

Article

Model of Price Optimization as a Part of Hotel Revenue Management—Stochastic Approach

Martin Petricek , Stepan Chalupa  and David Melas

Department of Economy and Economics, Institute of Hospitality Management in Prague,
181 00 Prague, Czech Republic; chalupa@vsh.cz (S.C.); melas@vsh.cz (D.M.)

* Correspondence: petricek@vsh.cz; Tel.: +420-728-886-631

Abstract: The paper is focusing on the problem of price optimization in the area of accommodation services. The main aim is to propose a novel simulation-based methodology of price optimization based on the customer's price acceptance. The authors create a model based on the known approaches but extended by the stochastic approach and optimization based on the coefficient of price elasticity. The whole model is created, the price is set and optimized in two steps. The first step makes segmentation and optimization (with the price elasticity approach). The second step then sets the price of the reservation—the final price for a customer. This reservation price is mainly determined by knowledge of the length of stay, occupancy and booking lead time. All those parameters are described in the text from the economic point of view and make the base for the whole and complex revenue management model.

Keywords: accommodation service; nonlinear programming; price optimization; revenue management; price elasticity



Citation: Petricek, M.; Chalupa, S.; Melas, D. Model of Price Optimization as a Part of Hotel Revenue Management—Stochastic Approach. *Mathematics* **2021**, *9*, 1552. <https://doi.org/10.3390/math9131552>

Academic Editors: Aleksandra Gawel, Miloš S. Krstić and Katarzyna Mroczek-Dąbrowska

Received: 21 May 2021

Accepted: 29 June 2021

Published: 1 July 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The current hospitality industry is highly affected by the intensive use of information and communication technologies, and potential customers can easily access an extensive amount of information generated not only by the accommodations themselves but the other customers via reviews or word of mouth as well [1]. This leads accommodation entrepreneurs to rethink their long term strategies and focus on their core objectives, while effectively allocating their resources to maximize their core strengths [2]. Ortega et al. [3] stated that one of the critical competencies to focus on while building a sustainable business strategy is e-commerce, the proper understanding of customers and tailoring company offers to their needs through e-commerce tools. Even though entrepreneurs and customers tend to use different online platforms, a well-developed online customer relationship management (CRM) platform can boost the competitive advantage not only in the online market but also in the offline one [3].

Developing or simply adapting the online platforms into a business strategy as the communication or distribution channels can improve a business' visibility and competitiveness [4]. On the other hand, this adoption leads to the need of adopting new technologies such as channel management tools that can help with labor efficiency as the process of data loading and updating on various online platforms can be labor-intensive [5] and expensive for smaller accommodation businesses and require the employment of other strategies in connection to the available management and their proper pricing.

These strategies are directly linked to revenue management, which can be described as the strategy of selling the right products to the right customers for the right price (rate) at the right time [6–8]. Current research in revenue management mainly focuses on pricing, more precisely, dynamic pricing on online platforms [9–12]. In this scope, it is crucial to mention that a considerable part of the sales in the hospitality industry are completed offline through traditional contracts, and dynamic pricing is mainly used while targeting

the online market [13]. Koushik et al. [14] state that revenue management and revenue management tools are mainly used to optimize revenue within the transient segment.

The use of modern technologies brings hoteliers great opportunities to use the available data to improve their decision-making processes and customer-centric strategies. The volume of data is still increasing as the behavior of hotel clients can be tracked from their first travel intention until their post-stay behavior, and the data analysis and data-driven procedures are being implemented in hotel operations. The negative aspect of big data is closely connected to the lack of knowledge within their analysis and unclear perception of their use within the operations [15].

There are many areas where big data are being used, for example, within the customer relationship management while identifying the most valuable customers and their groups [16], efficient forecasting and identification of hotel reservation cancellations [17,18], demand forecasting [19], and customer behavior identification and modelling [20]. Ivanov et al. [21] also highlight the current gap between revenue management practitioners and researchers where the big data are being mentioned as one of the topics mainly examined by the researcher with weak coverage in hotel operations. It is essential to mention that the focus of the big data-oriented studies is closely (mainly) connected to the topic of revenue management and dynamic pricing.

