Hospitality Revenue Management

Theory versus Practice

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Abstract

This paper is written as an essential part of the curriculum for the MSc in Business Analytics at the Vrije Universiteit Amsterdam. The goal of this paper is to present an overview of three main pillars in hospitality revenue management research. Furthermore, it contrasts this with some problems and issues from the professional revenue management practice in hotels to highlight areas where more research is needed.

Keywords: revenue management, literature review, theory, practice

Contents

Introduction

This paper focuses on revenue management in the hospitality industry, covering both the scientific literature involving this subject and the revenue management decisions that are made in actual hotels. The goal of this paper is twofold: on the one hand, the goal is to review the ever growing literature on revenue management, with a focus on hospitality; on the other hand, there is a gap between the scientific literature and revenue management in practice. This paper aims to discuss these gaps and to highlight opportunities for academics and industry.

First of all, this paper gives a brief introduction of revenue management in general to get the reader up to speed in the field. The second section reviews revenue management literature applied to hospitality specifically. The third section discusses hospitality revenue management in practice and it looks at the gaps between theory and practice, and possible ways to address this gap. The final section concludes the review and discusses future opportunities for research in hotel revenue management.

1 A brief introduction to revenue management

Revenue management has many (slightly) different definitions, but one of the most comprehensive yet clearest is "maximizing profit generated from a limited capacity of a product over a finite horizon by selling each product to the right customer at the right time for the right price" [1]. The idea of revenue management is one that can be applied in a large number of industries. The origins of it, however, are in the airline industry. Almost fifty years ago, while working at the British Overseas Airways Corporation, Littlewood [2] created the earliest model for revenue management. In this paper, Littlewood describes the application of mathematical models to passenger forecasting and revenue control for airlines. The paper also introduces the idea of maximizing revenue instead of the number of passengers on a single flight. This is now known as Littlewood's rule, and it has been the basis of revenue management in a multitude of industries. Before 1978, airlines in the USA were unable to set their own routes, schedules and prices. However, with the Airline Deregulation Act of 1978, revenue management really took off [3].

The first revenue management system was basically a rule-based system [4] which was later enhanced to a decision support system based on marginal revenues [5]. The expected marginal seat revenue model was an extension of Littlewood's rule [6] where multiple booking classes could be included. This model was called $EMSR_B$ [7] as a reasonable heuristic to determine optimal booking limits [8]. For a more extensive look at the history of (airline) revenue management, see [9] and [5].

The basic idea of revenue management is making 'smart' choices about when to offer which product, at what price, at what time to which customer. In this paper, revenue management will almost solely consider perishable products over a finite horizon. These choices are made based on information such as a demand forecast, price sensitivity and capacity constraints. Talluri and Van Ryzin [10] state that revenue management addresses three categories of decisions: structural decisions, price decisions and quantity decisions. The structural decisions define the selling formats that are used, the segmentation or differentiation to use, discounts, etc. The price decisions are the decisions in how to set the price, individual offers, how to price over time, etc. The quantity decisions are the decisions whether to accept or reject an offer, how to allocate capacity to different segments, products or channels, and restriction decisions. The structural decisions need to be made at a strategic level for the firm, and the pricing and quantity decisions are made more frequently and eventually determine the type

of revenue management strategy the firm applies. Talluri and Van Ryzin define these two types of revenue management strategies as either quantity (inventory) based revenue management, where the remaining inventory or allocation is optimized for a given price, or price based, where the prices are more flexibly adjusted to manage demand.

Three major topics have shaped the history of revenue management [11]. These topics are *demand forecasting*, *demand modeling* and *pricing optimization models*. These three subjects can be seen as pillars of revenue management. Demand forecasting is an essential part of any revenue management system. Lee [12] has shown that an improvement of 10% in forecasting accuracy can lead to a 3% increase in revenue for airlines. However, in order to create an accurate forecast, it is important to know the true demand for a certain product. This is where demand modeling, or unconstraining comes in the picture.

Demand unconstraining deals with the issue of censored data. That is, the estimation of demand that has not been observed. The fact that a hotel has sold all its rooms or an airplane has closed a certain booking class, does not mean that there is no more demand for this product. Furthermore, customers who find a cheaper price than the maximum price they are willing to pay "buy down", and customers who feel that the rate is too high for them, do not buy. Estimating the full, uncensored demand is demand unconstraining. Demand unconstraining is necessary since it has been reported that when the forecast for a revenue management system has a negative bias, up to 3% of potential revenue may be lost [12]. Another paper estimated that when demand is underestimated by 12.5-25%, it can hurt revenues by 1-3% [13]. Finally, Cooper et al. [14] note that a spiral down effect occurs when the historical booking data remains constrained, where the expected revenue decreases monotonically.

