Working Paper: Uncertainty in Airline Revenue Management – An Overview of Flexible and Stable Solutions

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Abstract

Revenue management (RM) strives to control inventory in a way that maximizes revenue given a set of assumptions about demand, capacity and prices. This makes RM a well-suited example for planning under uncertainty. This paper applies a definition of risk and uncertainty to the RM context before identifying sources of uncertainty affecting the RM process. We find that uncertainties can arise with regard to model data and parameters as well as from the formulation of a model structure and the optimization objective. However, especially considering assumptions regarding prices and capacity, uncertainties from beyond the scope of the RM process can also affect RM performance. In the light of these findings, existing research literature proposing stable and flexible solutions is summarized and categorized. The resulting review strives to present both a motivation and a basis for the future design of robust principles for revenue management.

1 Introduction

"Without risks, no company would be able to achieve anything or make a profit" (Lancaster, 2003). This statement motivates our paper, as it also applies to Revenue Management (RM) systems. This paper provides an overview of uncertainties and risks affecting RM and detail existing flexible and stable solutions from theory and practice. We propose a new approach for a methodical allocation of these topics. All structures and reviews provided are summarized in an overview table containing the dimensions of uncertainty and risk, related research directions, as well as some selected literature. This paper follows the tradition of literature reviews, highlighting several aspects of RM such as McGill and van Ryzin (1999), Shen and Su (2007) and Quante et al. (2009).

Revenue management aims to maximize a company's revenue by optimally allocating customer requests to a limited capacity. The airline industry strives to perfect this technology and still constitutes RM's most important application area. Therefore, the overall structure of this paper follows the conventional process of airline revenue management (ARM). The approaches proposed are considered as applying to ARM, although some research contributions and applied methods are related to other industries.

1.1 Risk versus Uncertainty

For our purpose, we have to establish a differentiated view of the terms *risk* and *uncertainty*, as these terms are used differently from one source to another. Knight (1921) can be seen as a thought leader in this regard. His ideas and considerations were picked up and discussed anew by Runde (1998). Within this paper, we apply the resulting definitions, while aware that other authors regard risk and uncertainty as synonyms (e.g. Huang and Chang (2009)). Knight (1921) distinguishes three concepts: a priori probabilities, statistical probabilities and estimates.

A priori probabilities exist in an environment where an outcome can be perfectly quantified by mathematics. E.g., the outcome of a coin flip can be seen as an a priori probability, as heads and tail can both be tagged with a mathematical chance of exactly 50% each. Thus, a decision maker knows an event's stochastic nature accurately before it takes place and is able to use this information in advance. Such a situation reflects the purest form of a *risk*.

Statistical probabilities exist the outcome of different realizations of the same experiment can be observed. This enables us to assume a stochastic process that can reflect the actual process behaviour. Consider the following experiment: A person receives the outcome of different dice casts. Even not knowing know how many sides the dice used had, she can continuously update her assumption about this process from observation. After a sufficient number of casts, the observer will be able to predict the chance for a specific outcome with growing accuracy – the correct probability can be estimated but not known for sure. As a decision in a situation characterized by statistical probability can be quantified, we still speak of a *risk*, however not of a perfect one.

Estimates emerge from a situation in which a decision maker is not able to use any quantitative information to predict an experiment's outcome. This can be due to a lack of a sufficient number of observations or to a biased set of data. As, when it comes to estimates, no quantitative basis for decisions is available, this is called an *uncertainty*.

1.2 Flexibility versus Stability

For every decision in an environment including risk and uncertainty, disruptions and discrepancies between a plan and its realization are to be expected. This calls for a methodology of robustness to deal with uncertainty and risk in a decision process and to respond to it efficiently.

The increasing inclusion of risk and uncertainty in models makes robustness one of the currently most interesting topics in economic research and practice. Robustness is seen as the ability of a firm, system or strategy to be tolerant of changing environmental influences. Mostly the loss aversion of individuals is the reason to incorporate robustness (Scholl, 2001; Lardeux et al., 2010). Roy (2010) defines robustness as a buffer zone for resisting uncertainty, risk as well as "zones of ignorance" in decision making. When Lardeux et al. (2010) talks about robustness, he means models that deal with input variability to provide the best results given this uncertainty. A common definition of robustness that we will take as a basis for this paper is provided by Scholl (2001) and Kaluza (2005). Here, robustness consists of three components: stability, elasticity and flexibility.

Stability can be defined as the ability to remain able to act successfully despite unforeseen disruptions (Ionescu and Kliewer, 2011).

Elasticity is the ability to adapt a structure or strategy as uncertain events occur (Scholl, 2001).

Flexibility is the target-oriented and optimal use of elasticity in order to act successfully in the face of changing environmental influences or a change in the personal perception of reality (Mandelbaum and Buzacott, 1990).

This definition shows that in contrast to robustness, flexibility is associated with costs or reachable benefits (Scholl, 2001). According to Kaluza (2005), flexibility can also be actively used to reach one's goals: Flexibility is a chance to use uncertainty in decision making to be more successful and to adapt pro- rather than re-actively.

Flexibility is an important research issue in almost all fields of economic planning, but especially in manufacturing, supply-chain and transport management (Mandelbaum and Buzacott, 1990; Scholl, 2001; Kaluza, 2005). Especially in scheduling, existing interdependencies between resources and plans have strong impacts and there is an inherent necessity to develop stable and flexible solutions (Ionescu and Kliewer, 2011).

As we will see in the following sections, the ARM process, too, includes great potential of uncertainty and risk. Flexibility has to be considered as a countermeasure and needs to be implemented within the process. Existing RM literature offers several robust and flexible approaches, but a universal definition of flexibility within the whole RM process does not exist.

The definition of RM stated earlier implies that the whole process and all decisions are based on uncertain information about expected environmental conditions. For example, demand estimation can include the quantity and temporal distribution of requests and the identification of price- or product-sensitive demand (Fiig et al., 2009). Across the RM process, flexible methods have to deal with risk and provide maximum possibilities of adaption to situations as these arise. An integration of flexibility in the RM process could mean that all possible adaptions and reactions in later steps are considered when an initial decision is made at an earlier stage (Mandelbaum and Buzacott, 1990; Roy, 2010): An initial decision about request acceptance should limit the range of feasible reactions as little as possible. As the RM model does not consider cost, the objective includes only achieved revenue; flexibility has to support maximizing this revenue by adapting methods and decision rules to changing environmental influences.

