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Resilient Revenue Management

A Literature Survey of Recent Theoretical Advances

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Recent Advances Towards Resilient Revenue Management: A Literature Review

Abstract Recently, resilience has emerged as a concept that describes a system's ability to persist and adapt under uncertainty. Revenue management is a textbook example of planning under uncertainty – any revenue optimisation model relies on a range of assumptions, among them the accuracy of the demand forecast. Revenue management's objective is to maximise revenue given uncertain market conditions, capacity, and even fares.

This contribution reviews recent advances in making revenue management more resilient. To this end, it identifies and categorises uncertainties that affect the revenue management process. In the resulting framework, we review contributions aiming to increase solutions' ability to persist or adapt, listing relevant references by their focus and character. Thereby, we contribute a comprehensive review of research accumulated in the last ten years, outline a research agenda and thus prepare the ground for further research efforts.

Keywords Air Transport · Revenue Management · Resilience · Uncertainty · Risk

1 Introduction

"Without risks, no company would be able to achieve anything or make a profit" (Lancaster, 2003, p. 158). This quote particularly applies to revenue management. Revenue management segments demand to control the offer price of a set of perishable products with limited capacity. Revenue management fails when selling too much too cheaply (spill) or when selling too little too expensively (spoilage).

Early revenue management ideas trace back to Littlewood (1972), who formulates an intuitive rule: As long as the expected marginal utility exceeds the fare of the more expensive fare class, sell tickets for the cheaper of two fare classes. Belobaba (1987) extends this approach to more than two fare classes, arriving at the expected marginal seat revenue heuristic (EMSR). Revenue management models evolved further, considering the network perspective (Williamson, 1992) and incorporating dependent demand (Talluri et al., 2008). McGill and van Ryzin (1999) and Chiang et al. (2007) review these developments, while Talluri and van Ryzin (2004) survey the underlying mathematical methods and models.

Recent research increasingly focuses on challenges posed by uncertainty. Revenue management systems rely on a range of expectations about market conditions and demand, as well as about products, capacity, and fares. When reality does not fulfil these expectations, researchers and practitioners increasingly strive to enable revenue management systems to persist and adapt – they strive to create resilient revenue management systems.

Currently, no thorough review of resilience-related revenue management research is available: While establishing the methodology and applicability of revenue management, contributions such as Talluri and van Ryzin (2004) or Chiang et al. (2007) are dated given the pace of research. Furthermore, they do not consider the field from the perspective of resilience or uncertainty.

1.1 Defining Resilience – and Uncertainty

Several concepts compete to respond to the challenge of planning under uncertainty, including robustness, anti-fragility, and resilience. Robust solutions promise to perform well for multiple possible scenarios. They accept a "cost of robustness", quantified as the gap to the performance achievable by non-robust solutions optimised under ideal conditions (Bertsimas and Sim, 2004). More recently, Gorgeon (2015) proposed to create anti-fragile information systems, which perform well even when facing unforeseeable disturbances.

We argue that "resilience" best describes the objective of recent revenue management research. The term is already widely used in domains such as psychology, organisation, or infrastructure planning. Recent contributions apply it to hospital information systems (Park et al., 2015) and supply chain management (Christopher and Peck, 2004).

Resilience is the ability to "bounce back" after disturbances. More specifically, revenue management strives for ecological resilience as described by Davoudi (2012): "the ability to persist and the ability to adapt", where adapting can mean moving forward and evolving rather than bouncing back.

Following the same logic, Carvalho et al. (2011) differentiates two aims of resilience: To persist in the face of a disturbance and to recover desirable system states after a disturbance. Pye (1978) provide a similar, much earlier differentiation for operations research: stable solutions maximise the lower bound of achievable revenue, whereas flexible solutions maximise the range of feasible reactions. In this contribution, we differentiate *persistent* and *flexible* solutions.

To understand efforts to create a resilient revenue management, we need to delineate our understanding of uncertainty. Picking up ideas introduced by Knight (1921), Runde (1998) differentiate a priori probabilities, statistical probabilities, and estimates. Notably, Weisberg (2014) challenges fundamental ideas about uncertainty. The author criticises that mathematical probability became the sole measure of uncertainty over the past three centuries, and suggests a dynamic interplay between qualitative and quantitative modes of research. Combining this with the differentiation of risk, uncertainty, and ignorance given in Roy (2010), we differentiate four phenomena related to uncertainty:

Risk in terms of a priori probability results when an outcome's probability, as for the result of a coin flip, can be correctly quantified in advance.

Risk in terms of statistical probability results when planners observe several realisations of an outcome. For example, after multiple flight departures, a planner will be able to state a statistical probability that the operating aircraft differs from the one initially planned.