The third topic is price optimization. After an accurate demand forecast has been made, the optimal price for the product can be determined. An optimal control policy for single resource problems, i.e. a single hotel room night or a single, non-connecting flight, is described in [3] and [15]. This is a dynamic programming optimization method, which gives an optimal control policy with regards to booking limits. It does, however, suffer from the curse of dimensionality. Several heuristics have been applied to this problem, some of which are discussed in Section 2.3 in the context of hospitality.

2   Revenue Management in hospitality

Hospitality is, together with the airline industry, one of the most established industries in terms of revenue management [3]. It shares several characteristics to the airline industry, Lai and Ng mention three key aspects. Both industries have a perishable product that cannot be stored for future sales, both usually have fixed capacity and high cost of expansion (i.e. loss of goodwill and high costs in moving guests from one hotel to another hotel, potentially a competitor) and finally, advanced reservations are allowed, which introduce the challenges of no-shows, overbooking and cancellations [16].

However, one of the main differences between airline and hospitality revenue management, and one that is rarely highlighted [16], is the length of stay (LOS). Two aspects are important here, both the network structure, and the multi-night displacement effect. Displacement is the effect where the value of a multi-night reservation is contrasted with the value of single room night bookings. Weatherford [17] determined that taking LOS into account could potentially increase revenues with close to three percent. Another complicating aspect of hotels with regards to revenue management is the fact that clients can check-out earlier than scheduled, or extend their stay relatively easily [3]. This aspect adds complexity to the whole forecasting cycle, and complicates for example the overbooking control as well [16].

One of the first examples of the application of revenue management in hospitality is the case of Marriot International. At Marriot they realized that they were, like airlines, dealing with perishable capacity constraints, budget competition and advance reservations. They managed to increase the revenue of the hotel chain with $150-$200 million on a yearly basis [18]. They managed to achieve this by creating a demand forecasting system that takes the length of stay into account.

Most research in revenue management is either done for airlines or for the general revenue management problem, without a link to a specific industry. This is partially due to the nature of the problem, since as discussed before, revenue management for hotels and airlines overlap on quite a few areas. Because of this, the first three sections of this section will discuss the literature without focusing only on hospitality. These three sections will cover research concerning the three main pillars in revenue management: demand modeling, demand forecasting and rate optimization. In Section 2.1, literature regarding demand modeling and unconstraining will be discussed, Section 2.2 will deal with demand forecasting and finally Section 2.3 will discuss the mathematical

optimization of room rates. After these three subjects, three other areas of research will be reviewed, with focus on hospitality related research only. These areas are *cancellations*, *overbooking control* and *competitors*.

2.1 Demand modeling

One of the first researchers to mention the effect of constrained data is Swan [19]. He studies the problem of *spill* estimation in the airline industry, which becomes the basis for practitioners to unconstrain demand. He later revisited this subject to expand on the implication of spill to revenue management [19] [20]. After Swan, the subject gained more attention, however it is one of the less researched areas within revenue management. An article by Weatherford [21] lists just over 40 articles dedicated to the subject in the last 38 years (up to 2016).

In an overview article in 2012, Guo et al. [22] describe five possible ways to deal with constrained data. These five methods are (1) directly observe and measure all demand, (2) ignore the fact that the data is constrained, (3) discard all data that is constrained, and use only instances where no constraining took place, (4) replace the censored data using simple imputation methods, and (5) statistically unconstrain the data.

Most unconstraining methods can be assigned to one of three main categories. These categories are (1) basic, (2) choice-based and (3) statistical [23]. Basic methods are somewhat naive, non-parametric methods. The choice-based models integrate a discrete choice framework in RM systems that provide more flexibility to take customer behavior into account. Finally, the statistical methods cover optimization based methods and can include parametric unconstraining methods.

2.1.1 Basic unconstraining methods

The first four solutions to constrained demand, as mentioned above, by Guo et al. [22], are discussed in this section. The first option, directly observe and measure all demand, is infeasible, since the observation of all demand is virtually impossible. Even with, for example, website traffic analysis, not all demand can be observed since a non-purchase can occur due to a guest booking at a competitor, a guest deciding that the room rate is too high (regrets) or a guest that is willing to book seeing that a room is not available anymore (denials). Bookings that do not occur due to lack of availability is considered latent demand [24]. Furthermore, only a small number of sales occurs through

a channel controlled by the firm directly [25]. This makes the true demand observation not possible.