In this paper we differentiate between dealing with uncertainty and risk through stable versus flexible solutions. Flexible solutions accept the existence of uncertainty and try to make the best of an uncertain outcome. Stable solutions aim to produce better results leading to an overall reduction of uncertainty. The latter do not have to be restricted to advancements in parameter estimation, but can also cover for instance a structural change in RM process organization. Stable solutions tend to be successful in transforming uncertainties into risk – as explained in Section 1.1 – or in reducing risks already quantified, whereas flexible solutions respond to both risks and uncertainties as they arise.

1.3 Revenue Management Process View

This section gives a brief overview of the traditional RM process. The considerations that started much of RM research can be found in Littlewood (1972). He mathematically formulated an intuitive rule that proposes to sell tickets in the cheaper of two booking classes, as long as the expected marginal utility exceeds the fare of the more expensive booking class. Later, Belobaba (1987) extended this approach to more than two booking classes, resulting in a still frequently applied concept: expected marginal seat revenue (EMSR). A review of developments and future directions of RM is given by McGill and van Ryzin (1999). Furthermore, Talluri and van Ryzin (2004) provide a comprehensive insight to the concept of RM and its elements. A more recent overview of mathematical models and methods in RM and its focus on simulations can be found in Talluri et al. (2008).

Figure 1 shows the abstract process in a schematically simplified manner. Data sets are figured as pillars, whereas rectangles are used to illustrate process components and last but not least are externalities symbolized by clouds. Typically, historical booking data, information about previous inventory controls and forecasts are used to predict the future demand. This forecast serves as an input for the revenue optimization step, which considers capacity and fares – in classical RM both quantities are considered as fixed in advance. The resulting inventory controls are balanced with real world demand when taking reservations. Demand is strongly influenced by the market conditions. The reservation step's result is again used as input data for the next demand forecast and so on; in the diagram, the next iteration is indicated by the dotted lines. This procedure demonstrates the classical concept of the RM feedback loop. It can be applicable within the booking horizon of one particular departure as well as from one to another.

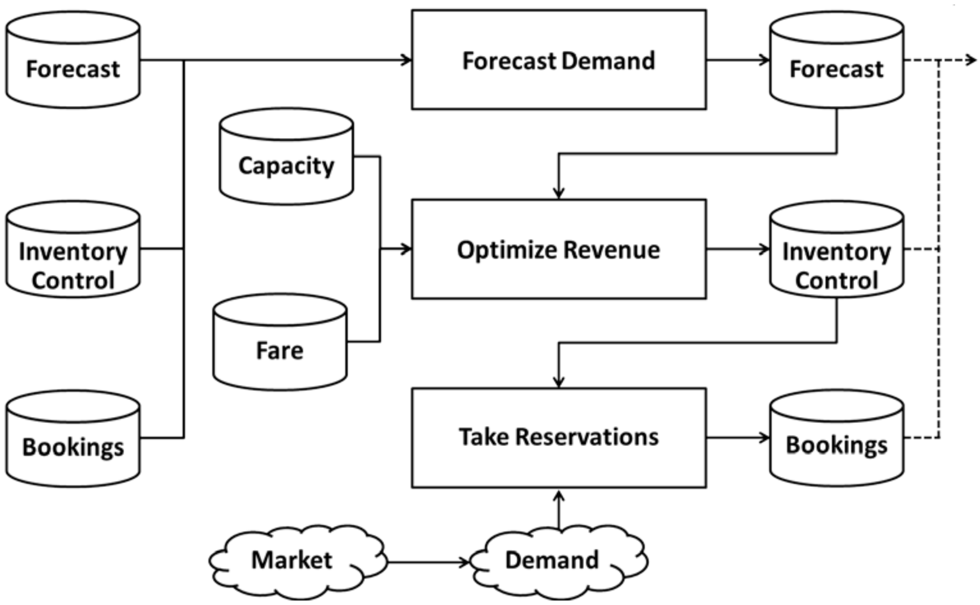

Figure 1: Revenue Management Process (adapted from Talluri and van Ryzin (2004))

In the scope of this paper, we neither consider uncertainties based on communication errors, nor those caused by analysts' influences. Communication errors can arise by system or organizational design, whereas analysts' influences can take effect in almost every point of the RM process (Belobaba, 1987). We predominantly focus on uncertainties that have been considered in the research literature without any claim to completeness.

The structure of next three sections follows the process displayed in Figure 1. In Section 2, we introduce uncertainties that arise within an RM system and that are based on flawed parameter estimates or data. In contrast, Section 3 focuses on model and objective based uncertainties that result from assumptions and decisions within the RM model. Section 4 discusses uncertainties emerging outside the scope of the traditional RM process: This pertains especially to information on capacity and fares. We conclude this paper by giving an outlook and suggestions for future research in Section 5.

2 Uncertainties inside Revenue Management: Data and Parameters

In this section we consider uncertainties that stem from within the borders of an RM system. We concentrate on parameter- or data-based uncertainties rather than uncertainties that derive from a particular RM model design. The latter type is considered in Section 3.

In Section 2.1, we first address the problem of missing historical booking data. Section 2.2 treats the uncertainty caused by an inaccurate demand forecast, while Section 2.3 considers the uncertainty given by the unavoidable variation of demand. The core of all these problems lies in the gap between forecasted and actual demand.

2.1 Missing Historical Booking Data

The problem of *missing booking data* can be seen as a special case of a forecast inaccuracy. As mentioned by Lennon (2004), this issue complicates the application of RM in new markets or industries. Without observing any previous sales development, revenue management's forecast quality necessarily will perform badly. However, the uncertainty caused by missing booking data differs from the forecast inaccuracy problem described in Section 2.2. If there is no sales data available for a specific product, e.g. due to a new launch, the RM system can hardly be blamed. In fact, one could argue that the problem lies outside the RM system entirely – yet, this is where it traditionally has to be resolved. Therefore, and also because the collection of historical booking data is considered to be part of the RM process, we categorize this particular uncertainty as lying inside RM. The research cited in the following sections causes us to believe that an RM system can be designed in a way that allows it to function given missing data.

In addition, it is important to note that we limit ourselves to the case where actually no sales took place. This excludes uncertainties that result from data loss or a shortfall of recording, which can be considered as a communication error.

2.1.1 Revenue Management without Forecast

An approximation of the no booking data case can be found in Lan et al. (2008). They investigate possible approaches given limited demand information. Only the lower and upper bound of demand is assumed to be known and no assumption on the arrival process is available. In the single-leg framework, the authors rate policies' performance given restricted information. They compare the performance of static and dynamic policies. However, note that the contribution does not completely forgo historical data.