Uncertainty describes the idea that planners are aware of divergent outcomes, but cannot quantify the outcomes' probabilities. For example, a seller may know from experience that some customers approach the buying decision strategically, but lacking data, cannot quantify the probability at a given time.

Unawareness describes a situation where planners do not foresee possible disturbances, as they are not aware of their existence. For example, a seller may not expect a competitor to be able to offer a promotional fare, thus being taken completely by surprise when this happens. Here, we regard challenges resulting from unawareness as a matter of rendering information systems anti-fragile (Gorgeon, 2015), and therefore neglect them in our further analysis.

In this context, we regard *ignorance* as a possible response to risk or uncertainty: While the decision maker knows that expectations and outcomes may differ, they chose to ignore this. Model parsimony or lacking data can justify ignorance. For revenue management, ignorance comes into play when, for example, employing a leg-based model to maximise revenue for a network product, or when employing a model of independent demand even though customers base their buying decisions on complex utility functions.

In conclusion, this review focuses on handling risk, uncertainty, or both through resilience. When considering risk, we emphasise statistical probabilities, as quantifying a priori probabilities is rarely feasible in practice. Our understanding of resilience encompasses both stable (*persistent*) and adaptive (*flexible*) solutions. These can handle situations characterized by *risk* or *uncertainty*. In the further text, we employ these dimensions to characterise contributions' primary focus.

1.2 A Common Airline Revenue Management System

The airline industry still constitutes revenue management's primary application area. Therefore, this paper concentrates on this domain. As Figure 1 illustrates,

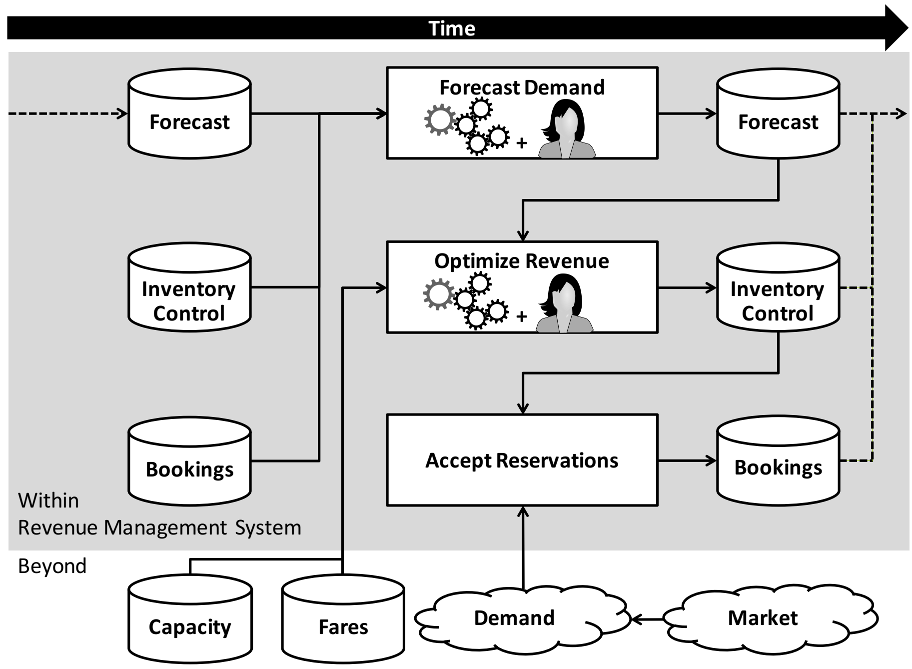

Fig. 1 Quantity-based Revenue Management System

airline revenue management systems rely on historical booking data and inventory controls to predict future demand. Demand forecast, capacity, and fares parametrize the revenue optimisation model, which calculates inventory controls. Inventory controls meet real demand in the airline's reservation system. The resulting bookings feed the next demand forecast – thereby, the feedback loop resumes; in the diagram, dashed lines indicate the next iteration.

Airlines traditionally implement quantity-based revenue management, allocating capacity to discrete fare classes (compare Talluri and van Ryzin, 2004, p. 33): A capacity-based optimisation controls offers based on the expected demand per offered set of fare classes. As an alternative approach, dynamic pricing continuously adjusts fares to exploit the expected willingness to pay of future customers, abandoning the need for static fare classes (Şen, 2013). This review does not consider dynamic pricing in depth: While not yet common in the airline industry due to technical and organisational obstacles (Isler and D'Souza, 2009; Pölt, 2010), it also represents a wide field of research, justifying a distinct review.

Figure 1 differentiates components within the revenue management system and beyond. Uncertain market conditions affect the demand responding to any of the firm's offers. Outside of revenue management proper, a pricing process sets fares for classes, whereas the fleet assignment process controls the capacity per flight.