The second option is to completely ignore the fact that data can be censored. This can lead to the *spiral-down* effect for revenue [14] and future demand is consistently underestimated [26]. Furthermore, Richard Zeni [27] discovered that protection levels are assigned incorrectly for higher rates, while the demand for lower rates seems to increase when it is decreasing. Queenan et al. [24] notice that this is method is still very prevalent in firms that use unsophisticated RM systems.

The third method, discarding all data points where constraining has taken place, is relatively simple and easy to implement [22]. The method can give relatively good results when the censoring takes place completely at random [27] with little missing data [26]. The disadvantage of this method is that data censoring often is not random, and the fact that data was censored is information itself, and should not be ignored by discarding the data.

The fourth option for dealing with constrained data is to replace the missing, constrained, data with other values, such as the mean or the median [27]. More information regarding the imputation can be found in [28]. Methods two, three and four are compared by Saleh [26], from which can be concluded that this fourth method performs best out of these options, and especially the third method can lead to heavy underestimation of demand.

2.1.2 Choice-based methods

One of the issues with a considerable number of demand modeling techniques is the assumption that demand is independent [29]. This is an assumption that ignores the substitution effect, where customers might prefer, in a hospitality setting, a room that is smaller but less expensive over a larger room. These two products cannot be seen as fully independent. Van Ryzin [30] noted that revenue management research should make a switch from product demand models to customer behavior models. This is where the choice-based methods come in.

McFadden [31] introduced the concept of a discrete choice framework in revenue management in 2001. Train [32] defined three restrictions, under which this framework provides additional flexibility to deal with customers considering alternatives (i.e. the choice sets). These restrictions list that in a choice based model, only one choice can be made at a given time, all available choices are included in the choice set and the number of alternatives (choices) is finite.

This framework assumes that a guest will always choose the alternative that gives him or her the maximum expected utility. This utility can be defined in

several ways, but usually includes a sum of deterministic and stochastic terms. The random terms can lead to several demand models, dependent on the distribution of the random term. The parameters of these models are usually estimated using maximum likelihood [23]. Vulcano et al. [33] reported significant improvements in estimated revenue by using choice-based methods on real airline transaction data.

The model that is almost always chosen is the multinomial logit model [29]. This is chosen since it has parameters that can be estimated relatively efficiently by maximum likelihood estimation, and the choice probabilities can be easily computed. More recently, a shift is made towards non-parametric choice models, see e.g. [34], [35] and [29]. These assume preference based on a strictly ranked list of preferences, including a non-purchase option.

2.1.3   Statistical methods

More advanced statistical unconstraining methods have been proposed as well. These have the advantage of avoiding the ad hoc nature of imputation methods and have a solid statistical foundation. However, these methods are more complex to implement, and can have multiple inherent assumptions that need to be validated [27].

Within these statistical unconstraining methods, one of the most popular is the Expectation Maximization (EM) method [23]. This is a method that was introduced into airline revenue management by Salch in 1997 [36], and developed by Dempster et al. in 1977 [37]. This algorithm is a two-step iterative process, where in the first step, the E-step, censored observations are replaced by the mean, and in the M-step the new parameters for the demand distribution are estimated by maximizing the log-likelihood function with respect to those parameters.

However, a few years earlier, Hopperstad [38] developed a probabilistic method while working at Boeing, Project Detruncation (PD). PD works similarly to the EM algorithm, but instead of the mean, it uses the median. Furthermore, it allows for a weighting constant. One disadvantage of PD is increased computational costs and no guaranteed convergence [39]. PD is outperformed by the EM algorithm in multiple studies, see [39], [27] and [24]. It still performs significantly better than the naive, basic unconstraining methods. One of the disadvantages of EM is that is works poorly when working with small numbers of data [40].

Queenan et al. proposed a method based on double exponential smoothing (DES) [24]. This method tries to forecast the total demand in the case where

there would have been no booking limits. DES makes use of two parameters. One for smoothing the base demand pattern, and the second for the trend component. This method has been proven to perform similarly to EM in most cases [41] [42].

2.2 Demand Forecasting

Forecasting is considered to be *the* critical component in a revenue management system [43]. Talluri and van Ryzin note that a revenue management system needs forecasts of variables like demand, price sensitivity and cancellation probabilities [15] [44]. This section will focus especially on the demand forecast within hotel revenue management. The booking limits of a system are based upon this forecast, and these booking limits are consequently one of the most influential determinants of total revenue of a firm [21]. The field of forecasting has developed over the years into a whole independent discipline. Early work was developed in the '60s [45] and a wide range of areas has shown interest in developing new and better forecasting methods [46]. Forecasting research in tourism exists since the '80s [47] [48], and research in this area continues to grow.