Even though there are many studies in revenue management and dynamic online pricing, there is still a lack of novel and evidence-based research describing the revenue management methods in a comprehensive and applicable way, and there is still a need for better understanding the customers' behavior and online pricing [22,23]. Based on a study by Ivanov et al. [21], it is essential to propose not only theoretical models but also examine their practical applications. As described in the literature review, there are primarily theoretical studies using simple models, including their detailed description or application studies without a detailed methodology description. The studies use many assumptions as well and do not reflect current changes in demand for hospitality services.

The main aim of this article is to propose a simulation-based methodology of price optimization based on the customer's price acceptance (based on the price elasticity of the demand coefficient). The whole approach is based on the two steps of price determination. The first step is linked with the general price optimization based on knowledge of the price elasticity of demand for the current segment. The second step is based on the multiplicative and additive approach of setting up the price of the current reservation. This approach would like to describe all direct and indirect determinants of price in the hospitality industry.

2. Literature Review

As mentioned in the previous section of this article, current research mainly focuses on the dynamic pricing on online markets, while omitting the need for a proper description of the methods used. The following sections are focused on the key evidence in the field of e-commerce in the hospitality industry and the description of pricing models used to match the customers' needs and their price acceptance characteristics.

Past research and revenue management tools and techniques were mainly focused on availability control [14,24], while current research highlights the need for price optimization and dynamic pricing [6,8,25]. A meta-study by Vives et al. [8] showcases the sources of price variability and demand segmentation as the reasoning for the price optimization models and their development.

Several studies are focused on price optimization using various outputs. Koushik et al. [14] describe price optimization using the updated PERFORM (the revenue management tools of InterContinental Hotel Group—IHG) methodology based on the hotel occupation, price demand elasticity and competitors rates. During this time, PERFORM used the assumption of independent demand and mainly controlled the availability and LOS (Length of Stay) inventory connected to the deterministic model of Baker and Collier [26]. The development of the internet and e-commerce caused a shift from availability control to dynamic pricing using

various factors (customer's behavior and competition characteristics). The updated model focused on price optimization for a specific date and LOS based on the demand (represented by the hotel and its competitors), room costs and hotel availability characteristics.

Another practical implementation of advanced price optimization is linked to the Carlson Rezidor Hotel Group, where the price optimization model was based on the price elasticity of demand, market (competitors) rates, room availability, forecasted demand (based on the historical data of hotel customers—length of stay, rate segment, day of the week and lead time) and business rules. The proposed price optimization model increased the revenue of compliant hotels by 2–4% more than the non-compliant ones [27].

Pimentel et al. [28] developed a revenue optimization method based on the demand estimates in a specific market segment ahead of the planning horizon, where the method optimizes the availability (overbooking levels) and allocation to the specific market segment. The same author [29] focused on comparing nested network and bid price allocation methods, where the nested network method overperformed the bid price method. The authors stated that the hoteliers should shift to nested network allocation as the current revenue management tools are more available.

Goldman et al. [30] focused on allocation optimization using the deterministic model of demand of Weatherford [31] and the stochastic model of De Boer et al. [32]. Both models were also tested in connection to the booking control policies mentioned by Pimentel et al. [29], the bid prices and nested booking limits. The best performing optimization was based on the stochastic model/programming with nested allocation methods. Lai and Ng [33] used the network optimization model, which is the stochastic programming approach in its nature as the optimization considers the uncertainty of the demand and customer behavior, mainly focusing on the number of hotel rooms demanded and the reserved length of stay. Other concepts such as cancellations and no-shows, business rules, early check-ins, overbooking and extended stays are discussed as well. The length of stay was later developed more in detail, using the stochastic approach [34,35]. The same approach, the dynamic stochastic programming model, was used not only for price optimizations within the hospitality industry but also for car rentals [36]. The authors based their model on the advanced demand information (ADI) and its combination with uncertain non-ADI customers.

Another approach, dynamic programming, can be used to identify the optimal selling rate based on the time variables and availability, mainly within small accommodation facilities [37].