Our review follows the layout of Figure 1: First, Section 2 considers resilient approaches to handling uncertain demand as intrinsic to revenue management. Subsequently, Section 3 discusses approaches to uncertainty and risk arising beyond the revenue management system, particularly regarding capacity and fares. Finally, the paper concludes with suggestions for future research in Section 4.

2 Within Revenue Management: Uncertain Demand

Uncertain demand estimates represent the predominant challenge considered in existing revenue management research. Early on, Weatherford and Belobaba (2002) highlighted the importance of accurate estimates by showing a substantial impact on revenue in simulation experiments. This section concentrates on three sources of demand uncertainty: lacking data, inaccurate estimates, and the inherent stochastic variation of demand.

2.1 Lacking Historical Booking Data

Most common approaches to demand forecasting rely on historical booking data. When this is not available in sufficient quantity and quality, forecasting becomes difficult. This issue is particularly relevant for revenue management in new markets or industries.

2.1.1 Optimization Without Initial Demand Estimates

Enabling revenue management to function without initial demand estimates, reduces the dependency on historical booking data. Related approaches are not just helpful when there is no historical data, but also when shifts in the marketplace have rendered existing data irrelevant.

Persistent solutions function without demand estimates. One such a solution is proposed by Ball and Queyranne (2009): The authors formulate online revenue management algorithms that do not rely on demand forecasts. In a less drastic approach, Lan et al. (2008) do not entirely dismiss demand forecasts, but assume that only lower and upper bounds on demand are available, also foregoing information on arrival times. They rate the performance of static and dynamic policies based on these bounds in a single-leg model. Lan et al. (2015) extend this idea by combining uncertain demand with uncensored knowledge about no-show probabilities for a joint control policy.

Considering practical applications, Lan et al. (2008) and Lan et al. (2015) appear rather pessimistic. E.g., Lan et al. (2015) state that an extended model may be too difficult for practical application. However, the contributions cited here overcome some common assumptions, such as the idea of risk neutral customers and the need for demand forecasts. Given the assumption of single-leg revenue management, the proposed methods deserve further consideration when a firm newly adopts revenue management rather than extending an existing system.

Flexible solutions enable revenue management systems to initially cope without a demand estimate, before adapting by building knowledge. As an example of such an approach for dynamic pricing, Besbes and Zeevi (2009) consider risk bounds and near-optimal solution algorithms for two situations: A known parametric demand function with unknown parameter values and an unknown demand function without parametric representation. Extending these results, Wang et al. (2014)

Table 1 Within Revenue Management: Uncertain Demand

Challenge	**Solution** *Focus*	*Character*	**References**
Lacking Data	Optimization Without Initial Demand Estimates	persistent	Lan et al. (2008)* Ball and Queyranne (2009)* Lan et al. (2015)
		flexible	Besbes and Zeevi (2009)* Wang et al. (2014) den Boer and Zwart (2015)
	Manually Supplementing Demand Forecasts	persistent	Lemke et al. (2012)*
		flexible	Zeni (2003)* Mukhopadhyay et al. (2007)* Weatherford (2015)*
Inaccurate Demand Estimates	Parametric Demand Estimation	persistent	Aviv and Pazgal (2005) Sen and Zhang (2009) Weatherford and Ratliff (2010) Stefanescu (2009) Vulcano et al. (2012)
	Nonparametric Demand Estimation	persistent	Farias et al. (2013) van Ryzin and Vulcano (2015) Azadeh et al. (2015) Jagabathula and Vulcano (2015)
	Updating Demand Estimates	flexible	Chen and Homem-de Mello (2010) Jasin and Kumar (2012) Jasin (2014) Jasin (2015)
Inherent Demand Variation	Offering Flexible Products	flexible	Gallego et al. (2004) Fay (2008) Petrick et al. (2010) Post (2010)* Lee et al. (2012) Petrick et al. (2012) Gönsch and Steinhardt (2013) Gönsch et al. (2014)
	Considering Real and Financial Options	flexible	Anderson et al. (2004) Akgunduz et al. (2007) Graf and Kimms (2001) Graf and Kimms (2013)* Aydın et al. (2016)
	Considering Revenue Risk	flexible	Lancaster (2003) Barz and Waldmann (2007) Feng and Xiao (2008) Ball and Queyranne (2009) Huang and Chang (2009) Phillips (2012)* Gönsch and Hassler (2013) Koenig and Meissner (2015a) Koenig and Meissner (2015b) Koenig and Meissner (2015)

* practice paper

also differentiate parametric and non-parametric learning. The authors favourably compare the results achievable by dynamic pricing to those achievable by customer-bidding. While the previously cited references focus on large levels of demand and inventory, den Boer and Zwart (2015) propose an approach with limited active price experimentation. Their approach is suitable for smaller inventory levels and shorter sales horizons. For dynamic pricing given network revenue management with unknown demand, Ferreira et al. (2016) handle the resulting exploration-exploitation trade-off via a Thompson sampling algorithm.