However, forecasting for hotels specifically is a subject area that is underdeveloped compared to areas such as forecasting in the airline industry [49] [50]. Over 500 papers have been published in tourism demand modeling and forecasting [49] [50] [51] [52] [53]. However, between 2000 and 2006, only three studies focused on hotel demand forecasting specifically [51], and in a recent literature review regarding tourism and hospitality forecasting done by Chenguang et al. [50], only 25 out of 171 articles, less than 15%, discussed hotel demand modeling and forecasting.

In their often cited article from 2008, Song and Li [51] divide quantitative hotel demand foresting into three categories: (1) time series forecasting, (2) econometric models and (3) AI-based forecasting techniques. This division is later used by Wu as well [54], and will be used in this section as well. None of these single methods, or even groups of methods, is proven to be universally superior [55], and the performance of the model is severely impacted by the choice of accuracy measure as well [49] [56]. These two final points will be addressed at the end of this section, after briefly discussing the most used methods in each category.

2.2.1   Time series methods

Time series models forecast only the final number of rooms for a particular arrival date. Within time series models, a distinction is made between basic time series models and advanced time series models [57]. The basic models include naive methods, simple moving averages and single exponential smoothing. The models that are included in the advanced category are double exponential smoothing and variations on AR(I)MA.

Basic methods

Two naive methods are possibly the most widely used forecasting methods [57]. These two methods are *Naive 1*, which constitutes of forecasting no change at all, and *Naive 2*, which takes a constant change into account. These are both used in practice, and are implemented as *Same Day Last Year*, where the forecast is the same as the actual performance on the same day in the previous year, and *Same Day Last Year Increased*, where the forecast is the same as the actual performance on the same day in the previous year, with a small percentage increase. These methods are often used as a benchmark for more advanced methods [49] [56], but often seems to outperform more sophisticated methods as well [58] [59]. This is shown in Pereira's paper [56], where out of a total of 120 forecasts, generated for three room types, five forecasting methods, two accuracy measures and four forecast horizons, only 41 forecasts (34.2%) performed better than the benchmark of Same Day Last Year. The first naive method lacks the ability to deal with unexpected structural changes in demand. However, in certain cases the second naive method is shown to outperform the advanced time series methods when dealing with unstable data [60].

Next to these two naive methods, the most used basic methods are moving average, and single exponential smoothing. The problem with the moving average method is that it gives equal weight to all observations [61]. This issue is apparent in the analysis of Pereira, where, in all testes cases, a forecast using the average over the past three years performs worse than Naive 1. The same holds for single exponential smoothing, which performs even worse than the moving average in 22 out of 24 cases (91.7%), and again worse than Naive 1 in all the cases [56].

Advanced methods

Since 2000, more advanced time series methods have often been of focus in the forecasting literature. One of the oldest methods is Double Exponential Smoothing, which was developed in 1963 [62]. It is applied across a wide range

of studies, first in 1975 by Geurts and Ibrahim [63]. It has been shown that it performs similarly to the Naive 1-method [64]. Since 2000, variations of ARIMA models have been applied in over two-thirds of the studies researched by [51], however it lacks the possibility to work with non-linear trends [65]. An adaptation to this method, called Holt-Winter's method, is essentially triple exponential smoothing. This method captures (non-linear) trends and seasonal variation. It generally performs best of the exponential smoothing methods [66] [67].

The ARMA process is the time series method that is applied most frequently [51] [68]. There is no consistent evidence of the performance of the several ARIMA or seasonal ARIMA (SARIMA) models. There are studies that show that ARIMA or SARIMA outperform other time series methods [69] [70]. However, there are also studies that show that ARIMA and SARIMA are both outperformed by the Naive 1 method [71]. Variants such as multi-variate SARIMA (MARIMA) [70], autoregressive ARMA (ARARMA) [72] and fractionally integrated ARMA (ARFIMA) [72] have been shown to outperform methods in specific cases, however no one single method has shown overall dominance. However, the ARIMA approach has often performed best in terms of accuracy [70] [73] [74] [75].

In recent years, nonlinear methods have received more attention. One of the most promising is single spectrum analysis (SSA) [51]. This method tries to filter the noise from a time series and forecast the signal only, whereas more traditional methods try to forecast both. It makes no assumptions regarding the data-generating process [76] [77]. Two studies compared it to, among other, ES, SARIMA, structural time series (STS) and a neural network, where it outperformed all tested methods. Next to SSA, the Markov switching model is showing promising results in recent research, having it perform on par with ARIMA and outperforming AR models and other time series models [78] [79] [80] [81].

