbook of Strategic Alliances*, Sage Publications, Inc., Thousand Oaks, pp. 17–37. (Cited on page 23.)

Çetiner, D. and Kimms, A., (2009), Approximate Nucleolus Revenue Allocation in Airline Alliances, Working Paper University of Duisburg-Essen. (Cited on pages 27 and 84.)

Chalos, P. and Haka, S., (1990), Transfer Pricing under Bilateral Bargaining, *The Accounting Review*, **65** (3), pp. 624–641. (Cited on page 79.)

Chapman, S. N. and Carmel, J. I., (1992), Demand/Capacity Management in Health Care: An Application of Yield Management, *Health Care Management Review*, **17** (4), pp. 45–54. (Cited on page 30.)

Chatwin, R., (1998), Multiperiod Airline Overbooking with a Single Fare Class, *Operations Research*, **46** (6), pp. 805–819. (Cited on page 13.)

Chen, Z. and Ross, T. W., (2000), Strategic Alliances, Shared Facilities, and Entry Deterrence, *The RAND Journal of Economics*, **31** (2), pp. 326–344. (Cited on page 24.)

Chiang, W.-C., Chen, J. C., and Xu, X., (2007), An Overview of Research on Revenue Management: Current Issues and Future Research, *International Journal of Revenue Management*, **1** (1), pp. 97–128. (Cited on pages 4, 6, 10, 13, 22, 25, and 26.)

Ciancimino, A., Inzerillo, G., Lucidi, S., and Palagi, L., (1999), A Mathematical Programming Approach for the Solution of the Railway Yield Management Problem, *Transportation Science*, **33** (2), pp. 168–181. (Cited on page 28.)

Cook, P. W. J., (1955), Decentralization and the Transfer-Price Problem, *The Journal of Business*, **28** (2), pp. 87–94. (Cited on pages 77, 78, 79, and 80.)

Corsten, H. and Stuhlmann, S., (1997), Das GAP-Modell als Orientierungsrahmen für ein Kapazitätsmanagement in Dienstleistungsunternehmungen, in: Corsten, H. and Stuhlmann, S., eds., *Kapazitätsmanagement in Dienstleistungsunternehmungen: Grundlagen und Gestaltungsmöglichkeiten*, Gabler, Wiesbaden, pp. 3–54. (Cited on page 7.)

Corsten, H. and Stuhlmann, S., (1999), Yield Management als Ansatzpunkt für die Kapazitätsgestaltung von Dienstleistungsunternehmungen, in: Corsten, H. and Schneider, H., eds., *Wettbewerbsfaktor Dienstleistung: Produktion von Dienstleistungen - Produktion als Dienstleistung*, Vahlen, München, pp. 79–107. (Cited on pages 4, 5, 6, and 7.)

Coughlan, J., (1999), Airline Overbooking in the Multi-Class Case, *Journal of the Operational Research Society*, **50** (11), pp. 1098–1103. (Cited on page 13.)

Cross, R. C., (1995), An Introduction to Revenue Management, in: Jenkins, D., ed., *The Handbook of Airline Economics*, McGraw-Hill, New York, pp. 443–458. (Cited on page 4.)

Cross, R. G., (2001), *Ressourcen erkennen - Umsätze steigern; Mit Revenue Management neue Einnahmequellen erschließen*, Wirtschaftsverlag Carl Ueberreuter, Wien. (Cited on page 4.)

Curry, R. E., (1990), Optimal Airline Seat Allocation with Fare Classes Nested by Origins and Destinations, *Transportation Science*, **24** (3), pp. 193–204. (Cited on pages 20 and 22.)

Dean, J., (1955), Decentralization and Intracompany Pricing, *Harvard Business Review*, **33** (4), pp. 65–74. (Cited on pages 77, 79, and 80.)

Defregger, F. and Kuhn, H., (2007), Revenue Management for a Make-To-Order Company with Limited Inventory Capacity, *OR Spectrum*, **29**, pp. 137–156. (Cited on page 30.)

Dolan, R. J., (1987), Quantity Discounts: Managerial Issues and Research Opportunities, *Marketing Science*, **6** (1), pp. 1–22. (Cited on page 81.)

Domschke, W. and Drexl, A., (2005), *Einführung in Operations Research*, 6 ed., Springer, Berlin. (Cited on page 54.)

Domschke, W., Klein, R., and Petrick, A., (2005), Revenue Management - Instrumente zur Erlösmaximierung im Luftverkehr, *thema Forschung, Forschungsmagazin der TU Darmstadt*, **3**, pp. 46–50. (Cited on page 15.)

Dunleavy, H. N., (1995), Airline Passenger Overbooking, in: Jenkins, D., ed., *The Handbook of Airline Economics*, McGraw-Hill, New York, pp. 469–476. (Cited on page 12.)

Dussauge, P. and Garrette, B., (1999), *Cooperative Strategy: Competing Successfully through Strategic Alliances*, John Wiley and Sons, West Sussex. (Cited on page 24.)

Eccles, R., (1985), *The Transfer Pricing Problem: A Theory for Practice*, Lexington Books, Lexington. (Cited on pages 77, 78, 79, and 80.)

Elmaghraby, W. and Keskinocak, P., (2003), Dynamic Pricing in the Presence of Inventory Considerations: Research Overview, Current Practices and Future Directions, *Management Science*, **49** (10), pp. 1287–1309. (Cited on page 6.)