Based on the previously mentioned studies, two different approaches to price optimization can be identified—deterministic and stochastic [24]. The deterministic models are suitable mainly when the customer's sensitivity to price changes varies during booking horizons, while the stochastic approaches are preferred in situations where more variables should be taken into account. When focusing on the output of the studies, the stochastic approaches outperform the deterministic ones [38] and are more relevant to customer behavior [39].

When focusing on more recent studies, for example [8], the concept of price optimization is mainly focused on the identification of the variability of customer behavior under specific conditions and demand forecasting, mainly on historical data (previous performance of accommodation facility) [40] and current data [41,42], a stochastic approach to price optimization.

Respecting the current focus of research within the price optimization, it is important to mention that several of the previously mentioned optimization studies [14,28,29] are mainly (some of them only) focused on the transient leisure segment, the most essential segment within e-commerce and online sales. The proposed optimization model takes into account the differential behavior of market segments, which is why it is beneficial to focus on the various approaches to market segmentation and price demand elasticity measuring as well.

The studies mentioned in the previous section of the literature review use the key characteristics of customers (in most cases, mainly the price elasticity of demand) mostly

nested within the market segments. None of these studies mention the process of market segmentation and segments development. Revenue management is mainly based on the understanding of the behavior of various market segment. Koushik et al. [14] describe the broad perception of market segmentation in the hospitality industry where the transient and group segments are identified. Lee et al. [43] propose a more analytical approach to market segmentation, where the transient segment is divided into the retail and negotiated segments, and the retail segment, consequently, into restricted and non-restricted segments. The authors focused mainly on the acceptance of the selling rates and the development of the willingness-to-pay in time for restricted and non-restricted stay offers.

A very complex overview of market segments and segmentation criteria is proposed by Ivanov [44], where the whole process of market segmentation is being described from various perspectives. When focusing on the revenue management point of views, it is crucial to focus on the behavioral criteria and the data-driven market segmentation. Vives et al. [8] identified two approaches toward market segmentation, the internal and external market segmentation, where the external segmentation focuses on the factors that cannot be controlled in short terms by the revenue managers and the internal segmentation focuses on the controllable ones.

In short terms, the booking dates, rate fences, type of tourist and seasonality are considered. Aziz et al. [45] described the behavior of low-price tourists who tend to occur in early booking stages, while the increased prices can be identified in close to arrival stages. This is proved by the findings of other studies [37,43], which consider the different behavior of customers across the booking horizons. The goal of revenue management is to effectively balance the structure of the customers based on their variable behavior in the booking horizon (lead time) [46].

Rate fences are the rules that are used to segment the demand more comprehensively in order to justify the differential pricing [47]. The most commonly used fences are closely connected to the refundability of the offers, minimum length of stay and group size [44], hedonic product characteristics, loyalty, lead time, corporate membership or reservation conditions [48,49].

The commonly used segmentation of customers into business and leisure is closely connected to a specific marketing strategy. Many studies describe the difference between leisure and corporate clients [13,43,44,50]. Moreover, it is crucial to understand the possible seasonality of the demand on a yearly or even on weekly basis, while targeting various market segments as the leisure segment is mainly travelling during weekends and corporates during weekdays [13]. Other studies within the seasonality of the demand also focused on the school holidays, religious festival and special events and differences between low and high seasons [43,49,51].

From this perspective, we can see that there are many approaches toward market segmentation, while all of them are closely connected to the domain of big data and data-driven market segmentation. One of the key characteristics of the current market segmentation stated by Dolnicar [52] is the fact that the data-driven market segmentation should be always considered as an exploratory study focusing on the individual behavior of hotel customers.

While taking into account the previously mentioned factors, we can state that one of the key customer characteristics that represents behavior is the price demand elasticity [53]. The concept of price demand elasticity is describing the connection between public (visible online) rates and the quantity of hotel rooms demanded. The resulting coefficient can be used to describe the reactivity of the client to the price change. When focusing on the price demand elasticity, several approaches can be identified. Price demand elasticity is estimated based on the rate segments [27], log-log regression model [54], autoregressive distributed lag model [55], linear and non-linear demand function [43], logistic regression [50] and multiple logistic model [56,57].