The flexible solutions summarized above cannot be trivially transferred to practice. They either lack of algorithm efficicency Besbes and Zeevi (2009) or rely on unrealistic assumptions regarding the demand function Wang et al. (2014). Furthermore, several contributions focus on dynamic pricing – however, when moving from quantity-based revenue management to dynamic pricing, it may be worth considering to also use the opportunity to let the resulting system cope without initial demand forecasts.

2.1.2 Manually Supplementing Demand Forecasts

Revenue management gains *flexibility* when analysts can supplement given estimates based on new information that may not be available to the automated systems. Figure 1 indicates this idea by analyst icons in the relevant steps. In this regard, Zeni (2003) formulates a business process that lets revenue management analysts receive feedback on the revenue resulting from their influencing the demand forecast. Similar suggestions focused on measuring forecast quality can be found in Mukhopadhyay et al. (2007). Weatherford (2015) argue for analysts adding multipliers to existing forecast to flexibly adapt to market information.

While researchers and practitioners seem to agree that manually supplemented forecasts are a good thing when done right, little research focuses on this topic in the area of revenue management. However, a wealth of general forecasting research considers analysts interventions ((Petropoulos et al., 2015, compare) for an introduction). We believe that this research area should be examined closer from the perspective of revenue management.

Clearly, manually supplementing forecasts implicates a general practical applicability. To our knowledge, most if not all airlines allow for such manual interventions by revenue management analysts. While this should be a motivation for researchers, systematically measuring the effect of such interventions and on improving their support is still in rare.

Alternatively, Lemke et al. (2012) suggest to make revenue management more *persistent* by enabling to initialize demand estimates even when lacking precise observations. However, this model relies on assumptions about the cancellation probabilities that may complicate practical applications.

2.2 Inaccurate Demand Estimates

Several aspects of demand have to be forecasted to support revenue optimisation, as summarised for instance in Cleophas et al. (2009): Historical sales have to be unconstrained to estimate the actual demand volume; demand arrival times and customers' choice behaviour have to be predicted. This section concentrates on recent efforts to improve demand estimation and to update demand estimates based on new information.

2.2.1 Parametric Demand Estimation

Several approaches to estimating dependent demand with parametric methods have been previously reviewed in Weatherford and Ratliff (2010). This includes Vulcano et al. (2012) and Stefanescu (2009), both of which focus on Maximum-Likelihood Estimation to estimate demand estimation. Vulcano et al. (2012) models customer arrivals via a Poisson process and assumes customer choice to follow a multinomial-logit model. The authors focus on the demand that materialises for a product when all alternatives are available. Stefanescu (2009) models demand not as the consequence of choices, but via a multivariate Gaussian distribution. In this model, demand correlation to accounts for dependencies over time and products. As they demonstrate the applicability of their results on an empirical data set from the airline industry, the research documented in Stefanescu (2009) and Vulcano et al. (2012) seems well-suited to be implemented in state-of-the-art revenue managements systems.

Bayesian learning is applied in both Aviv and Pazgal (2005) and Sen and Zhang (2009), assuming that customers arrivals are a Poisson process with an unknown rate. Aviv and Pazgal (2005) model arrival rate uncertainty as a Gamma distribution to achieve a simple update rule for the belief distribution. They model price-sensitivity as an exponential distribution with a known mean. The authors find that the benefits of active estimation are minor when demand uncertainty is not high. Sen and Zhang (2009) consider an unknown reservation price distribution that is derivable from a finite set of candidate distributions. The authors use Bayesian Learning to estimate the arrival rate and the reservation price distribution jointly.

Both Aviv and Pazgal (2005) and Sen and Zhang (2009) provide forecasts that are suitable for dynamic pricing. To be applicable for the more common quantity-based optimisation approaches, the results would have to be adapted to predict demand for discrete fare classes. Nevertheless, this stream of research may gain relevance for airline revenue management with the implementation of new distribution capabilities as outlined in Harteveldt (2016)

2.2.2 Nonparametric Demand Estimation

Demand is the sum of individual customers' choices. Therefore, modelling and accounting for customer choice behaviour are the focus of much recent revenue management research. However, when the choice models determine the parameters to be estimated, some assumptions about customer's behaviour, for example about their utility function, have to enter the estimation.