Essig, M., (2000), Purchasing Consortia as Symbiotic Relationships: Developing the Concept of "Consortium Sourcing", *European Journal of Purchasing & Supply Management*, **6**, pp. 13–22. (Cited on page 30.)

Falkenauer, E., (1998), *Genetic Algorithms and Grouping Problems*, Wiley, New York. (Cited on pages 63, 64, 66, and 67.)

Faßnacht, M., (1996), *Preisdifferenzierung bei Dienstleistungen - Implementierungsformen und Determinanten*, DUV, Wiesbaden. (Cited on page 11.)

Faßnacht, M. and Homburg, C., (1997), Preisdifferenzierung als Instument eines Kapazitätsmanagements, in: Corsten, H. and Stuhlmann, S., eds., *Kapazitätsmanagement in Dienstleistungsunternehmungen: Grundlagen und Gestaltungsmöglichkeiten*, Gabler, Wiesbaden, pp. 137–152. (Cited on page 12.)

Field, D. and Tacoun, F., (2005), Collective Gains, *Airline Business*, **21** (9), pp. 44–46. (Cited on page 26.)

Fitzsimmons, J. A. and Fitzsimmons, M. J., (2006), *Service Management: Operations, Strategy, Information Technology*, 5 ed., McGraw-Hill, New York. (Cited on page 7.)

Friege, C., (1996), Yield-Management, *WiSt - Wirtschaftswissenschaftliches Studium*, **25**, pp. 616–622. (Cited on pages 6 and 15.)

Fu, M. C., (2002), Optimization for Simulation: Theory vs. Practice, *INFORMS Journal on Computing*, **14** (3), pp. 192–215. (Cited on page 53.)

Fudenberg, D. and Tirole, J., (1991), *Game Theory*, The MIT Press, Cambridge. (Cited on page 83.)

Gallego, G. and Phillips, R., (2004), Revenue Management of Flexible Products, *Manufacturing & Service Operations Management*, **6** (4), pp. 321–337. (Cited on pages 28 and 31.)

Gallego, G. and van Ryzin, G., (1994), Optimal Dynamic Pricing of Inventories with Stochastic Demand over Finite Horizons, *Management Science*, **40** (8), pp. 999–1020. (Cited on pages 5 and 10.)

Geraghty, M. K. and Johnson, E., (1997), Revenue Management Saves National Car Rental, *Interfaces*, **27** (1), pp. 107–127. (Cited on page 29.)

Geske, R., (1979), The Valuation of Compound Options, *Journal of Financial Economics*, **7** (1), pp. 63–81. (Cited on page 33.)

Glover, F., Glover, R., Lorenzo, J., and McMillan, C., (1982), The Passenger-Mix Problem in the Scheduled Airlines, *Interfaces*, **12** (3), pp. 73–79. (Cited on page 13.)

Gönsch, J. and Steinhardt, C., (2010), Revenue Management with Opaque Products, Working Paper University of Augsburg. (Cited on page 28.)

Goldman, P., Freling, R., Pak, K., and Piersma, N., (2002), Models and Techniques for Hotel Revenue Management Using a Rolling Horizon, *Journal of Revenue and Picing Management*, **1** (3), pp. 207–219. (Cited on page 29.)

Gosavi, A., (2003), *Simulation-Based Optimization: Parametric Optimization Techniques and Reinforcement Learning*, Kluwer, Boston. (Cited on page 53.)

Gosavi, A., Ozkaya, E., and Kahraman, A. F., (2007), Simulation Optimization for Revenue Management of Airlines with Cancellations and Overbooking, *OR Spectrum*, **29** (1), pp. 21–38. (Cited on pages 41, 53, and 54.)

Graf, M. and Kimms, A., (2009), An Option-Based Revenue Management Procedure for Strategic Airline Alliances, Working Paper University of Duisburg-Essen. (Cited on pages 31 and 53.)

Graf, M. and Kimms, A., (2010), Transfer Price Optimization for Option-Based Airline Alliance Revenue Management, Working Paper University of Duisburg-Essen. (Cited on page 77.)

Haake, C.-J. and Martini, J. T., (2008), Negotiating Transfer Prices, Working Paper Bielefeld University. (Cited on page 79.)

Harris, F. H. and Pinder, J. P., (1995), A Revenue Management Approach to Demand Management and Order Booking in Assemble-to-Order Manufacturing, *Journal of Operations Management*, **13**, pp. 299–309. (Cited on pages 9 and 15.)

Hartley, H. O. and Hocking, R. R., (1971), The Analysis of Incomplete Data, *Biometrics*, **27** (4), pp. 783–823. (Cited on page 10.)

Hellermann, R., (2006), *Capacity Options for Revenue Management*, Springer, Berlin. (Cited on page 31.)

Hendler, R. and Hendler, F., (2004), Revenue Management in Fabulous Las Vegas: Combining Customer Relationship Management and Revenue Management to Maximise Profitability, *Journal of Revenue and Pricing Management*, **3** (1), pp. 73–79. (Cited on page 29.)

Hersh, M. and Ladany, S., (1978), Optimal Seat Allocation for Flights with One Intermediate Stop, *Computers & Operations Research*, **5**, pp. 31–37. (Cited on page 13.)