Tran [55] used an autoregressive distributed lag model for the evaluation of economic factors and their connection to demand for a luxury hotel in the US. The study works with

the price demand elasticity coefficient that varies from -0.03 in the long term to -0.02 in the short term. A study by Rosselló et al. [58] focused on the demand for accommodation services in Germany, the UK, France and the Netherlands, while focusing on the elasticity of demand, finding values of the coefficient from -0.51 to -4 . A combination of the previously mentioned approaches towards the elasticity of demand (destination level and narrow product level category) can be found in a study by Damonte et al. [59], where the price demand elasticity differs based on the level of services and the destination size, where the properly defined region can bring better results than the aggregate approach. The same results are proposed by Canina and Calver as well [60].

A study by Hiemstra and Ismail [61] focused on the elasticity of demand considering several variables and the impact of taxes as well, where the supply elasticity coefficient reached the level of 2.86, contrary to the -0.44 price demand elasticity for lodging services. Similarly to the output of this study, Bayoumi et al. [62] identified the price demand elasticity of -0.4 as one of the main multipliers in revenue management optimization. Aziz et al. [45] used price demand elasticity in the optimization model.

Based on the results of the previously mentioned studies, it is clear that the proposition of a novel approach toward price optimization must be connected with its applicability in the hospitality industry [21] and proper methodology description.

3. Model Proposal (Methodology)

The whole process of price optimization based on the price demand elasticity can be described using the following Figure 1:

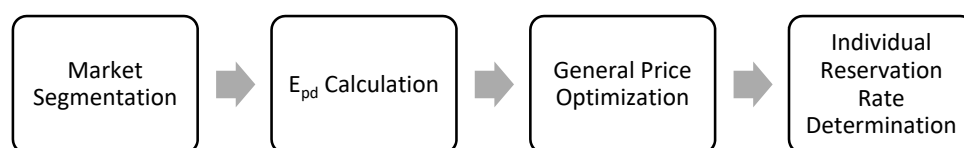


Figure 1. Process of Price Optimization and Setting.

The whole process consists of four major steps (1) the market segmentation, (2) the calculation of price demand elasticity, (3) general price optimization (optimization of the price level), and (4) the optimization and determination of the rate of the specific (individual) reservation.

3.1. Market Segmentation

The following model describes the steps of price optimization using customer's characteristics, mainly the price demand elasticity of identified market segments. Due to the fact that the data-driven market segmentation can identify differences in market segments' behavior based on the property characteristics, we assume four basic market segments with the possibility of their behavior set up based on the individual hotel characteristics. From the model development perspective, the segments and their description should mainly capture the connection of the segment with the specific price level and price demand elasticity coefficient distribution, as well as, for example, the preferred distribution channel.

3.2. Price Demand Elasticity Estimation

As proposed in the literature review, there are various approaches toward measuring the price elasticity of the demand. Within this model, we assume three different options that can be applied, namely using (1) the log–log linear model used by Petricek et al. [54], (2) an arc elasticity estimate using the Monte Carlo simulation, or (3) an individual coefficient values setting.

The log–log linear model is based on the linear regression function and the coefficient of price elasticity is then the estimated parameter β_1 in the following regression function:

$$\log Q_i = \beta_0 + \beta_1 \times \log P_i + \varepsilon_i, \quad (1)$$

To determine the coefficient of price elasticity using the Monte Carlo simulation, it is possible to use the following approach based on the arc elasticity. This new approach is based on the probabilistic distribution function (in this example normal distribution), which is an input into the iteration algorithm for the Monte Carlo simulation solution.

The normal distribution was used as an example to realistically capture the complexity of the proposed methodology. On the other hand, the whole method can be updated for a specific case-estimated distribution function that would reflect the specifics of selected characteristics [45,62]. In previous research, the binomial distribution was used to simulate the arrivals and demand in general [26,63] or the Poisson process [26,64]. Alternatively, the BetaPERT distribution can be used, as it is commonly used in the Monte Carlo simulation. The advantage of this model is its flexibility and possible general application.