The approach by Ball and Queyranne (2009) constitute a model enhancement reducing the problem of missing booking data: They try to avoid the necessity of this data in the first place. The approach proposed search for optimal policies when no knowledge of historical bookings is available. The authors formulate an alternative RM policy, which allows for skipping the demand forecast by using online algorithms. They call it more *robust*, as it is no longer dependent on demand data. The proposed approach also allows avoiding the traditional assumption of a risk-neutral RM approach. For an elaboration of risk-sensitive RM, see Section 3.2.2.

2.1.2 Manually Supplemented Forecast

The most intuitive approach to overcome missing historical booking data is to have it manually supplemented by expert analysts. Lemke et al. (2012) state that usually, the existing forecast data from a similar flight is applied as initial reference for a new one. In the following periods, the reference is updated with observed booking data.

A more general approach is provided by Zeni (2003) who investigate the value of manually introduced forecasts by RM analysts. The author formulates a business process where RM analysts get feedback on their decisions. Similar results are stated by Mukhopadhyay et al. (2007) who also analyze the improvements when RM analysts manually adjust existing forecast because of incidents not captured in the historical data. In contrast to Zeni (2003) they concentrate on the forecast quality as measure instead of achieved revenue.

We consider this as a stabilizing approach: An RM system including analysts is supposed to perform better when booking data is missing.

2.1.3 Adaptive Forecast

Another approach to overcome the lack of historical data is to use an adaptive forecast method. This requires that, the problem of establishing an initial demand estimate is overcome. This may be realized as explained in the previous subsection. Given an initial estimate, the way is open for the flexible solutions listed below.

A first approach is offered by Popovic and Teodorovic (1997). The authors develop a model allowing for missing historical booking data and propose an adaptive inventory control procedure based on the Bayesian approach. Numerical studies show that this technique could lead to results comparable to more standard procedures.

An alternative adaptive concept is proposed by van Ryzin and McGill (2000), considering the single-leg, multiple-fare class problem. The authors developed an iterative algorithm calculating nested booking limits. With the help of numerical studies, they show that the computed output converges to the optimum. Beside these works, iterative approaches are proposed by Huh and Rusmevichientong (2006) and Kunnumkal and Topaloglu (2009). A combined approach to overcome the lack of historical data due to an adaptive approach, while using the concept of dynamic pricing, is provided by Lin (2006).

2.2 Forecast Inaccuracy

Inaccurate demand forecasts are probably the most considered uncertainty in RM theory and practice tantamount. Weatherford and Belobaba (2002) highlight the importance of an accurate forecast: By executing simulations with different forecast precision they observe a strong impact on the revenue. Let us think of a forecast's typical elements: trend, seasonality and noise (see for example Armstrong, 2001). Forecast inaccuracy results from the flawed estimation of any of these elements. However, noise can never be accurately predicted. Therefore, an RM system's forecast will never perfectly estimate the demand to come and a residual risk will always remain. This is why we explicitly consider demand variation in Section 2.3.

In this section, we focus on three approaches reducing forecast inaccuracy that do not rely on attempting to eliminate the need for a forecast in the first place (see Section 2.1.1 for this).

2.2.1 Modelling the Booking Process

A stable approach to avoiding forecast inaccuracy could entail trying to understand the volatile arrival of customers over time. This constitutes a challenging undertaking. However, a well estimated theoretical probability distribution with structural similarities to real demand can be expected to significantly improve forecast accuracy.

The first attempt at modelling an airline's booking process can be credited to Beckmann and Bobkoski (1958). Their paper highlights the possibility of modelling the arrival of customers via a Poisson Process, an approach that remains standard today. Adelson (1966) extends these insights and suggests a particular case of a compound Poisson process: the stuttering Poisson. Lee (1990) tests the forecasting ability of a censored Poisson model using actual airline data. There has been extensive research in this field and a succinct overview of the different approaches for modelling airline arrivals stochastically can be found in McGill and van Ryzin (1999).

In this context, Kimms and Müller-Bungart (2007) justify today's common usage of simulations for testing RM policies. They show how demand data could be generated in a RM network simulation; without realistic demand data, different models of a booking process could not be tested sufficiently.

In contrast, van Ryzin and McGill (2000) develop a self-adjusting inventory control scheme that does not depend on estimating the demand distribution. Thus, the approach avoids the complex feedback loop between forecast, optimization and bookings. However, the authors emphasize the importance of observing historical bookings, as their approach is based mainly on these. Without data, the alternative forecast method could not work at all.

2.2.2 Demand Parameter Enhancement

A general overview of the differences between stochastic and dynamic optimization models when dealing with demand parameter uncertainties is given by Adida and Perakis (2010). They consider for both approaches a closed-loop formulation and models in an open-loop setting. As results they state that robust optimization models perform better especially for closed-loop models and that stochastic models are only as good as the underlying distributional assumptions. Also, Perakis and Roels (2010) formulate a robust capacity allocation policy motivated by and circumventing the problem of accurately characterizing expected demand.

Another facet of demand parameter uncertainty is caused by the issue of *unconstraining* historical data. Inventory controls constrains the booking data used to calculate new forecasts. To calculate the true demand parameters from the truncated historical data, unconstraining techniques are needed.

Although not referring to RM, a first formulation for a technique of uncensoring data is provided by Lawless (1982). Furthermore, Zeni (2001) compares the achieved revenue given different unconstraining methods within a simulation setup. Weatherford and Poelt (2002) also compare unconstraining methods and conclude that in the airline industry, true demand can never be accurately extrapolated. Queenan et al. (2007) formulate a new approach that integrates information on the point of time when demand was constrained. Their numerical results demonstrate efficiency in comparison to established techniques.

In his thesis, Iancu (2010) provides a distributional robust model for a linear demand function. The aim is to calculate solutions that are feasible for any realization of the uncertain demand parameters and to "focus on formulations that allow the computation of adjustable policies" (Iancu (2010), p.118). The author assumes that the model is most likely incorrect and incorporates this into his approach while using robust formulations.

Within the previously listed approaches we can speak of RM model stabilization, as the overall goal is to minimize the risk a priori.

2.2.3 Self-Monitoring Forecast

Adaptive approaches might be used to self-monitor the performance and quality of forecasting. These approaches aim for a more stable solution, reducing the uncertainty that can result in a flawed forecast.

Chen et al. (2005) build on this idea by using a flexible neural tree model to forecast time-series. The authors demonstrate that the flexible neural tree model can automatically select input variables given a set of possible variables. In simulation studies, the general feasibility and effectiveness is shown for time-series-forecasting problems. The model is designed to forecast the same data set over multiple runs, but the model is demonstrated to lend itself to effective generalization.