Hilpisch, Y., (2006), *Options Based Management: Vom Realoptionsansatz zur optionsbasierten Unternehmensführung*, Gabler, Wiesbaden. (Cited on page 31.)

Hintsches, A., Spengler, T., Volling, T., Witting, K., and Priegnitz, G., (2009), Capacity Control in Make-To-Order Manufacturing: Introducing Revenue Management to ThyssenKrupp VDM, Working Paper, Braunschweig University of Technology. (Cited on page 30.)

Hirshleifer, J., (1956), On the Economics of Transfer Pricing, *The Journal of Business*, **29** (3), pp. 172–184. (Cited on pages 77, 78, and 80.)

Holland, J. H., (1975), *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor. (Cited on page 63.)

Homburg, C. and Krohmer, H., (2009), *Marketingmanagement: Strategie - Instrumente - Umsetzung - Unternehmensführung*, 3 ed., Gabler, Wiesbaden. (Cited on page 11.)

Hoseason, J., (2002), Capacity Management in the Cruise Industry, in: Ingold, A., McMahon-Beattie, U., and Yeoman, I., eds., *Yield Management: Strategies for the Service Industries*, vol. 2, Continuum, London, pp. 289–302. (Cited on page 29.)

Hoseason, J. and Johns, N., (1998), The Numbers Game: the Role of Yield Management in the Tour Operations Industry, *Progress in Tourism and Hospitality Research*, **4**, pp. 197–206. (Cited on page 29.)

Hull, J., (2008), *Options, Futures, and Other Derivatives*, vol. 7, Prentice Hall International, New Jersey. (Cited on page 31.)

Johns, N. and Rassing, C., (2004), Revenue Management in Restaurants: A Case Example from Bornholm, Denmark, in: Yeoman, I. and McMahon-Beattie, U., eds., *Revenue Management and Pricing: Case Studies and Applications*, Thomson Learning, London, pp. 46–56. (Cited on page 29.)

Jong, K. D., (2007), Parameter Setting in EAs: a 30 Year Perspective, in: Lobo, F. G., Lima, C. F., and Michalewicz, Z., eds., *Parameter Setting in Evolutionary Algorithms*, Springer, Berlin, pp. 1–18. (Cited on page 69.)

Kaplan, R. S. and Atkinson, A. A., (1998), *Advanced Management Accounting*, The Robert S. Kaplan Series in Management Accounting, 3 ed., Prentice Hall, Upper Saddle River. (Cited on pages 77 and 79.)

Karp, A., (2004), Airlines Pairing Off, *Air Cargo World*, **94** (1), pp. 20–25. (Cited on page 28.)

Kasilingam, R. G., (1996), Air Cargo Revenue Management: Characteristics and Complexities, *European Journal of Operational Research*, **96** (1), pp. 36–44. (Cited on page 28.)

Kelton, W., Sadowski, R., and Sturrock, D., (2004), *Simulation with Arena*, 3 ed., McGraw-Hill, New York. (Cited on page 41.)

Kimes, S. E., (1989), Yield Management: A Tool for Capacity Constrained Service Firms, *Journal of Operations Management*, **8** (4), pp. 348–363. (Cited on pages 5, 6, 7, and 8.)

Kimes, S. E., (2002), A Strategic Approach to Yield Management, in: Ingold, A., McMahon-Beattie, U., and Yeoman, I., eds., *Yield Management: Strategies for the Service Industries*, vol. 2, Continuum, London, pp. 3–14. (Cited on page 7.)

Kimes, S. E. and Schruben, L. W., (2002), Golf Course Revenue Management: A Study of Tee Time Intervals, *Journal of Revenue and Pricing Management*, **1** (2), pp. 111–120. (Cited on page 30.)

Kimes, S. E., Wirtz, J., and Noone, B. M., (2002), How Long Should Dinner Take? Measuring Expected Meal Duration for Restaurant Revenue Management, *Journal of Revenue and Pricing Management*, **1** (3), pp. 220–233. (Cited on page 29.)

Kimms, A. and Klein, R., (2005), Revenue Management im Branchenvergleich, *Zeitschrift für Betriebswirtschaft, Ergänzungsheft 1 "Revenue Management"*, pp. 1–30. (Cited on pages 5, 6, 7, 8, 9, 10, 11, 12, 13, 15, 25, and 29.)

Kimms, A. and Müller-Bungart, M., (2003), Revenue Management beim Verkauf auftragsorientierter Sachleistungen, Working Paper Technical University Bergakademie Freiberg. (Cited on pages 7, 11, 12, 16, and 25.)

Kimms, A. and Müller-Bungart, M., (2006), Revenue Management unter Berücksichtigung des Kundenwahlverhaltens, *WiSt - Wirtschaftswissenschaftliches Studium*, **35** (8), pp. 434–439. (Cited on page 15.)

Kimms, A. and Müller-Bungart, M., (2007a), Revenue Management for Broadcasting Commercials: the Channel's Problem of Selecting and Scheduling the Advertisements to Be Aired, *International Journal of Revenue Management*, **1** (1), pp. 28–44. (Cited on pages 28 and 30.)

Kimms, A. and Müller-Bungart, M., (2007b), Simulation of Stochastic Demand Data Streams for Network Revenue Management Problems, *OR Spectrum*, **29** (1), pp. 5–20. (Cited on page 41.)