2.2.2   Econometric methods

Like the time series methods, the econometric models are divided into two groups of methods: static and dynamic econometric models. The static models, including methods like traditional regression, perform badly in demand forecasting tasks in the hospitality setting [57] [82], and often cannot compete with the, simpler, Naive methods [83]. The inherent complexities of demand forecasting, such as seasonality, are one of the reasons these methods do not perform well [84], and spurious regression is a often noted problem [82] [83] [84] .

Dynamic econometric methods

The set of dynamic econometric methods perform relatively well compared to other methods [57]. This set of methods includes, among others, vector autoregressive (VAR) models, time varying parameter models (TVP) and error correction models (ECM) [85], which all solve some of the problems that occur with the static econometric methods. One of the advantages of ECM is that it overcomes the spurious regression problem [86] [87] [88], and it is shown to produce more accurate forecasts than the traditional econometric methods [89]. VAR models have been shown to forecast accurately on the medium and long term [90] [91], having the advantage that it is not necessary to produce forecasts for the explanatory variables before forecasting the dependent variable [57]. Furthermore, the TVP model accounts for variations over time which makes it a very flexible solution for the sudden changes in demand that can occur over time [57] [85].

2.2.3 Machine learning methods

The recent increase in popularity of machine learning applications is visible in hotel revenue management research as well. The first application of neural networks, however, dates back to 1996 [92], but in recent years the number of studies researching machine learning methods in the demand forecasting area has increased significantly [57] [51]. It was clear early on that a neural network performs well in forecasting situations, with studies showing their superior performance in the early 2000s [93] [94] [95]. One of the disadvantages of the neural networks is that there is no one standard procedure to create the perfect model, and the solution to that is trying [95] [96]. Another downside is that it is hard to produce a meaningful explanation of the explanatory variables [97].

2.2.4 Performance

Peng et al. [57] performed an extensive meta-study regarding forecasting accuracy and performance, and noted several interesting findings. The main conclusion was that in general dynamic econometric (DE) models performed best overall, while the static econometric models performed worst. AI based methods rank second, and advanced time series third. However, when models are broken down with more specific characteristics taken into account, the performance of the several groups of models is not so consistent. For example, with yearly data, the dynamic econometric models perform best, but when the data is quarterly or monthly, DE becomes one of the lowest performing model groups. Something

similar holds when the tourism destination is taken into account. [57]

Furthermore, the accuracy measure used should be taken into account, since different accuracy measures can yield contradictory results when comparing multiple models [49] [56]. Is should also be noted that even within the same model, but with different forecast horizons, different models can perform very well on the short term (i.e. less than 3 months in advance) but not well on the longer term (i.e. forecasting more than a year ahead), and here it again matters according to which model the performance is measured [57] [49] [56]. From this it can be concluded that in forecasting research it depends on the situation which method will perform best, and several options should be explored, compared and possibly combined in order to achieve the best performance [98].

2.3 Pricing

Following on the unconstrained demand and the subsequent demand forecast, optimal pricing is the third pillar in revenue management [11]. The pricing step is considered to *solve* revenue management, since it applies the final step and returns a solution, i.e. a price, based on the demand. Two of the most often used techniques to solve revenue management are deterministic linear programming (DLP) and dynamic programming (DP) [99]. It has been shown that DLP can generate almost three percent more revenue compared to older methods like EMSR [17]. This is due to the fact that DLP can deal with guests that stay multiple nights, where multi-night stays are viewed analogously to multi-leg itineraries in the airline industry [100].

2.3.1 Dynamic programming

The advantage of DP over DLP is that it has a stochastic component integrated, which takes the uncertainty regarding demand, which has been discussed in the previous sections of this paper, into account. However, the most common disadvantage to DP is that the state space of the optimization grows exponentially and hence it notes the effects of Bellman's curse of dimensionality [99]. In the seminal 2004 book, Talluri and van Ryzin [3] describe a version of the DP model that has been widely applied in both the airline industry and the hospitality sector [99]. The problem is intractable to solve [101], since it suffers from the dimensionality curse for all but the smallest problems [102], and the equation is complex to maximize [99]. This is why several heuristics have evolved over time to approach these problems.