Another approach that incorporates the idea of flexibility and adaptation is proposed by Deutsch et al. (1994). The authors introduce a forecast model, in which the weights used in combining estimators are variable rather than fixed. A time-varying combination approach of the weights is proposed and shown to substantially reduce the sum of squared forecast errors. A related approach is developed by Guidolin and Timmermann (2009). They provide an approach to fuse different estimators into one predictable forecast. Their main finding is that flexible forecast combinations can overcome the problem that relative precision of different forecast approaches varies over time. Although this model is not focused on RM, the basic ideas and especially the findings could be easily transferred and used in RM forecasting.

More general results about the performance of forecast models with fixed or variable specifications are provided by Swanson and White (1997). Forecast models with variable specifications are allowed to adjust their parameters at each point in time, whereas fixed specification models have constant parameters over time. The authors compare different linear and nonlinear forecast models with fixed or variable specifications and evaluate the accuracy of the results in different environmental setups, providing mixed evidence. On the one hand, some improvements are achieved by using variable models to forecast time-series; on the other hand, the authors propose further research into more generalized variable approaches.

2.2.4 Iterative Forecast and Optimization

Repeated iterations of forecast and optimization throughout the booking horizon allow the RM system to react to new information. Although online algorithms would perform the best, most RM systems cannot handle the huge computational volume. For that reason, a frequently repeated offline optimization is commonly suggested.

In their overview, McGill and van Ryzin (1999) state that “the performance of a given revenue management system depends, in large part, on the frequency and accuracy of updates to control limits and the number of distinct booking classes that can be controlled”. An approach widely used to model the time component of the RM process is dynamic programming – see Bertsekas (2005) for an overview of this concept. At each point in time, request acceptance is decided based on the current inventory, the expected future demand and past sales (Bertsimas and Popescu, 2003). To improve the performance by using this particular control method, the dynamic program has to be recalculated several times within the booking horizon. This enables the inclusion of sudden developments and disruptions in the control strategy.

As the basic model has been extended by cancellations, network aspects and the theory of bid-prices (Bitran and Mondschein, 1995; Talluri and van Ryzin, 1998; Chen et al., 2003), current research focuses on formulating computationally more efficient approximations so as to make the concept practical. Bertsimas and Popescu (2003) provide a formulation with adaptive, non-additive bid prices, based on approximate dynamic programming techniques with a good performance. An approximating of the multi-stage stochastic programming formulation is offered by Chen and Homem-de-Mello (2010). The authors demonstrate some interesting insights about robustness and computational efficiency and develop some heuristics where the timing of updates could be chosen independently. In this context robustness is used "in the sense that solving more successive two-stage programs can never worsen the expected revenue obtained with the corresponding allocation policy" (Chen and Homem-de-Mello, 2010).

2.3 Demand Variation

Finally, we have to consider the uncertainty of natural demand variation. In basic forecast models, this is often referred to as noise. As noise cannot be fully eliminated from forecasts, possible improvements have to address the other RM process components. In the following section, we present some approaches that deal with demand variation and try to find the best response.

2.3.1 Flexible Products

One concept coping with demand variation is to introduce so-called *flexible products*. A flexible product consists of a menu of alternatives, for which the final characteristics are not yet defined when the product is sold. For example, this can mean the possibility to book a ticket for a specific day and an origin-destination pair without knowing the exact in advance departure time and itinerary.

Flexible products were first examined by Gallego and Phillipps (2004). The authors introduce them in a two class, single-leg context, formulate the basic model and develop algorithms to calculate booking limits while handling flexible products in RM. With numerical studies, they show that apart from a more efficient use of capacity and revenue improvements, the concept has the potential benefit of addressing more customers without cannibalization. In a follow-up paper, Gallego et al. (2004) extend the concept to the network model and incorporate a dependent demand model. They introduce a stochastic revenue management approach for this setup and show that it can be approximately solved as a deterministic control problem. As a second result, the authors propose a column generation algorithm, which could be used to efficiently calculate the optimal controls for the deterministic problem in case of dependent demand.

A slightly different view on this topic is provided by Chen et al. (2010). The authors assume a demand segment to be indifferent between a set of flights. Based on this concept, they formulate an allocation model controlling this specific demand segment.

Petrick et al. (2010a) extend the basic model from Gallego et al. (2004) while allowing arbitrary notification dates. They formulate control mechanisms and propose a numerical study. The benefits from using flexible products and late notification dates in an uncertain environment are explicitly shown with numerical studies. In a second paper, Petrick et al. (2010b) focus on dynamic capacity control mechanisms that could be used to determine the final allocation of flexible products over the booking horizon. The authors compare different methods with regard to their proposed flexibility and their practicability and establish a correlation between forecast quality and revenue gain for the different mechanisms.

Fay (2008) takes a look at firms selling opaque products through an intermediary. He formulates an analytical model and discusses questions about assumptions and requirements used. He also states some managerial implications when using an opaque selling channel and some future research topics evolving from his work. Another approach dealing with a special form of opaque products is proposed by Post (2010). The author introduces the concept of variable opaque products, for which the customer is able to select the acceptable degree of uncertainty. After presenting the theoretical framework for variable opaque products, a pricing heuristic is proposed.

2.3.2 Flexible Capacity Allocation

Flexible capacity allocation constitutes an alternative approach to flexibly circumventing the uncertainty caused by demand variation. This idea lies outside traditional RM assumptions, which consider capacity as fixed. However, the potential gains from reacting dynamically to unexpected demand outliers justify rethinking this assumption: For instance, Berge and Hopperstad (1993) refer to a 1-5% revenue improvement caused by dynamic aircraft assignment.

Wong et al. (1993) propose an approach of flexible seat allocation in a flight network under uncertain demand. The authors combine two well-known methods for allocation, bucket control and fixed assignment using EMSR, to calculate the dynamic adjustment of the allocations to local and network demand. The technique improves on more traditional methods in a single fare class, two-leg network; additional insights on using it in a complex hub-and-spoke network are provided. Smith et al. (1998) also allow adjusting the capacity within a network by introducing the fleet assignment model (FAM). The authors numerically demonstrate the intuitive negative influence of demand uncertainty with regard to load factors and total revenue and also explain why FAM provides better opportunities for increasing revenue than pricing could.