Klein, R., (2001), Revenue Management: Quantitative Methoden zur Erlösmaximierung in der Dienstleistungsproduktion, *Betriebswirtschaftliche Forschung und Praxis*, **53** (3), pp. 245–259. (Cited on pages 5, 6, 9, 12, 19, and 21.)

Klein, R., (2005), *Revenue Management: Grundlagen und Methoden der Kapazitätssteuerung*, Habilitation thesis, TU Darmstadt. (Cited on pages 3, 4, 5, 6, 7, 9, 11, 12, 13, 14, 15, 17, 18, 19, 20, 41, 47, 53, 54, 63, 78, and 94.)

Klein, R., (2007), Network Capacity Control Using Self-Adjusting Bid-Prices, *OR Spectrum*, **29**, pp. 39–60. (Cited on page 41.)

Kleindorfer, P. R. and Wu, D. J., (2003), Integrating Long- and Short-Term Contracting via Business-to-Business Exchanges for Capital-Intensive Industries, *Management Science*, **49** (11), pp. 1597–1615. (Cited on page 32.)

Klophaus, R., (1998), Revenue Management: Wie die Airline Ertragswachstum schafft, *Absatzwirtschaft - Zeitschrift für Marketing*, **41**, pp. 146–152. (Cited on pages 4 and 12.)

Koide, T. and Ishii, H., (2005), The Hotel Yield Management with Two Types of Room Prices, Overbooking and Cancellations, *International Journal of Production Economics*, **93-94**, pp. 417–428. (Cited on page 29.)

Kolisch, R. and Zatta, D., (2009), Stand und Perspektiven des Einsatzes von Revenue Management in der Prozessindustrie, *Zeitschrift f¨ur Planung & Unternehmenssteuerung*, **20**, pp. 197–214. (Cited on page 30.)

Kuhn, A. and Wenzel, S., (2008), Simulation logistischer Systeme, in: Arnold, D., Isermann, H., Kuhn, A., and Tempelmeier, H., eds., *Handbuch Logistik*, 3 ed., Springer, Berlin, pp. 73–94. (Cited on page 41.)

Ladany, S. and Bedi, D., (1977), Dynamic Booking Rules for Flights with an Intermediate Stop, *Omega*, **5** (6), pp. 721–730. (Cited on page 13.)

Law, A. M., (2007), *Simulation Modeling and Analysis*, 4 ed., McGraw-Hill, New York. (Cited on pages 40, 41, and 53.)

Lee, L. H., Chew, E. P., and Sim, M. S., (2007), A Heuristic to Solve a Sea Cargo Revenue Management Problem, *OR Spectrum*, **29**, pp. 123–136. (Cited on page 29.)

Lee, T. C. and Hersh, M., (1993), A Model for Dynamic Airline Seat Inventory Control with Multiple Seat Bookings, *Transportation Science*, **27** (3), pp. 252–265. (Cited on pages vii, 10, 16, 17, 18, and 21.)

Leguizamón, G., Blum, C., and Alba, E., (2007), Evolutionary Computation, in: Gonzalez, T. F., ed., *Handbook of Approximation Algorithms and Metaheuristics*, chap. 24, Taylor & Francis Group, Boca Raton, pp. 24–1 – 24–15. (Cited on page 67.)

Lewicki, R. J., Saunders, D. M., and Minton, J. W., (1999), *Negotiation*, 3 ed., McGraw-Hill, New York. (Cited on page 83.)

Little, R. J. A., (1982), Models for Nonresponse in Sample Surveys, *Journal of the American Statistical Association*, **77** (378), pp. 237–250. (Cited on page 10.)

Littlewood, K., (1972), Forecasting and Control of Passenger Bookings, in: *Proceedings of the Twelfth Annual AGIFORS Symposium*, Nathanya, Israel, pp. 95–117. (Cited on pages 4, 10, 13, and 20.)

Liu, Q. and van Ryzin, G., (2008), On the Choice-Based Linear Programming Model for Network Revenue Management, *Manufacturing & Service Operations Management*, **10** (2), pp. 288–310. (Cited on page 22.)

Luecke, R., (2003), *Negotiation: Authoritative Answers at Your Fingertips. Your Mentor and Guide to Doing Business Effectively*, Harvard Business School Press, Boston. (Cited on page 83.)

Lutz, V., (1993), *Horizontale strategische Allianzen*, vol. 5, Duisburger Betriwebswirtschaftliche Schriften, S+W Steuer- und Wirtschaftsverlag, Hamburg. (Cited on page 23.)

Maryak, J. L. and Chin, D. C., (2001), Global Random Optimization by Simultaneous Perturbation Stochastic Approximation, in: Peters, B. A., Smitha, J. S., Medeiros, D. J., and Rohrer, M. W., eds., *Proceedings of the 33nd Conference on Winter Simulation*, Arlington, Virginia, pp. 307–312. (Cited on pages 56 and 72.)

Mayer, G., (2001), *Strategische Logistikplanung von Hub&Spoke-Systemen*, DUV, Wiesbaden. (Cited on page 3.)

McAfee, R. P. and McMillan, J., (1987), Auctions and Bidding, *Journal of Economic Literature*, **25**, pp. 699–738. (Cited on page 8.)