Persistent solutions to the problem of demand estimation can be achieved by employing nonparametric estimation methods. These fit the functional form to the data without being constrained by prior assumptions. For example, Farias et al. (2013) estimate a distribution of customers over demand segments that produces the worst-case revenue compatible with the observations on a given set of availability data. Based on the same dataset, van Ryzin and Vulcano (2015) create maximum likelihood estimates of the choice demand model based on historical booking and availability data. Going beyond the knowledge of product availabilities, Azadeh et al. (2015) provide a nonparametric estimation approach that requires no information about product characteristics, whereas Jagabathula and Vulcano (2015) consider panel data to estimate customers' preference orders.

Compared to parametric methods, nonparametric methods require larger data sets. This can be problematic for applications where data is already sparse. This is even more relevant when the method calls for panel data. Furthermore, manually determining customer clusters, as suggested in Jagabathula and Vulcano (2015), may not be as easy as that. By assuming independent demand, the approach outlined in van Ryzin and Vulcano (2015) is hardly applicable to current service markets.

2.2.3 Updating Demand Estimates

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". Updating demand forecasts – and consequentially inventory controls – throughout the booking horizon lets revenue management react to new information, creating *flexible solutions*.

A widely used approach to real-time revenue management is dynamic programming – see Bertsekas (2005) for an overview. Dynamic programming decides the acceptance of each individual request based on the current inventory, the expected future demand, and past sales. Iteratively updating the dynamic program throughout the booking horizon lets control strategies flexibly consider unexpected developments. However, for realistic problem instances, revenue management systems cannot handle the computational effort resulting from applying exact dynamic programming. Therefore, current research primarily focuses on improving computational efficiency. To that end, Chen and Homem-de Mello (2010) approximate the multi-stage stochastic programming formulation.

Jasin and Kumar (2012) study the benefits of re-solving a deterministic linear program by probabilistically implementing the solutions at predetermined times. They provide an upper bound for the expected revenue loss and construct a schedule of re-optimizations to limit this loss. They call the resulting heuristic probabilistic allocation control (PAC). In a follow-up paper, Jasin (2015) shows that frequently re-optimizing PAC, even without re-estimation, reduces the asymptotic revenue impact of uncertain demand.

The work of Jasin (2014) improves the static inventory control model, outperforming some approaches using re-optimization. Their self-adjusting heuristic only needs a single optimisation step at the beginning of the booking horizon. Expressly in dynamic situations, this provides a computational advantage. Furthermore, implementing the heuristic and performing only a few re-optimizations during the sales period achieves a superior revenue performance.

As computing power steadily increases, we see one of the biggest opportunities for revenue management in the ability to implement frequent updates. However, depending on the complexity of the demand model and of the product portfolio in terms of fare classes and network structure, recently published approaches would still require enormous computational effort in practice.

2.3 Inherent Demand Variation

Even if it was possible to perfectly estimate the average number of requests expected or the probability of customers buying a product, latent demand variation still challenges revenue management. For individual sales horizons, increasing the solution space can compensate this, such as by introducing flexible products or options-based modelling. As a recommendation for further reading, Gallego and Stefanescu (2012) comprehensively consider the idea of service engineering as an opportunity to navigate uncertain service markets successfully. Alternatively, it can be useful to limit the acceptable risk in the mathematical model explicitly. Risk plays a particularly significant role for smaller sales industries, such as event promotion, which can only afford low levels of risk (Koenig and Meissner, 2015).

2.3.1 Offering Flexible Products

As the concept's name implies, flexible products increase revenue management *flexibility*. Each flexible product entails multiple alternative manifestations; the firm only specifies the outcome after the customer has bought the product. E.g., this can mean booking a ticket for one of three possible destinations, with the airline announcing each ticket's destination only after the sale is complete.

Petrick et al. (2010) focus on dynamically allocating flexible products to specific resources. The authors establish that forecast quality and revenue gain correlate for the evaluated methods. Petrick et al. (2012) extend the model from Gallego et al. (2004) to allow for arbitrary notification dates, demonstrating the benefits of flexible products with late notification dates. Gönsch and Steinhardt (2013) provide a more general view on flexible products by extending the classical dynamic program decomposition. Gönsch et al. (2014) present similar results by adjusting product valuation in the deterministic linear optimisation model to capture the monetary benefits.

Introducing the concept of opaque products, Fay (2008) considers selling flexible products through an intermediary. The author formulates an analytical model, discusses its assumptions, requirements, and managerial implications. Post (2010) extend the concept to variable opaque products, for which the customer can select a degree of variability.

Continuing this customer-centric perspective, Lee et al. (2012) investigate customer preferences for the possible manifestations of a flexible product. The authors empirically analyse customers' likelihood to exclude alternatives and emphasise the importance of considering customer preferences when offering flexible products.