Model formulation

The following model formulation is able to handle inhomogeneous arrivals over time [99]. The model considers T time stages, with $t = 1,...,T$. Each time stage has some arrival rate $\lambda(t)$ which is constant for each time interval, but may change depending on t. For every period, the probability of one arrival is λ, and the no-arrival probability is $1 - \lambda$. To account for inhomogeneous arrival processes, every time stage can be divided into a number of segments with stationary parameters. Define the vector r with all prices, and r_j as the price of product j. An arriving customer purchases product j at time t for price r with probability $P_j(r)$. The no-purchase probability $P_0(r)$ is defined such that $\sum_{j=1}^{n} P_j(r) + P_0(r) = 1$. Define x as the remaining capacity at time t, and let $v_t(x)$ the value function representing the maximum expected revenue at time t given state x. The Bellman DP equation is then given by:

$$v_t(x) = \max_{r_t \in R_t(x)} \left\{ \sum_{j=1}^{n} \lambda P_j(r_t)[r_{t,j} - \Delta_j v_{t+1}(x)] \right\} + v_{t+1}(x) \qquad (1)$$

with $\Delta_j v_{t+1}(x) = v_{t+1}(x) - v_{t+1}(x-1)$ as the opportunity cost of selling one unit of product at the current time, i.e. t. This function is bounded by $v_{T+1}(x) = 0 \ \forall x$ and $v_t(0) = 0 \ \forall t$.

Solutions

The dynamic programming equation, as shown in Equation 1, can be expressed in a linear programming (LP) formulation. This was done by, among others, Powell [103] in his book about approximate dynamic programming, and by Adelman [104] in his seminal paper on revenue management pricing. Several linear programming variations have been introduced, to include dependent demand [105], called choice based linear programming. Since this model still grows exponentially depending on the number of products [102], Liu and Van Ryzin [106] formulated a solution that solved the LP using column generation. However, this problem was still shown to be NP-hard [107] when choice sets overlap. However, in 2015 [108] and 2016 [109] proposed two algorithms that solve the choice based LP nearly optimal, with provable efficiency. Talluri [110] introduced a new solution where the DP was decomposed by customer segments, since these are loosely linked and provide an upper bound for the choice based model.

2.4   Other subjects

Next to the three main pillars in revenue management discussed in the previous sections, several other interesting topics have arisen in the field of hospitality

revenue management. In this section, prediction of cancellations, overbooking policies and the influence of competition will be discussed briefly.

2.4.1   Cancellations and overbookings

Forecasting cancellations is a subject that has risen in popularity in recent years, especially due to the availability and popularity of machine learning models to aid with these tasks. This purpose of forecasting demand is twofold: on the one hand it will help with determining an acceptable level of overbooking, on the other hand it helps with estimating the net demand for hotels [111]. Errors in the forecast of the cancellation rate will have effects down the road of the whole revenue management cycle. Overestimating the cancellation rate could lead to underestimation of the net demand, which will in turn lower the room rate in order to attract higher demand. There are two main approaches to tackle the cancellation forecasting problem [112] [113]. The first is to predict the fraction of all total reservations that will be canceled. The second approach consists of using a passenger name record (PNR) to forecast if a specific reservation is likely to cancel based on attributes of the booking and the booker, such as the country of origin and the moment when a reservation was made. Data has shown that cancellation rates around 20 to 30% are not uncommon in the hotel and airline industry [113] [114].

Forecasting the cancellation rates using time series is a relatively straightforward approach. Methods such as ARIMA, linear regression and exponential smoothing [115] [116] have been applied in the airline context. However, it has been argued that these methods are inaccurate whenever the passenger mix on a flight changes [117] since they do not take any passenger characteristics into account. This is why the PNR approach has become more popular in recent years, especially with the increase in popularity in machine learning methods [112]. It has been noted that over the booking horizon, the set of relevant variables changes significantly [113].

Overbooking is the practice of accepting reservations after the capacity of the hotel has been reached. Given an estimate of the number of bookings that will cancel, this can lead to increased accuracy in demand estimation and, hence, increased revenue. Little research has been done on the extension of integrating cancellations in the customer choice pricing model [118]. However, Sierag [118] has results that lead to revenue gains up to 20% compared to the base model from Talluri and van Ryzin [15] with relatively straightforward linear cancellation rates. Other research shows equally promising results. Using the combination of more advanced cancellation forecasting and overbooking control

has led to estimated increases in total revenue of 1.15% up to 4.16% according to Petrary [112]. Taking potential costs into account for having to deny access for passengers, net revenue gains can be up to 2.8%, and when the cancellation rates are high even 3.6%.

2.4.2 Competitors

Most revenue management models are monopoly models, where the demand faced by the hotel is assumed to depend only on the price set by the hotel itself, and not on the competition [3]. Here, the models do not consider the reaction of a competitor to the increase or decrease of a room rate. This model can be justified considering model tractability, and is partly validated since the observed historical competitor responses are inherently taken into account in the historically observed price response from customers. However, any changes in competition strategy, not observed historically, will not be taken into account.