McGill, J. I., (1995), Censored Regression Analysis of Multiclass Passenger Demand Data Subject to Joint Capacity Constraints, *Annals of Operations Research*, **60**, pp. 209–240. (Cited on page 10.)

McGill, J. I. and van Ryzin, G. J., (1999), Revenue Management: Research Overview and Prospects, *Transportation Science*, **33** (2), pp. 233–256. (Cited on pages 4, 10, 12, 13, 14, 17, 19, 21, 22, 25, and 41.)

Milgrom, P., (1989), Auctions and Bidding: A Primer, *Journal of Economic Perspectives*, **3** (3), pp. 3–22. (Cited on page 8.)

Mitchell, M., (1999), *An Introduction to Genetic Algorithms*, MIT Press, Cambridge. (Cited on page 68.)

Müller-Bungart, M., (2006), *Revenue Management with Flexible Products – Models and Methods for the Broadcasting Industry*, Springer, Berlin. (Cited on pages 4, 6, 7, 8, 9, 14, 16, 17, 18, 19, 28, 29, 30, and 53.)

Moore, W. T., (2001), *Real Options and Option-Embedded Securities*, John Wiley and Sons, New York. (Cited on page 33.)

Morris, D. and Hergert, M., (1987), Trends in International Collaborative Agreements, *Columbia Journal of World Business*, **22** (2), pp. 15–21. (Cited on page 24.)

Morrison, S. and Winston, C., (1995), *The Evolution of the Airline Industry*, The Brookings Institution, Washington, D.C. (Cited on page 3.)

Myers, S. C., (1977), Determinants of Corporate Borrowing, *Journal of Financial Economics*, **5** (2), pp. 147–175. (Cited on page 31.)

Nash, J. F., (1950), The Bargaining Problem, *Econometrica*, **18** (2), pp. 155–162. (Cited on page 84.)

Nash, J. F., (1953), Two-Person Cooperative Games, *Econometrica*, **21** (1), pp. 128–140. (Cited on page 84.)

Netessine, S. and Shumsky, R., (2002), Introduction to the Theory and Practice of Yield Management, *INFORMS Transcations on Education*, **3** (1), pp. 34–44. (Cited on pages 5 and 7.)

Netessine, S. and Shumsky, R. A., (2005), Revenue Management Games: Horizontal and Vertical Competition, *Management Science*, **51** (5), pp. 813–831. (Cited on page 24.)

Nieuwmeijer, L., (1992), *Negotiation: Methodology andTraining*, 2 ed., HSRC Publishers, Pretoria. (Cited on page 83.)

O'Neal, J. W., Jacob, M. S., Farmer, A. K., and Martin, K. G., (2007), Development of a Codeshare Flight-Profitability System at Delta Air Lines, *Interfaces*, **37** (5), pp. 436–444. (Cited on pages 24, 26, and 27.)

Opdemom, P., (1998), *Strategische Allianzen und Wettbewerb: Das Beispiel des US-Marktes für internationale Telekommunikation*, Institut für Wirtschaftspolitik, Universität zu Köln, Köln. (Cited on page 23.)

Oum, T. H. and Park, J. H., (1997), Airline Alliances: Current Status, Policy Issues, and Future Directions, *Journal of Air Transport Management*, **3** (3), pp. 133–144. (Cited on pages 26 and 27.)

Oum, T. H., Park, J.-H., and Zhang, A., (1996), The Effects of Airline Codesharing Agreements on Firm Conduct and International Air Fares, *Journal of Transport Economics and Policy*, **30** (2), pp. 187–202. (Cited on page 27.)

Oum, T. H., Taylor, A. J., and Zhang, A., (1993), Strategic Airline Policy in the Globalizing Airline Networks, *Transportation Journal*, **32** (3), pp. 14–30. (Cited on page 26.)

Oum, T. H., Yu, C., and Zhang, A., (2001), Global Airline Alliances: International Regulatory Issues, *Journal of Air Transport Management*, **7** (1), pp. 57–62. (Cited on pages 24 and 26.)

Pak, K., (2005), Revenue Management: New Features and Models, Ph.D. thesis, Erasmus Research Institute of Management (ERIM), Erasmus University Rotterdam, Netherlands. (Cited on pages 11, 13, 15, and 19.)

Pak, K. and Dekker, R., (2004), Cargo Revenue Management: Bid-Prices for a 0-1 Multi Knapsack Problem, ERIM Report Series Research in Management 55, Erasmus University Rotterdam. (Cited on page 28.)

Pak, K. and Piersma, N., (2002), Overview of OR Techniques for Airline Revenue Management, *Statistica Neerlandica*, **56** (4), pp. 479–495. (Cited on pages 11 and 13.)

Park, J.-H., (1997), The Effect of Airline Alliances on Markets and Economic Welfare, *Transportation Research Part E*, **33** (3), pp. 181–195. (Cited on page 27.)

Park, J.-H. and Zhang, A., (1998), Airline Alliances and Partner Firms' Outputs, *Transportation Research Part E*, **34** (4), pp. 245–255. (Cited on pages 26 and 27.)

Park, J.-H. and Zhang, A., (2000), An Empirical Analysis of Global Airline Alliances: Cases in North Atlantic Markets, *Review of Industrial Organization*, **16**, pp. 367–383. (Cited on page 27.)