Regarding applicability, all contributions cited above neglect implementation issues, such as visa considerations as relevant for international travel. Such issues restrict the possibilities of flexible products. Furthermore, all papers assume customer's choice of flexible products to be independent of the set of currently offered specific products. Regarding customer behaviour, Petrick et al. (2012) state, for instance, that the presented results "are strongly dependent on application-specific assumptions about consumer behaviour." Employing flexible products as more than a niche product requires handing these drawbacks.

In practice, few airlines offer opaque products; to our knowledge, Eurowings is the only European airline offering an opaque product at the time of this writing. However, airlines commonly work with online travel agencies (OTA) such as

Priceline or Hotwire to attract more customers. Such cooperations allow them to handle opaque products without setting up their own models and infrastructure. OTAs also benefit from this set-up, as they can offer “mix-and-match” concepts with different airlines and hotels.

2.3.2 Considering Real and Financial Options

While not common in classical airline revenue management, the concept of real options as common in finance and energy markets provides another approach to handling uncertainty. For car rentals, Anderson et al. (2004) show that real options can improve revenue given latent demand variation. They consider the decision of whether or not to tie up capacity by accepting a current booking as the exercise decision, which is priced to determine the minimally acceptable price of the next booking.

Akgunduz et al. (2007) even apply the concept of financial options to revenue management, suggesting that airlines implement a call option product, through which they can re-call already sold tickets, and a put option product, which allows airlines to sell low-fare products late in the booking period. The idea appears like an interesting version of flexible products but has apparently not been received well in practice.

In the context of airline revenue management, Graf and Kimms (2001) suggest an iterative, option-based approach to allocate code-share capacity in alliances. Their research is extended by negotiated option prices in Graf and Kimms (2013). As yet another view of options in revenue management, Aydın et al. (2016) highlight that most airline customers book a commitment option when booking a ticket, as they can still cancel the reservation before making a final purchase decision.

2.3.3 Limiting Revenue Risk

Risk neutral revenue management accepts negative performance outliers to maximise average expected revenue. However, a firm’s strategy may not be risk neutral. Therefore, risk averse or risk seeking analysts can flexibly overrule the automated, risk-neutral system as described in Isler and Imhof (2008) (compare Figure 1).

However, first experimental research on human decision makers in revenue optimisation, as documented in Bearden et al. (2008), has revealed significant decision biases. Furthermore, Kocabiyikoglu et al. (2015) have shown that the existing body of research on human decisions for the newsvendor problem does not necessarily apply to revenue management. Thus, further research in this area, particularly considering the interplay of human analysts and automated systems, is needed.

Alternatively, embedding a parameter controlling the acceptable risk in the mathematical model can also render revenue management more flexible: Instead of attempting to attain a fragile revenue optimum when the market situation entails considerable uncertainty, they can switch to a more risk-averse mode. However, as Huang and Chang (2009) show, reducing revenue variation in such a way comes at the cost of reducing average revenue.

The approach by Barz and Waldmann (2007) promotes risk-sensitive capacity controls for the static and dynamic single-resource problem. Also assuming discrete price points, Feng and Xiao (2008) present structural results from a revenue management policy that includes a risk-sensitive parameter while Ball and Queyranne (2009) apply online algorithms to account for risk in revenue management.

An approach to risk-sensitive dynamic pricing is proposed in Levin et al. (2008). Koenig and Meissner (2010) compare the effects of dynamic pricing and capacity control given discrete price points by measuring risk via expected revenue, standard deviation, and conditional-value-at-risk.

Revenue risk is also measured in terms of value-at-risk or conditional-value-at-risk in Koenig and Meissner (2015a), Koenig and Meissner (2015b), Gönsch and Hassler (2013), and Koenig and Meissner (2015). In contrast, Lancaster (2003) recommends relative risk measures and proposes a revenue-per-available-seat-mile indicator.

Last but not least, Phillips (2012) analyses efficient frontiers when the revenue management optimisation model considers not just revenue maximisation but also load factor. Rather than considering risk explicitly, revenue management approaches that consider multiple optimisation objectives may support firms seeking to maintain a given market share for strategic reasons. However, research in this area is still sparse. Finally, from the perspective of long-term strategy, revenue may not be the only objective: When revenue is high on the short-term but market shares dwindle on the long-term, allowing for multi-criteria decision making increases *solution flexibility*.

Some of the approaches cited above, such as online algorithms, require exceptional computational effort, which renders their practical implementation difficult and expensive. To our knowledge, the most common approach to handling risk-sensitivity in airline revenue management is to let analysts adjust inventory controls. However, considering the decision biases found in Bearden et al. (2008), this approach may have some drawbacks. Thus, improving revenue management systems to support considerations of risk-sensitivity appears advisable for practice.