The calculation is then based on the following formula:

$$E_{pd} = \left(\frac{Q_{d2} - Q_{d1}}{Q_{d1} + Q_{d2}} \right) / \left(\frac{P_2 - P_1}{P_1 + P_2} \right), \quad (2)$$

where the individual indices 1 and 2 indicate the initial (1) or new (2) price and the quantity of the demanded data. If we focus on the whole process of determining the price elasticity in terms of accommodation facilities, then it is evident that the value of the price is defined as an external variable. The value of Q_{d1} is known as well. The objective is to describe the behavior of consumers when changing the price to the value of P_2 , i.e., explaining the change in the form of a new Q_{d2} . With the availability of historical data, this process can be determined relatively easily. However, it is necessary to implement a certain element of chance in the entire calculation, which reflects the fact that the determination of the price elasticity coefficient always depends on the current market situation. Still, this market situation may be different (albeit slightly) from a situation based on a historical perspective. Therefore, the entire calculation is modified to a formula that can be written as follows:

$$E_{pd} = \left(\frac{\left(\int_0^{Q_{d2}} \frac{1}{\sigma \times \sqrt{2\pi}} e^{-\frac{(Q_{d2}-\mu)^2}{2\sigma^2}} dQ_{d2} \right) \times Q_{d2} - Q_{d1}}{Q_{d1} + \left(\int_0^{Q_{d2}} \frac{1}{\sigma \times \sqrt{2\pi}} e^{-\frac{(Q_{d2}-\mu)^2}{2\sigma^2}} dQ_{d2} \right) \times Q_{d2}} \right) / \left(\frac{P_2 - P_1}{P_1 + P_2} \right), \quad (3)$$

Hence, the role of chance is implemented in the entire calculation in the form of a certain probability (defined by the mean value and standard deviation in a normal distribution) that customers will react to the price change. However, this element must be addressed in the calculation in a way different than the traditional one. The use of the calculation with the help of the Monte Carlo simulation is offered as a suitable solution here, as this successfully respects the probability distribution related to the expected change in the quantity demanded of a given service (or product).

The use of the Monte Carlo simulation is proposed by several researchers to faithfully simulate hotel processes such as arrivals, cancellation, and length of stay, no-shows, seasonality and trends [62]. Other researchers used the Monte Carlo simulation to forecast the arrivals and hotel occupancy [63], arrivals, cancellations and, for example, group reservations using non-linear programming [45], dynamic pricing for low-cost providers [65] or to improve the overall performance of the accommodation facility [66].

As stated by Bayoumi et al. [62], the Monte Carlo simulation can be used to describe the current situation as realistically as possible. The whole procedure can be easily implemented in various processes as well [65], which is why the probability-based approaches can improve the quality of forecasting and overall business performance [67].

3.3. Price Optimization Based on E_{pd}

The issue of the relationship between price and price elasticity was illustrated in the previous part of the paper. For the purpose of this article, it is important to focus on how to execute a specific optimization, which results in a recommendation to adjust the price with respect to the expected or historically known price elasticity of the customer segment.

The optimization is then based on the assumption of the existence of a link between the price elasticity of demand and the change in price. Once the data on price elasticity are obtainable, it is then possible to define the whole optimization model of linear programming as follows:

$$TR = \sum_{i=1}^n \left[Q_i + E_{(pd)i} \times (P_{pi} - P_i) \times \frac{Q_i}{P_i} \right] \times P_{pi} \rightarrow \max, \quad (4)$$

where TR stands for total revenues, Q_i for the quantity demanded, $E_{(pd)i}$ for the elasticity of the given product, P_i the initial sales price and P_{pi} the planned sales price. The planned sales price is the same size as the initial price, with the difference that it represents the input to the optimization process as one of the variables, where the range in which the optimization will be performed is set.