Park, J.-H., Zhang, A., and Zhang, Y., (2001), Analytical Models of International Alliances in the Airline Industry, *Transportation Research Part B*, **35**, pp. 865–886. (Cited on pages 26 and 27.)

Pasternack, B. A., (1985), Optimal Pricing and Return Policies for Perishable Commodities, *Marketing Science*, **4** (2), pp. 166–176. (Cited on page 81.)

Petrick, A., (2009), Multimodale Produkte im Revenue Management - Potenziale und Ansätze zur Realisierung einer Kapazitätssteuerung, Ph.D. thesis, TU Darmstadt. (Cited on page 28.)

Phillips, R. L., (2005), *Pricing and Revenue Optimization*, Stanford University Press, Stanford. (Cited on pages 6 and 12.)

Pulugurtha, S. S. and Nambisan, S. S., (2003), A Decision-Support Tool for Airline Yield Management Using Genetic Algorithms, *Computer-Aided Civil and Infrastructure Engineering*, **18**, pp. 214–223. (Cited on page 64.)

Quante, R., Meyr, H., and Fleischmann, M., (2009), Revenue Management and Demand Fulfillment: Matching Applications, Models, and Software, *OR Spectrum*, **31**, pp. 31–62. (Cited on page 30.)

Reeves, C., (2003), Genetic Algorithms, in: Glover, F. and Kochenberger, G. A., eds., *Handbook of Metaheuristics*, chap. 3, Kluwer, New York, pp. 55–82. (Cited on page 68.)

Reeves, C. R. and Rowe, J. E., (2002), *Genetic Algorithms – Principles and Perspectives: A Guide to GA Theory*, Kluwer, New York. (Cited on pages 63 and 65.)

Rehkopf, S., (2006), *Revenue Management-Konzepte zur Auftragsannahme bei kundenindividueller Produktion: Am Beispiel der Eisen und Stahl erzeugenden Industrie*, Gabler, Deutscher Universitäts-Verlag, Wiesbaden. (Cited on page 13.)

Robinson, L. W., (1995), Optimal and Approximate Control Policies for Airline Booking with Sequential Nonmonotonic Fare Classes, *Operations Research*, **43** (2), pp. 252–263. (Cited on page 53.)

Rothlauf, D. F., (2006), *Representations for Genetic and Evolutionary Algorithms*, 2 ed., Springer, Berlin. (Cited on page 64.)

Rothstein, M., (1971), An Airline Overbooking Model., *Transportation Science*, **5**, pp. 180–192. (Cited on pages 4 and 13.)

Rothstein, M., (1974), Hotel Overbooking as a Markovian Sequential Decision Process, *Decision Sciences*, **5**, pp. 389–404. (Cited on pages 4 and 29.)

Rothstein, M., (1985), OR and the Airline Overbooking Problem, *Operations Research*, **33** (2), pp. 237–248. (Cited on page 12.)

Rubinstein, A., (1982), Perfect Equilibrium in a Bargaining Model, *Econometrica*, **50** (1), pp. 97–109. (Cited on page 84.)

Rudi, N. and Pyke, D. F., (2000), Teaching Supply Chain Concepts with the Newsboy Problem, in: Johnson, M. E. and Pyke, D. F., eds., *Supply Chain Management: Innovations for Education*, vol. 2, Production and Operations Management Society, Miami, pp. 170–180. (Cited on page 32.)

van Ryzin, G. J. and Vulcano, G., (2008a), Computing Virtual Nesting Controls for Network Revenue Management Under Customer Choice Behavior, *Manufacturing & Service Operations Management*, **10**, pp. 448–467. (Cited on page 22.)

van Ryzin, G. J. and Vulcano, G., (2008b), Simulation-Based Optimization of Virtual Nesting Controls for Network Revenue Management, *Operations Research*, **56** (4), pp. 865–880. (Cited on pages 22 and 54.)

Schulte, G., (2003), Die Kooperation im europäischen Wettbewerb, in: Zentes, J., Swoboda, B., and Morschett, D., eds., *Kooperationen, Allianzen und Netzwerke: Grundlagen – Ansätze – Perspektiven*, Gabler, Wiesbaden, pp. 333–358. (Cited on page 24.)

Shlifer, E. and Vardi, Y., (1975), An Airline Overbooking Policy, *Transportation Science .*, **9** (2), pp. 101–114. (Cited on page 13.)

Shumsky, R., (2006), The Southwest Effect, Airline Alliances and Revenue Management, *Journal of Revenue and Pricing Management*, **5** (1), pp. 83–89. (Cited on pages 24, 25, 26, 32, 80, and 81.)

Silver, E., Pyke, D., and Peterson, R., (1998), *Inventory Management and Production Planning and Scheduling*, John Wiley and Sons, New York. (Cited on page 80.)

Simchi-Levi, D., Kaminsky, P., and Simchi-Levi, E., (2004), *Managing the Supply Chain: The Definitive Guide for the Business Professional*, McGraw-Hill, New York. (Cited on page 30.)

Slager, B. and Kapteijns, L., (2004), Implementation of Cargo Revenue Management at KLM, *Journal of Revenue and Pricing Management*, **3** (1), pp. 80–90. (Cited on page 28.)