Talluri and van Ryzin [3] note that a perfect competition model is another possible approach. In this model, it is assumed that the influence of each firm is small compared to the market size. Combining this with the assumption that every hotel is offering (roughly) the same product, they conclude that each firm is a *price taker* that is able to sell as much as it wants at the prevailing market price, but nothing when they are above that price. This would also mean that these models are not directly useful for pricing, and these assumptions have severe consequences for all pricing models since this influences the maximum rate by assuming that it cannot go above the market price.

The most promising model seems to be the oligopoly model. One disadvantage of oligopoly models is that there are assumptions about the strategy of the competitor. The belief may exist that competitors price rationally, instead of following some optimal strategy, which may result in poor prediction of competition behavior. Shugan [119] notes that sometimes the assumption of no competitive responses is better than the assumption of optimal competition behavior. In the oligopoly model, the individual hotels are assumed to be large enough to elicit at least some effect on market demand upon changing their pricing. This creates a strategic incentive, which can be modeled using game-theory and the Nash-equilibrium. Fiala [120] modeled competition as an extension of a deterministic linear program that was used to optimize rates. However, some strong assumptions were made, including fixed prices for all hotels and independent demand, and bookers only try to book with their two most preferred hotels, otherwise they do not book. The approach can be extended into network revenue management. No results of research in this area is published currently.

Arenoe [121] et al. worked on research in this building on oligopoly markets in hospitality, and published some results regarding equilibrium prices. However they note the limitations that the model has in terms of assuming rational competition and complete information.

3 Revenue management in practice

Extensive theory exists on the subject of revenue management, especially with the focus on airlines and hospitality. The review above tries to cover some of the most important subjects regarding hospitality. But there are many more subjects that have not been discussed. However, revenue management in practice is somewhat opaque in the sense that it does not give open access to its inner workings [122]. There is not much literature comparing scientific algorithms to the performance of implemented real-world revenue management systems. One attempt lists the performance of several theoretical models versus the simple method used by a real-world hotel [123]. Here, the theory outperforms the used model, but it is noted that implementing the theoretic models comes with several difficulties and might be infeasible and error-prone, which will likely result in worse performance. Discussions with revenue management practitioners, online research and literature research led to several aspects of practical revenue management that are not considered extensively in the scientific literature. This section will focus on some gaps that revenue management research has not focused on, either not at all or in a small amount.

A second note that has to be made is the fact that many hotels do not apply revenue management tactics [124]. It is estimated that fewer than 7% of hotels and resorts that have over 50 rooms use revenue management software [125]. This means that despite of all the research being done in the field of revenue management, there is a large possibility for that knowledge to be applied more widely and to validate the scientific research being done by comparing revenue management system performance to the scientific methods discussed here.

The practice within hotel revenue management tends to exhibit a larger variation between hotels than in, for example, the airline RM industry [3]. This is mainly due to the more fragmented nature of the industry, where hotels can be managed by different, independent owners, they can be managed as part of a larger chain, or they can be franchises. Some chains manage hotels which they do not own, and the other way around happens as well.

3.1 Practical problems in revenue management

3.1.1 Transparency

Hoteliers are not mathematicians, and hence do not want to know, let alone understand, all the intricate details of the methods discussed in Section 2. However, hospitality being a relatively conservative industry, convincing hotel

revenue managers to actually trust the results coming from the mathematical models is a hard problem. The rise in popularity of complex, data driven, models makes it hard for hoteliers to simply follow the suggestions from some black-box machine learning method. They question the results, and have a hard time convincing their own gut feeling that some scenario might actually be happing in a way contradicting their long-held beliefs.

3.1.2 Secondary revenue sources

One of the most significant differences between the theoretical models and the practical aspects of revenue management is that only the room rate is taken into account in almost all pricing algorithms (see Section 2.3). However, hotels utilize many more sources of revenue than just the room rate. Ancillary revenue sources in hotels consist of, among others, food & beverages, paid parking, meeting rooms, room service, casino facilities and spa facilities [126]. Real world revenue management needs to take all those aspects into account. Research into the single revenue centers is being done (see [127] [128] [129] [130] for restaurants, [131] [132] for function rooms, [133][134] for casinos and [135]), but one pricing strategy to take this all into account is hard to figure out. The trade-off between attracting more customers to engage with the secondary revenue sources due to lower room rates and higher room rates to maximize room revenue is a difficult problem to solve, both for revenue managers in practice and the scientific researchers.