3 Beyond Revenue Management: Fares and Capacities

During the tactical planning stage, the pricing process sets fares, whereas fleet assignment determines flight capacities. Revenue management only begins afterwards, with operative planning (Belobaba, 2009, Chapter 6). This section discusses such sources of uncertainties from beyond revenue management (compare Figure 1). Table 2 lists related literature.

Feng and Xiao (2006) propose to integrate capacity and pricing decisions in revenue management to eliminate both capacity and fare related uncertainty. The idea's practicability strongly depends on system performance and on simplifying assumptions, which in turn can cause new uncertainties.

3.1 Uncertain Capacity

Often, the idea of optimally allocating a fixed capacity motivates revenue management. However, actual demand can either exceed capacity or fall short. Demand exceeding capacity may be regarded as less severe, as revenue management inherently reserves capacity for the most valuable customers. Nevertheless, this means

Table 2 Beyond Revenue Management: Fares and Capacities

Uncertainty	**Solution** *Focus*	*Character*	**References**
Uncertain Capacity	Revenue-Driven Capacity Changes	persistent	Frank et al. (2006) Sherali et al. (2006) Wang and Regan (2006) Burke et al. (2010)
	Anticipated Capacity Changes	persistent	Wang and Regan (2006)
Static Fare Structures	Integrating Pricing Decisions	persistent	Feng and Xiao (2006) Kocabiyikoglu et al. (2013)
	Name-Your-Own-Price	flexible	Lochner and Wellman (2004) Wilson and Zhang (2008)* Wang et al. (2009) Anderson and Wilson (2010)* Hinz et al. (2011)

* practice paper

that the full revenue potential cannot be realised, resulting in spill. If demand falls short of capacity, some units are left to perish, and revenue suffers from spoilage. Revenue management research considers two types of capacity-based uncertainty: the initial fit between capacity and demand and exogenous demand changes that occur over the booking horizon.

3.1.1 Revenue-Driven Capacity Changes

The majority of existing research underlines the importance of an optimal fleet assignment, on which revenue management can rely. For example, Barnhart et al. (2009) focus on creating a tractable model of fleet assignment that takes an approximation of revenue maximisation into account. However, changes in the marketplace can worsen the fit of capacity to demand. For that reason, different approaches of dynamically adjusting a fleets capacity to flight legs within the booking horizon emerged in research.

One of the first to propose implementing this concept using aircraft families are Berge and Hopperstad (1993). By reducing the problem, Bish et al. (2004) only take swaps of two aircraft within one aircraft family into account, calling the approach “demand driven swapping”. Wang and Regan (2006) also study aircraft swaps as an extension of leg-based revenue management, albeit from a perspective of continuous time.

As an extension to the well known EMSR-b algorithm introduced in Belobaba (1987), de Boer (2004) considers “dynamic capacity management”. The author proposes a dynamic version of the algorithm called EMSR-d, which adjusts the revenue management policy for effects of capacity adjustments and performs best for a small set of fare classes. The approach by (Frank et al., 2006) also allows for continuously adjusting capacity. However, the authors focus on a realistic demand model considering demand dependencies between fare classes.

Those contributions that do address revenue-driven capacity changes mostly assume cockpit-compatible aircraft. In practice, this assumption may apply to low-cost carriers, but it cannot hold for network carriers. At the same time, the idea of adjusting the fleet assignment to variable demand presumes a heterogeneous fleet, which contradicts cockpit-compatibility. Furthermore, short-term adjustments cause requirements on the availability of diverse aircraft at airports and on the organisational flexibility that appear not realistic. Therefore, the related research still seeks practical validation.

3.1.2 Anticipated Capacity Changes

Technical defects, crew scheduling problems, and weather conditions can induce exogenous capacity changes within the booking horizon. In consequence, a previously optimal revenue management solution may no longer be valid. Anticipating exogenous capacity changes in revenue management would improve solution stability.

However, to the best of our knowledge, so far only a single contribution integrates exogenous capacity changes within revenue management. Wang and Regan (2006) introduce the idea to support their framework of repeated aircraft swaps – compare Section 3.1.1. However, their approach only allows for a single capacity change over time. Additionally, the authors assume that the timing of swaps is known in advance. As exogenous capacity changes are frequent in practice, we see further research potential in this area. In this regard, an approach predicting and anticipating multiple potential final capacities could provide practical applicability.

3.2 Uncertain Fare Structure

Most airline revenue management systems relying on capacity controls optimise the availability of discrete booking classes. Each booking class can represent a set of fares. However, these fares may not be revenue optimal. A single booking class representing many fares adds the challenge of estimating a typical fare for optimisation (Weatherford and Belobaba, 2002). Integrating pricing and revenue management may be one step on the way from capacity control to dynamic pricing. On the other side of the spectrum lies the idea to make revenue management persistent by handing over pricing to the customer, as in name-your-own-pricing.