Smith, B., Leimkuhler, J., and Darrow, R., (1992), Yield Management at American Airlines, *Interfaces*, **22** (1), pp. 8–31. (Cited on pages 4, 12, and 13.)

Smith, B. C. and Penn, C. W., (1988), Analysis of Alternative Origin-Destination Control Strategies, in: *AGIFORS Symposium Proceedings*, vol. 28, New Seabury, MA. (Cited on page 22.)

Spall, J. C., (1988), A Stochastic Approximation Algorithm for Large-Dimensional Systems in the Kiefer-Wolfowitz Setting, in: *Proceedings of the 27th Conlerence on Decision and Control*, Austin, TX, pp. 1544–1548. (Cited on page 56.)

Spall, J. C., (1992), Multivariate Stochastic Approximation using a Simultaneous Perturbation Gradient Approximation, *IEEE Transactions on Automatic Control*, **37** (3), pp. 332–341. (Cited on pages 53, 54, and 56.)

Spall, J. C., (1997), A One-Measurement Form of Simultaneous Stochastic Approximation, *Automatica*, **33** (1), pp. 109–112. (Cited on page 54.)

Spall, J. C., (1998a), Implementation of the Simultaneous Perturbation Algorithm for Stochastic Optimization, *IEEE Transactions on Aerospace and Electronic Systems*, **34** (3), pp. 817–823. (Cited on pages 55 and 57.)

Spall, J. C., (1998b), An Overview of the Simultaneous Perturbation Method for Efficient Optimization, *Johns Hopkins APL Technical Digest*, **19** (4), pp. 482–492. (Cited on page 54.)

Spall, J. C., (2003), *Introduction to Stochastic Search and Optimization: Estimation, Simulation, and Control*, Wiley, New York. (Cited on pages 53, 54, 56, 63, and 64.)

Spall, J. C., (2004), Stochastic Optimization, in: Gentle, J., Härdle, W., and Mori, Y., eds., *Handbook of Computational Statistics*, chap. 6, Springer, Heidelberg, pp. 169–197. (Cited on page 67.)

Spengler, T. and Rehkopf, S., (2005), Revenue Management Konzepte zur Entscheidungsunterstützung bei der Annahme von Kundenaufträgen, *Zeitschrift für Planung & Unternehmenssteuerung*, **16** (2), pp. 123–146. (Cited on page 30.)

Spengler, T., Volling, T., and Hintsches, A., (2008), Integration von Revenue Management Konzepten in der Auftragsannahme - konkretisiert für Unternehmen der eisen- und Stahlerzeugenden Industrie, *Zeitschrift für Betriebswirtschaft*, **Special Issue 4**, pp. 125–151. (Cited on page 30.)

Steinhardt, C. and Gönsch, J., (2009), Dynamic Programming Decomposition Approaches for Revenue Management with Planned Upgrades, Working Paper University of Augsburg. (Cited on page 29.)

Stone, W. E., (1956), Intracompany Pricing, *The Accounting Review*, **31** (4), pp. 625–627. (Cited on pages 77, 79, and 80.)

Strasser, S., (1996), The Effect of Yield Management on Railroads, *Transportation Quarterly*, **50** (2), pp. 47–55. (Cited on page 29.)

Stuhlmann, S., (1999), Die Bedeutung des externen Faktors in der Dienstleistungsproduktion, in: Corsten, H. and Schneider, H., eds., *Wettbewerbsfaktor Dienstleistung: Produktion von Dienstleistungen - Produktion als Dienstleistung*, Vahlen, München, pp. 23–58. (Cited on page 9.)

Subramanian, J., Stidham, S. J., and Lautenbacher, C. J., (1999), Yield Management with Overbooking, Cancellations and No Shows, *Transportation Science*, **33** (2), pp. 147–167. (Cited on pages 10, 13, and 21.)

Swisher, J., Hyden, P., Jacobson, S., and Schruben, L., (2000), A Survey of Simulation Optimization Techniques and Procedures, in: Joines, J., Barton, R., Kang, K., and Fishwick, P., eds., *Proceedings of the 2000 Winter Simulation Conference*, pp. 119–128. (Cited on page 53.)

Talbi, E.-G., (2009), *Metaheuristics: From Design to Implementation*, Wiley, Hoboken. (Cited on pages 64, 66, 67, 68, and 69.)

Talluri, K. T. and van Ryzin, G. J., (2004a), Revenue Management Under a General Discrete Choice Model of Consumer Behavior, *Management Science*, **50** (1), pp. 15–33. (Cited on pages 17 and 21.)

Talluri, K. T. and van Ryzin, G. J., (2004b), *The Theory and Practice of Revenue Management*, Springer, New York. (Cited on pages 1, 3, 4, 5, 6, 10, 14, 15, 16, 17, 18, 19, 20, 21, 22, 25, 37, 39, 40, 41, 42, 45, 51, and 92.)

Tang, R. Y. W., (1979), *Transfer Pricing Practices in the United States and Japan*, Praeger Publishers, New York. (Cited on page 78.)

Tang, R. Y. W., (1993), *Transfer Pricing in the 1990s: Tax and Management Perspectives*, Quorum Books, Westport. (Cited on page 77.)

Taylor, T. A., (2002), Supply Chain Coordination under Channel Rebates with Sales Effort Effects, *Management Science*, **48** (8), pp. 992–1007. (Cited on page 81.)