De Boer (2004) provides an estimation of potential benefits from adjusting the RM policy for the effects of dynamic capacity management. He proposes a dynamic version of EMSR called EMSRd. This method explicitly addresses the effect of allowing for future capacity changes is. Numerical examples show that EMSRd is very useful when demand is changing and uncertain. A shortcoming of this approach is that best results can only be achieved by using a small number of fare classes.

Another conceivable reaction to uncertain demand that involves flexible capacity would be to swap aircrafts to adjust fleet assignment. Frank et al. (2006) present continuously adjusted fleet assignments as part of a simulation model incorporating dependent demand. The authors' experiments show a clear positive effect on the achievable revenue. Wang and Regan (2006) study the RM problem for this situation as an extension of the traditional leg yield management problem. The authors assume that there are exactly two potential aircrafts with fixed capacities and that there exist given probabilities for each aircraft to be assigned on one of the flights. They propose an aircraft swap method and show numerical results that indicate significant revenue improvements. The authors also provide an estimate for the upper bound of the total achievable revenue. Last but not least, Burke et al. (2010) introduce a multi-objective scheduling approach for a real airline that adds flexibility to the schedule's execution, taking different robustness objectives into account.

2.3.3 Flexible Compartments

The simplest approach to adapting the existing capacity without needing equipment changes is to upgrade some passengers when the originally booked class has been depleted. Such an approach is formulated by Alstrup et al. (1986), solving a dynamic overbooking problem with two segments by substitution. In Karaesmen and van Ryzin (2004), the possibility of multiple substitutable inventory classes is described. Shumsky and Zhang (2004) formulate a model to calculate optimal protection limits by backward induction and present some heuristics to solve large problem instances.

To our knowledge, some airlines already allow a last-minute adjustment by making the physical demarcation between business and economy compartment flexible on continental flights. The only differentiation between the two compartments, apart from service, is that in business class the middle seat remains empty.

3 Uncertainties inside Revenue Management: Model and Objective

In contrast to the previous section, we now focus on uncertainties in RM that are rooted in the model and specifically, the optimization objective. Section 3.1 discusses the most important demand model inaccuracies that have been addressed by research, while Section 3.2 highlights two alternative optimization objectives that have been in the focus of research literature recently.

3.1 Demand Model Inaccuracy

Subsequently, we chronologically list well-known demand model inaccuracies. Section 3.1.1 introduces work on cancellations and no-shows, while Section 3.1.2 considers uncertainties arising from the ignorance of demand dependencies. In Section 3.1.3, we discuss current approaches to anticipating customers' strategic behaviour.

Van Ryzin (2005) already pointed out the importance of understanding demand and of modelling it accurately. The author speaks of previous research advantages and puts the customer-centred consideration of demand in the focus of future RM research. Shen and Su (2007) give an overview of literature related to customer behaviour. They also address dependent demand and strategic customers in the context of RM and auctions.

Another important aspect of modelling dependent demand in RM is *spill*. There exist several categories of spill, all of which have in common that the customer cannot choose the preferred alternative as it is not available. Thus, spill equals the number of passengers that exceed the capacity of an aircraft. In this context, *unconstraining* aims to make this demand visible and countable in history building. Belobaba and Farkas (1999) illustrate the importance of being able to estimate the related spill and present different estimation approaches. Swan (1999) summarizes the history of 20 years of spill modelling literature and discusses some common application in airline industry. Defects in unconstraining could lead to fuzziness in parameter estimation (see Section 2.2.2) and the reason behind these defects is often the negligence of dependent demand within demand model assumptions.

3.1.1 Cancellations and No-Shows

Cancellations and no-shows are established phenomena of customer behaviour, and have therefore been targeted by RM research for a long time. Cancellations are bookings recalled in advance, while no-shows are cancellations that are realized just at a service's time of execution. Considering cancellations and no-shows renders solutions more stable.

To our knowledge, Rothstein (1971) is one of the first dealing with the question of how to respond to this aspect of customer behaviour. His answer is *overbooking*, i.e. selling a virtually bigger amount of capacity than actually available. The author presents policies to determine this optimal *virtual* capacity. Alstrup et al. (1986) discussed those policies for the case of two different types of customers, which is a standard minimum assumption in RM.

One of the first attempts to include cancellations in existing RM methods was made by Subramanian (1999). He models cancellations over time as a Markov decision process for a single-leg flight with multiple fare classes and explicitly allows the use of overbooking. The formulation depends on the well-known dynamic program formulation for revenue management problem. The results affect the monotony assumption according to the nesting order for booking limits and that a decision about accepting a request depends not only on the associated fare but also on the possible refund. Another solution technique is used by Chiu and Tsao (2004), who propose a method to calculate a suitable overbooking strategy using a genetic algorithm. In their model they consider various uncertainties like demand model, forecast inaccuracies and competitor's strategies. They use a meta-heuristic search strategy and a system simulation approach to develop a model for a competitive scenario with given prices. Through numerical studies, they show that their approach has can be extended to more general scenarios.

An attempt to improve the demand model is made by Gallego and Sahin (2010). They state a consumer choice model, in which customer valuations are unknown at the beginning of the booking horizon and companies' knowledge evolves over time. In this context, the authors focus on partially refundable fares and show that introducing such fares can create a win-win situation for customers and seller.

3.1.2 Dependent Demand

From a historical point of view, the assumption of independent demand has a long tradition in RM. Independent demand as a theoretical construct states that a customer is only interested in one specific combination of product and price. However, this assumption leads to a plurality of inaccuracies, as it does not cover the realistic customer decision process: Given the relevant information, a rational customer will prefer the cheapest of a set of products he is indifferent between. Understanding and incorporating this decision process in RM constitutes a stable solution a priori reducing uncertainty. A comprehensive overview of the numerous efforts that have been made to solve the question of how to model the more realistic case of a dependent demand can be found in van Ryzin (2005).

One of the most dangerous effects of an a independent demand assumption is the *spiral-down effect*, analysed mathematically by Cooper et al. (2006) and numerically by Cleophas (2009). The spiral-down effect is a result of confronting the feedback loop of an RM system assuming independent demand with customers displaying dependent choice behaviour. The absence of bookings in high-fare booking classes can cause such an RM system to reduce the expected demand for those classes, resulting in a structural decline: The reduced expectation of high-fare demand will lead to a policy allowing more bookings in cheaper booking classes, which induces a decline in high-fare bookings and so on. This effect can be avoided by implementing a model including dependent demand.

Gallego et al. (2009) present a choice based formulation of the EMSR algorithm for a single-leg, multiple fare class RM-problem where customer choice is assumed to follow a multinomial logit model. They provide solutions and numerical studies for different orders of customer arrivals and show the computational efficiency of their methods.