3.1.3 Profit management

Online sources indicate that hotels are shifting more towards profit management instead of 'just' revenue management [136][137]. Where currently revenue per available room (RevPAR) is one of the key indicators [124] for hotel revenue management, this is shifting towards gross operating profit per available room (GOPPAR) as their main key performance indicator. According to a survey [138], 71% of the revenue managers believe the discipline of revenue management should be renamed to profit management. Already in 1990, scientific literature mentioned that profit management was the next step beyond yield management [139] to focus more on the long term effect of pricing. However, no recent research was found regarding this subject.

3.1.4 Hotel interaction

As was already touched upon in Section 2.4.2, the influence of other hotels is an important topic. Not only the hotels of competitors have influence on your pricing strategy, also the location of the hotels of a chain in the same area are of importance [124]. The hotel chain of one of the interviewed revenue managers has three properties in the same city. For example, a hotel of the same brand in the outskirts cannot have a higher rate than the hotel in the city center. So the rate of one hotel influences the rates of all three properties in that city. This is without even considering competition of all those hotels.

3.1.5 Group reservations

How to deal with group reservations in a revenue management setting is a difficult problem [140]. Group reservations are unpredictable in terms of when they arrive and how many people are involved. The opportunity cost usually used when determining whether to accept or reject a reservation is not applicable anymore, and they immediately cut into the available demand. However, if a group cancels, this can ruin the pricing strategy of the hotel, since a block of rooms suddenly becomes available again [124].

3.2 Open challenges and new developments

Revenue management in both research and practice still has several open challenges. In their foundational paper back in 2003, Weatherford and Kimes [98] already mentioned several challenges in hotel forecasting. When looking at the research encountered in this paper, that has emerged since 2003, it seems that these challenges still exist. Among their challenges, Weatherford and Kimes ask "what to forecast?", and discuss "forecast accuracy". Both of these challenges are still alive in the recent research. For example, regarding forecasting accuracy, there is no definite *best* forecasting accuracy measure [49] [57] [56], they all differ depending on the method and the specifics of the forecast such as the forecast horizon and the hotel location. Regarding the "What to forecast" question, this is disputed as well. Forecasting happens on room night level, arrivals or occupancy forecasting [98], [21] [46]. This immediately touches upon the unconstraining problem, which deals with similar problems as the forecasting.

There is no one academic solution which incorporates all the aspects of full hotel revenue management. Revenue management is a complex topic, with all the topics noted in the literature review in this paper, and taking the hotel wishes into account mentioned in Section 3, makes the problem computationally

very complex. However, new developments in recent years regarding artificial intelligence/machine learning do offer more opportunities to handle the complexity associated with revenue management. Hotels are adapting and storing increasingly large amounts of data. This allows for more advanced models to be applied with greater ease. As discussed mainly in the forecasting Section 2.2 of this review, applications of machine learning methods contrasted with for example time-series forecasting yield promising results and the continuous improvement of this area of research gives hope to make these forecasts even more accurate.

3.2.1 Ethics

Revenue management is sometimes already perceived as unfair [141], and the increasing amounts of data that are being stored lead to even more questions regarding the ethical ramifications of revenue management. The increase in application of machine learning based models in general has led to questions about discrimination and biased algorithms [142] [143]. Charging guests different rates based on when they book and through which channel has been accepted practice for a long time. However, in practice [124], talk is now veering into pricing based on characteristics such as gender, country of origin or age.

4 Conclusion

Revenue management is an area that has matured over the past 50 years. This started with the method developed by Littlewood in the seventies, and currently faces the rapid development in forecasting and optimization using machine learning techniques, to process the enormous amounts of guest/passenger data that is created every second. These developments, using advanced and data-driven methods, yield promising results for more efficient computation and solutions that are closer to the maximal possible revenue.

However, this research has also shown that even though the existing research into revenue management is very extensive, the extent to which these scientific methods are applied in practice is unclear. The larger revenue management systems do not disclose their methods. Even if they would do so, those methods are applied only within a small set of the hospitality firms. This implies that most hotels still do not profit optimally from the possibilities that have been developed and discovered in the academic revenue management community.

Further research into revenue management lies with the points addressed in Section 3. There are many subjects that have not been addressed extensively within revenue management research. Secondly, a lot of topics have not yet been combined with other solutions to provide the total revenue management solution that the revenue management practice is waiting for. Especially the question regarding demand unconstraining and forecasting will keep researchers occupied in the coming period, with the advances in advanced machine learning forecasting techniques promising to step the revenue management game up.

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