3.2.1 Integrating Pricing and Revenue Management

One way to avoid fare uncertainty is to integrate the pricing decision into revenue management. By controlling not just fare availability, but the fares themselves, revenue management can more *flexibly adjust* to disturbances in the marketplace.

To this end, Feng and Xiao (2006) analyse integrating pricing and capacity decisions in revenue management. They propose a booking control policy that can incorporate the demand intensity, inventory status, and fare. In the same vein, Kocabiyikoglu et al. (2013) evaluate potential benefits when revenue management and pricing are either coordinated or combined hierarchically. The authors analyse four approaches differing in the degree of coordination and the stochastic of pricing decisions. However, both of these contributions include assumptions about the market situation, competition, and customer behaviour that limit their applicability in practice.

Clearly, dynamic pricing represents the ultimate integration of pricing and revenue management. As Şen (2013) point out, dynamic pricing can provide an edge over capacity-based controls even given well-adjusted fare structures. However, while theoretically superior, dynamic pricing is still slow to pervade airline revenue management practice (Isler and D'Souza, 2009). Nevertheless, a current IATA initiative is piloting a new distribution capability to change this (Harteveldt, 2016). The resulting technological advances will necessitate further work on the state and extension of resilient dynamic pricing.

3.2.2 Name-Your-Own-Pricing

Name-Your-Own-Price (NYOP) mechanisms turn pricing over to the customer. However, because they leave the decision to accept a price to the firm, they still enable revenue management. Wilson and Zhang (2008) show how to optimise this acceptance decision when customers are aware of the probability that their price is accepted and try to maximise individual profit. From the perspective of marketing, Hinz et al. (2011) consider the effects of a firm thus adapting the acceptance threshold of customer perception.

Integrating the customer more firmly into the process thus creates *more persistent solutions*, which continue to work even given unexpected changes. However, this increased persistence comes at the expense of the firm losing some control. Wang et al. (2009) mathematically analyse this trade-off. As benefits, the authors point out improved capacity utilisation and reduced demand uncertainty. As a major pitfall, they emphasise the loss of reliability when capacity is scarce. Anderson and Wilson (2010) thoroughly review NYOP, discussing existing models and pointing out opportunities for future research.

Most NYOP related papers consider customers' reserve prices to be uniformly distributed (c.f. Anderson and Wilson (2010)). Other assumptions that complicate the implementation in practice consider special market situations (c.f. Wang et al. (2009)) or a large inventory of the seller (c.f. Wilson and Zhang (2008)). If NYOP models overcome such assumptions, they could provide a good opportunity to tackle uncertainties, particularly via online travel agencies.

4 Conclusion

As it relies on many assumptions and estimates, airline revenue management is a picture-book example for planning under uncertainty. This paper reviewed research to make revenue management more resilient by enabling them to persist or to adapt flexibly when confronted with disturbances. To this end, we predominantly considered recent research, published in the last ten years. When considering the practical applicability of the proposed approaches in terms of managerial implications, one must note that such research is that it is rarely intended for direct implementation. Instead, it anticipates a future state of practice. In the case of revenue management, this includes assuming the availability of large data sets, computational resources, new distribution capabilities, and the willingness of firms and customers to accept new business models.

Within Revenue Management. The need to manually supplement forecasts (Section 2.1) indicates a methodological gap when historical data is sparse. Future research could develop approaches to supplementing forecasts automatically from other data sources. For flexible products, existing research neglects the consequences of customers' preferences as well as implications of offering flexible products to strategic customers.

Analysts respond to uncertainty by adjusting data and parameters. However, manual adjustments may introduce new errors and thereby new uncertainty. We regard the evaluation and support of manual adjustments as an opportunity for both researchers and practitioners.

As research has clearly shown the positive effect of accurate demand forecasts, implementing state-of-the-art forecasting methods should be a priority for firms relying on revenue management. In this regard, it is crucial to align the firm's reporting capabilities, its forecasting system and the subsequent optimisation model. Furthermore, to be able to react to changes in the marketplace, investments in computational resources on the one hand and human experts complementing automated systems, on the other hand, are advisable. To effectively act in uncertain markets, new business models such as offering flexible products could be worth consideration.

Beyond Revenue Management. Integrating exogenous capacity changes in revenue management also requires closer consideration. Existing contributions treat changes in overall capacity and capacity allocation more or less as separated fields. An integrated approach could lead to more robust control strategies, opening opportunities for revenue improvement.

For industry decision makers, this means critically considering organisational processes and information flows. For example, there is little sense in reporting capacity changes if this information is not aggregated and used for decision support. Investing in a revenue management system may be in vain if the system's information on fares and capacities is rarely accurate.

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