Another approach to incorporate dependent demand in static and dynamic optimization methods is presented by Fiig et al. (2009). The authors develop a method to transform fare and demand resulting from a general discrete choice model into an independent demand model. These transformed fares allow continuing the usage of known models and algorithms for independent demand models.

Meissner and Strauss (2012) model the customer choice with a Markov decision process and approximate it with a nonlinear function. The main enhancements resulting from this approach are computational efficiency and improved accuracy. In Meissner et al. (2013) the authors extend their approach and formulate a concave approximation for the linear program with customer decision and prove the computational efficiency.

3.1.3 Strategic Customers

Strategic customers could be regarded as a special case of dependent demand. In contrast to dependencies considered in the previous section, strategic customer behaviour is dependent in the timing of request rather than in the choice of product. Goensch et al. (2013) provide an overview of relevant literature in the field of strategic customers and dynamic pricing as well as a classification scheme.

A combined view of strategic customers and the use of opaque selling channels can be found in Jerath et al. (2010). The authors focus on last minute offerings, the anticipation of customers for such sales and on the corrective reaction on this behaviour that most providers start using opaque intermediaries. Their research shows that the use of such intermediaries leads to a better use of capacities and to an increasing demand level, compared to direct last-minute sales by the firm itself.

Gorin et al. (2012) present a method that is able to anticipate and integrate a customer's particular strategic behaviour in network RM. In their framework, they allow customers to cancel a product if they can observe a lower priced equivalent product and rebook this inexpensive version of a ticket. The authors support their findings by numerical results.

A different insight in consumer behaviour is given by Nasiry and Popescu (2011). They propose that some behavioural regularities influence the benefits that could be gained through dynamic price setting because customers form expectations based on historical prices; see Section 4.2.2 for an extensive discussion of *dynamic pricing*.

All these approaches have in common that they add stability in in the demand model process.

3.2 Optimization Objective

This section addresses the uncertainty introduced through a lack of clarity in defining optimization objectives. Traditional RM tries to maximize the short-term revenue earned in average over time. However this is not necessarily compatible with a firm's overall target. Section 3.2.1 highlights the idea of integrating customers' long-term value into the acceptance decision of RM optimization, while Section 3.2.2 introduces literature dealing with a reduction of revenue variation to accommodate the concept of risk.

3.2.1 Customer Value

The consideration of long-term customer value to achieve higher revenues over time is a very up-to-date topic in RM theory and practice; existing approaches from the discipline of customer relationship management (CRM) supports this undertaking. Companies have come to understand that a rejection of well-paying, frequently-buying customers due to short-term optimization could result in suboptimal future revenues. To create more opportunities to include long-term customer value in an RM process without risking revenue, more information about customers and their behaviour is needed. Its inclusion constitutes a more stable solution over time.

Buhl et al. (2011) state that a direction often proposed in literature is to change the view on the exchange between customer and company and to incorporate customer loyalty in revenue management.

Dwyer et al. (1987) developed a general framework considering transactions as relationships instead of discrete events. The first authors to offer a more formalized approach were Berger and Nasr (1998). They present a range of mathematical formulations based on a customer behaviour based choice model. As a result some applications and practicable directives about customer lifetime value (CLV) are stated.

An approach to identify potential customers and predict their values using the realized value is made by Verhoef and Donkers (2001). A first approach to estimate the relation between customer loyalty and profitability is made by Reinartz and Kumar (2002). As conclusion of their research they state that integrating a measureless customer loyalty approach without valuating exactly the relationship does not lead to an improvement. In Reinartz and Kumar (2003), some factors are identified that could explain the variation over customers' lifetime. A dynamic framework to predict the customer value is presented in Venkatesan and Kumar (2004). In this context, Rygielski et al. (2002) use data mining techniques.

Wirtz et al. (2003) describe potential customer conflicts when revenue management is introduced by a customer oriented firm. The paper includes several guidelines regarding actions a firm could possibly implement to avoid customer dissatisfaction and to reach a first step in getting an integrated approach. Kumar et al. (2004) compare CLV approaches on different aggregation levels. The focus lies on organizational and implementation issues and the advances for a firm when using a CLV approach. Kumar and George (2007) point out the common features between different approaches and give a more general view on the conceptual differences between these strategies.

A model incorporating strategic customers with uncertain valuations in their buying decision is presented by Nasiry and Popescu (2009). The authors deal with anticipated consumer regret and develop guidelines about price-setting and the design of effective campaigns to induce or mitigate regret.

A more detailed view on RM strategies and their general compatibility with a CLV approach is offered by Noone et al. (2003), whereas a more pricing oriented approach is can be found in Shoemaker (2003). Von Martens and Hilbert (2009) take a more detailed view on this topic and show simulation studies through which the benefits from incorporating customer value in traditional revenue management approaches are highlighted. The authors conclude that the most potential exists in scenarios during which no positive correlation between willingness to pay and customer value exists. Additionally, Mohaupt and Hilbert (2013) consider RM in cloud services and show that incorporating long-term customer relationships RM can be success factor.

Also beyond the scope of established RM application areas, Hendler and Hendler (2004) focus on the gaming industry. The authors formulate a combined approach of RM and CRM. They point out that in this area a lot of research is required and that existing insights are sparse.

3.2.2 Revenue Variation and Risk

Risk neutrality is a classic assumption in RM due to a typically huge frequency of sell realizations. However, smaller sales industries, as for example event promotion, are in jeopardy of losing liquidity by a few negative outliners (see e.g. Koenig and Meissner, 2010). But also traditional RM industries such as hotels or airlines can be interested in a more stable, risk-sensitive approach. For example, company divisions can have deviating subgoals, as reaching a minimum seat load factor that differ from an overall revenue-maximizing strategy. Additionally, there is a growing trend in RM practice to emphasize planning and therefore revenue reliability. For that reason, this subsection deals with the question of how to integrate risk sensitivity in an overall risk-neutral RM approach.

One of the first contributions dealing with the topic of risk sensitivity in RM is Feng and Xiao (1999). Their work extends the model of Feng and Gallego (1995), by enabling a penalty based on the revenue variation – the higher the variation the stronger the penalty. This leads to an objective function that considers a decision maker's risk aversion. Within their framework, the authors present an optimal pricing policy. The result of a higher risk aversion leads to a more conservative policy. The contrary case of a risk seeking approach can also be realized by changing the risk factor's sign. The authors extend their framework and present some structural results of an optimal risk-averse policy in Feng and Xiao (2008).