Tobin, J., (1958), Estimation of Relationships for Limited Dependent Variables, *Econometrica*, **26** (1), pp. 24–36. (Cited on page 10.)

Trigeorgis, L., (1996), *Real Options: Managerial Flexibility and Strategy in Resource Allocation*, MIT Press., Cambridge. (Cited on pages 31 and 33.)

Tsay, A. A., (1999), The Quantity Flexibility Contract and Supplier-Customer Incentives, *Management Science*, **45** (10), pp. 1339–1358. (Cited on page 81.)

Tscheulin, D. K. and Lindenmeier, J., (2003a), Yield Management - Ein State-of-the-Art, *Zeitschrift für Betriebswirtschaft*, **73** (6), pp. 629–662. (Cited on pages 4, 5, 13, and 25.)

Tscheulin, D. K. and Lindenmeier, J., (2003b), Yield Management - Erlösoptimale Steuerung von Preisen und Kapazitäten, *WISU - Das Wirtschaftsstudium*, **32**, pp. 1513–1518. (Cited on pages 6 and 15.)

U.S. GAO, (1996), Airline Deregulation: Changes in Airfares, Service, and Safety at Small, Medium-Sized, and Large Communities, United States General Accounting Office, Report to the Chairman, Committee on Commerce, Science, and Transportation, U.S. Senate, URL: http://www.gao.gov/archive/1996/rc96079.pdf, Date of Access: 27. Sept. 2010. (Cited on page 3.)

Varian, H. R., (1999), *Intermediate Microeconomics - A Modern Approach*, 7 ed., W. W. Norton & Company, New York. (Cited on page 11.)

Verlage, H. C., (1975), *Transfer Pricing for Multinational Enterprises*, Rotterdam University Press, Rotterdam. (Cited on page 77.)

Vinod, B., (1995), Origin-and-Destination Yield Management, in: Jenkins, D., ed., *The Handbook of Airline Economics*, McGraw-Hill, New York, pp. 459–468. (Cited on page 21.)

Vinod, B., (2005), Alliance Revenue Management, *Journal of Revenue and Pricing Management*, **4** (1), pp. 66–82. (Cited on pages 24, 26, and 27.)

Vulcano, G., van Ryzin, G., and Maglaras, C., (2002), Optimal Dynamic Auctions for Revenue Management, *Management Science*, **48** (11), pp. 1388–1407. (Cited on page 8.)

Weatherford, L. R., (1998), A Tutorial on Optimization in the Context of Perishable-Asset Revenue Management Problems for the Airline Industry, in: Yu, G., ed., *Operations Research in the Airline Industry*, Kluwer Academic Publishers, Boston, pp. 68–100. (Cited on page 6.)

Weatherford, L. R. and Belobaba, P. P., (2002), Revenue Impacts of Fare Input and Demand Forecast Accuracy in Airline Yield Management, *Journal of the Operational Research Society*, **53**, pp. 811–821. (Cited on page 10.)

Weatherford, L. R. and Bodily, S. E., (1992), A Taxonomy and Research Overview of Perishable-Asset Revenue Management: Yield Management, Overbooking, and Pricing, *Operations Research*, **40** (5), pp. 831–844. (Cited on pages 4, 5, 6, 7, and 8.)

Wiggershaus, J., (2008), *Ein wertorientiertes Auftragsannahmeverfahren für das Revenue-Management in der Sachgüterindustrie*, Kovač, Hamburg. (Cited on pages 11 and 13.)

Williamson, E. L., (1992), Airline Network Seat Control: Methodologies and Revenue Impacts, Ph.D. thesis, Massachusetts Institute of Technology, Cambridge, MA. (Cited on pages 1, 14, 15, 16, 19, 22, 34, and 92.)

Wollmer, R. D., (1992), An Airline Seat Management Model for a Single Leg Route when Lower Fare Classes Book First, *Operations Research*, **40** (1), pp. 26–37. (Cited on pages 13 and 20.)

Wright, C. P., Groenevelt, H., and Shumsky, R. A., (2010), Dynamic Revenue Management in Airline Alliances, *Transportation Science*, **44** (1), pp. 15–37. (Cited on pages 27, 84, and 88.)

Zeni, R. H., (2001), Improved Forecast Accuracy in Airline Revenue Management by Unconstraining Demand Estimates from Censored Data, Ph.D. thesis, Rutgers University, Newark, NJ. (Cited on page 10.)

Zentes, J., Swoboda, B., and Morschett, D., (2005), Kooperationen, Allianzen und Netzwerke – Grundlagen, "Metaanalyse" und Kurzabriss, in: Zentes, J., Swoboda, B., and Morschett, D., eds., *Kooperationen, Allianzen und Netzwerke: Grundlagen – Ansätze – Perspektiven*, 2 ed., Gabler, Wiesbaden, pp. 3–32. (Cited on page 23.)

Zhang, A. and Zhang, Y., (2006), Rivalry Between Strategic Alliances, *International Journal of Industrial Organization*, **24**, pp. 287–301. (Cited on pages 23, 24, and 29.)

Zhao, W. and Zheng, Y.-S., (2001), A Dynamic Model for Airline Seat Allocation with Passenger Diversion and No-Shows, *Transportation Science*, **35** (1), pp. 80–98. (Cited on pages 13 and 21.)