Lancaster (2003) discusses different measures of risk suiting RM. In contrast to other authors that actually use the VaR (value-at-risk) or CVaR (conditional-value-at-risk) approach (e.g. Koenig and Meissner 2009a, 2009b, 2010; Goensch and Hassler, 2013) for measuring the monetary risk in RM, Lancaster argues against this particular measure. To him, relative risk measures are a good alternative, e.g. measuring the risk of not achieving a specific benchmark. Lancaster uses RASM (revenue per available seat mile) as measure for his analysis and performs a sensitivity analysis on the different influences on revenue variation. Variations in overall demand volume, demand mix and fare ratio are tested by a simulation. The results are intuitively traceable.

A first approach to integrating risk-sensitivity in the EMSR logic can be found in Weatherford (2004). The author proposes an alternative called EMSU (expected marginal seat utility). As the name indicates, the aim of an optimization is not only to maximize the expected revenue but the utility that can be achieved by earning revenue. This logic bears similarities with the findings of Kahneman and Tversky (1979) in that the perception of winning or losing the same amount of money differs strongly. Thus, Weatherford (2004) deals with the idea of disestablishing revenue management's traditional risk-neutral assumption.

Within the field of bandwidth provisioning and routing, Mitra and Wang (2005) take a decision maker's risk aversion into account. They state that the TVaR (Tail-Value-at-Risk) as a risk index is difficult to handle and therefore suggest the usage of revenue's standard deviation as a compromise. An intuitive finding is that their approach results in more conservative booking limits than a risk-neutral one. Furthermore, Barz and Waldmann (2007) analyse the risk-sensitive capacity control for the static and dynamic single-leg problem.

The first to combine revenue risk and dynamic pricing (see Section 4.2.2 for more details) are Levin et al. (2008). Huang and Chang (2009) also deal with the topic of risk-sensitivity in RM. They show via simulation results that reduction in revenue variance comes along with a reduction in average revenue when the optimality condition in a classic dynamic program is relaxed.

In general, the approaches addressed allow for an a priori reduction of revenue risk and therefore strive to establish stable solutions. However, some allow a decision maker to change a particular risk factor as an RM policy's instant adjustment. For that reason, flexibility plays a role when reducing the revenue variation, too.

4 Uncertainties outside Revenue Management

Given a limited scope of planning, RM experts and systems have to work with structural restrictions that come about beyond RM's sphere of influence. Thus, this discusses uncertainties arising from two input parameters that are traditionally seen as decided outside RM: capacity and fare.

To avoid the resulting uncertainty in the first place, Feng and Xiao (2006) propose to integrate the capacity and pricing decision in the process of RM. A sequence of threshold points allows their mutual determination of price and inventory control to reach optimality condition.

4.1 Fixed Capacity

In the assumption of a fixed capacity, RM has to deal with the consequences of planning decisions taken before the RM process begins. Fixed capacity bears two dangers: the actual demand may be higher or lower than the overall capacity. Probably, the first is less fatal, as it is RM's task to find an optimal allocation of customers to capacity and to reject the right requests. Nevertheless, this means that not the entire potential revenue can be realized, resulting in spill again. However, if capacity exceeds the entire demand for a product, units will remain unsold, resulting in revenue loss. We see two types of capacity uncertainty: an initially inappropriate chosen capacity or an external conditioned change.

4.1.1 Long-Term Capacity Adjustment

One of the biggest planning challenges is the allocation of a firm's available capacity to physical products before the RM process begins. For example in the airline industry, this means to assign a particular aircraft from the fleet to a specific flight given an inflexible schedule. The intuitive rule is to optimally assign the aircrafts with the most seats to flights that have the most expected requests (e.g. De Boer, 2004). The better this initial assignment is executed, the less uncertainty will result. For that reason, efforts to improve fleet assignment constitute improvements in terms of stability. In the following, we present just a few works that deal with this particular problem – being in our view essential.

Abara (1989) was first who solved this problem via linear integer model. His objective function allows for keeping different optimization goals in view as e.g. minimizing costs *and* maximizing profits. Farkas (1996) takes network effects into account and highlights the importance of a correct estimation of spill and spill costs within this concept. Also Barnhart et al. (2002) concentrate on network effects. They present a new formulation for solving the fleet assignment problem even better.

Sherali et al. (2006) present an overview of different approaches and advancements for the fleet assignment problem so far. The still continuing number of research efforts thereafter (e.g. Barnhart et al., 2009; Jacobs et al., 2008), show how important an optimal initial capacity is.

4.1.2 Integrating Capacity Changes

A second uncertainty for capacities in RM arises when it comes to external capacity changes. For example, a technical defect or a crew schedule problem can force an RM system to change last-minute the originally capacity. As a result a previous calculated optimum is not achievable anymore. To the best of our knowledge there is only one theoretical approach allowing for an integration of a probability that a capacity can change during the booking horizon due to external reasons. Wang and Regan (2006) however only use this approach for introducing their overall framework. This framework's major goal is to suggest a heuristic that allows for repeated aircraft swaps and thus observe an increase in revenue.

However, external caused capacity changes are not as rare as desired, we herein see a tremendous potential for further research. Such kind of integration would raise an RM system's stability.

4.2 Static Fare Structure

A second uncertainty that lies outside the responsibility of RM is the concept of fare structures. Traditionally, at least one particular fare is assigned to a particular booking class; actually most airlines have a set of differentiated fare classes assigned to a particular booking class. The underlying idea can be traced e.g. in Botimer and Belobaba (1999). Besides the problem that the a priori chosen fares may not be optimal, this additionally introduces the challenge of estimating a representative mean fare to RM practice. Weatherford and Belobaba (2002) analysed this problem through simulation to mixed results. Most of their instances support the assumption that a greater error in the estimation of mean fare diminishes revenue, however, some instances indicate the opposite.

The following three subsections give a brief overview of alternatives to the traditional RM system relying on static fare structures.

4.2.1 Integrating Pricing

The first approach to avoiding the uncertainty presented by an a priori fixed and static fare structure is to integrate the pricing decision into RM, creating a more stable solution a priori. Some first ideas leading in this direction can be found in Federgruen and Heching (1999). The authors consider the impact of the chosen fares on demand to come. In his thesis, de Boer (2003) studies i.a. "joint pricing and resource allocation problem". In his framework, structural results and distinct solutions for choosing the optimal price are presented. As already mentioned, Feng and Xiao (2006) analyse an integration of pricing and capacity in RM. The authors propose a capacity control policy that can mutually incorporate the intensity of demand, inventories and prices.

4.2.2 Dynamic Pricing

The idea of dynamic pricing is simple: If fares can be continuously adjusted throughout the booking horizon, no fare structure problem arises. Introducing dynamic pricing within an existing RM system does not increase the number of possible adaption but it provides a more stable framework as a capacity oriented RM system. An overview of dynamic pricing approaches and models is presented by Bitran and Caldentey (2003).

Gallego and van Ryzin (1994) formulate a universal dynamic pricing problem under stochastic demand. They provide an optimal pricing policy for a set of exponential demand functions and an extension for Poisson-distributed demand in a closed form and calculate an upper bound on the expected revenue.

In contrast, Lin (2006) provides a dynamic pricing approach, in which no complete demand forecast is available at the beginning of the sales horizon. During the sales period, the method uses real-time sales data to fine-tune the estimation to the arrival rate. This new information is directly incorporated to dynamically adjust the product price in order to maximize the expected total revenue.

Sen (2013) provides a comparison of one fixed and two dynamic pricing policies in revenue management that continuously update prices based on remaining inventory and time. He compares two heuristics: One approximates the expected revenue and the other one solves the deterministic problem continuously. The theoretical work and numerical studies show that dynamic pricing heuristics could lead to improvements over traditional fixed pricing methods.

There are some works that join dynamic pricing and risk sensitive approaches as discussed in Section 3.2.2 (Feng and Gallego, 1995; Boyd and Bilegan, 2003; Levin et al., 2008; Nasiry and Popescu, 2009 and Hinz et al., 2011). The enormous number of authors highlighting these research fields indicates its present and future importance.

Finally, Isler and Imhof (2008) suggest an approach combining game theory and dynamic pricing. The authors additionally support the inclusion of RM analysts, as mentioned in Section 2.1.2, to avoid the danger of a spiral-down pricing.

However theory speaks up for dynamic pricing due to its huge potential, practice still runs after its implementation. One of the main obstacles to using dynamic pricing in the airline industry is that the logic of global distribution systems (GDS) is not compatible yet (see e.g. Isler and D’Souza (2009) and Poelt (2010)).

4.2.3 Customer-centred Price Setting

Name-Your-Own-Price (NYOP) mechanisms and auctions constitute two different approaches of a customer-centred price setting. They both provide more flexibility in short-term sells late in the booking-horizon by introducing a fast-responding dynamic customer-oriented component into the price-setting mechanism. However, as this component comes into play before anything is sold, this could also be considered both as stable solution in terms of robust capacity usage.

NYOP mechanisms provide a great opportunity to sell excess inventories in markets with perishable products. The buyer places a bid for a product and the seller decides if this bid is accepted or not. One of the first firms that used this mechanism was *Priceline* (Anderson and Wilson, 2010).

A technical approach to integrating NYOP mechanisms in existing systems is described by Lochner and Wellman (2004). They provide some general insights using customer-interactive mechanisms in computational markets. A firm that does not want to implement such mechanisms single-handedly could rely on external retailers to overcome demand uncertainty with NYOP mechanism. Wilson and Zhang (2008) prove the existence of an optimal solution for a NYOP problem where the customers are aware of the acceptance probability of their bid and try to maximize their individual profits.

In Wang et al. (2009) an analytical model is provided to understand the opportunities and shortcomings of using a NYOP selling channel. The authors point out the benefits in increasing capacity utilization, reducing demand uncertainty and outline possible shortcomings. In this regard, especially the loss of reliability when capacity is scarce and prices increase could be seen as a major disadvantage.

A good overview of various approaches to model Name-Your-Own-Price auctions in revenue management is given by Anderson and Wilson (2010). The contribution presents many existing models and formulates implications for future research in this area.

Hinz et al. (2011) check the usage of dynamic pricing on NYOP markets. Within this context they i.a. point out the dominance of dynamic prices over thresholds and explain NYOP's positive influence on customer satisfaction.

Auctions are similar to NYOP in presenting an approach to customer-centred price setting. However, at auctions, customers compete with each other, while in NYOP concepts, customers bargain with the seller. An introduction to auctions in RM can be found in Talluri and van Ryzin (2004). Some further works are presented by Chiang et al. (2007). Due to limitations in scope we want the reader to know that the topic of auctions is a completely separate entity with research efforts many in number.

5 Conclusion and Research Prospects

This paper contributes an overview of existing research dealing with uncertainty in the revenue management context and proposing flexible or stable solutions. As a conclusion, in this section, we point out some further research opportunities that may overcome existing approaches or explore completely new fields. For a better classification, this section follows the structure of the paper as a whole:

Inside Revenue Management: Data and Parameters

The need to supplement forecasts manually as mentioned in Section 2.1.2 reveals an existing gap within the forecast process when historical data is missing or sparse. A possible direction of research, which is to our knowledge not yet considered in the area of RM, consists in the development of integrated approaches automatically selecting data from other sources to supplement sparse forecasts. This may help to avid uncertainties arising from inaccuracies and rule of thumb estimations contributed by human RM-analysts.

The whole concept of human -analysts contributing to RM decisions is another mostly neglected aspect. A lot of uncertainties may be resolved by analysts adjusting data and parameters after the system's initial calculation. But these adjustments can again trigger new uncertainties and disturb the systems before further iterations. The impact of manually adjusted parameters and data is an underexplored field of revenue management research.

Inside Revenue Management: Model and Objective

All proposed approaches in Section 3.1 try to overcome defects within the demand model, while proposing extensions for the existing model. However, we see a major challenge in estimating these newly introduced parameters. All of the presented approaches neglect the problem of setting initial values for the newly introduced parameters. Future research has to deal with this challenge and to provide reliable methods for estimating these parameters.

Outside Revenue Management

The idea of integrating capacity changes within the revenue management process should be considered more closely: We expect there are great practical opportunities within this field. Existing literature and research approaches treat capacity changes and capacity allocation more or less as separated fields. An integrated approach could overcome the existing issues and lead to more robust and successful control strategies in revenue management.

In general, we observed a dominance of stable (rather than flexible) solutions for uncertainties in revenue management. This may be motivated by the idea of risk averse analysts and decision makers. Flexible solutions do not reduce risks a priori, as is the promise of stable solutions. As a consequence, the potential of flexible solutions is not completely exploited at this moment. However, all flexible approaches considered in our study show great potential to overcome uncertainties within the revenue management process. Future research has to explore more facets of flexible solutions with the aim of proposing new flexible methods with a greater expected acceptance in practice.

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