The approach to price optimization based on the price elasticity described above can then be extended in such a way as to capture the fact resulting from the determination of price elasticity using the Monte Carlo simulation. In the optimization model, it is, therefore, necessary to capture the coefficient of the price elasticity of demand in the form of a probability distribution. Let us assume that the determined price elasticity coefficient using the Monte Carlo simulation has a normal distribution at the parameter $N(\mu, \sigma^2)$. Then, it is possible to rewrite the above optimization equation to the following form of nonlinear programming model:

$$TR = \sum_{i=1}^n \left[Q_i + \left(\int_{-\infty}^{E_{(pd)i}} \frac{1}{\sigma \times \sqrt{2\pi}} e^{-\frac{(E_{(pd)i} - \mu)^2}{2\sigma^2}} dE_{(pd)i} \right) \times E_{(pd)i} \times (P_{pi} - P_i) \times \frac{Q_i}{P_i} \right] \times P_{pi} \rightarrow \max \quad (5)$$

The above approach must then be solved using nonlinear programming and the Monte Carlo simulation, thus ensuring that the final form of the sought price will consider the appropriate role of chance in the form of the probabilistic distribution of inputs (price elasticity). All optimization makes sense only under the following limiting conditions:

$$Q_i \leq BL_i, \quad (6)$$

$$\sum_{i=1}^n Q_i \leq Cap \quad (7)$$

$$P_i \wedge P_{pi} \geq P_{min} \quad (8)$$

The above conditions state that it is necessary to respect such an offered quantity, which is based on the set booking limits for the given segment (BL_i). This is, therefore, the maximum expected quantity offered, determined, for example, based on the EMSR model. The latter condition respects the total capacity of the accommodation and the third respects the minimum price level. This in turn respects the minimum price (set, for example, as a cost price). The solution is also possible only under the following non-negative conditions:

$$Q_i > 0, \quad (9)$$

$$P_i \wedge P_{pi} > 0 \quad (10)$$

To show the result of the presented model, an example based on the real market data is presented in this part. To combine the non-linear and linear programming, the Monte Carlo simulation and basic statistical approaches, the model was developed in the scripting language “R”.

The main assumption of this application is to define the accommodation facility, its capacity, make the segmentation, basic cost analysis, market analysis, etc. It is also important to compute the coefficient of price elasticity for each segment and different periods. In case of having those data, the model can make the recommendation based on the price elasticity for the segment. The result of the previously mentioned model and its simulation is presented in the Figure 2.

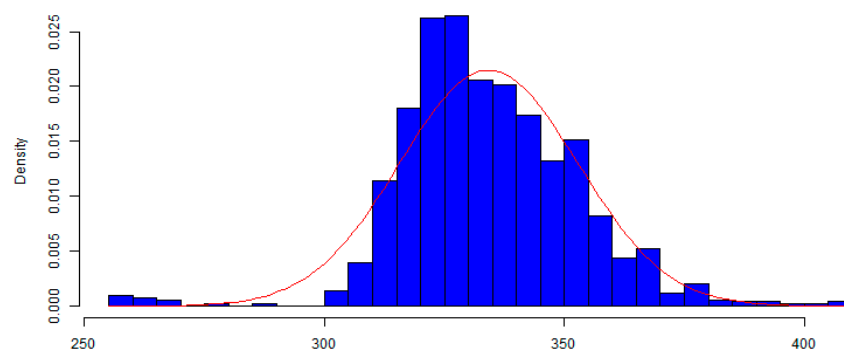


Figure 2. Monte Carlo simulation - price.

The coefficient of price elasticity was measured at the value -0.85 (as the mean value). The picture shows how we can assume that price should change in accordance with the different scenarios. The different scenarios were based on the parameters of normal distributions of the coefficient of price elasticity. Those parameters, as well as distribution, can be changed. One thousand simulations of scenarios were made to create the result. Based on the simulation, there is a recommendation to increase the initial price by 11.41% on the mean value of the distribution (334.2 PLN). This change will lead to an increase in the sales for this segment by more than 2%.

3.4. Specific Reservation Pricing

The proposed optimized rate is mainly reflecting the segment characteristics, namely the price demand elasticity, but cannot be used as the final selling rate as this proposed rate still omits several other factors that have a direct impact on the product pricing.

At the moment when it is possible to start from the basic offer price, it is time to determine the price of a specific reservation. This approach is what we could call dynamic price formation because the price changes virtually on a daily basis (in some cases even more often) and it also needs to always reflect the current situation but take into account the minimum acceptable price as well. When guaranteeing the price of a particular reservation, it is then necessary to focus on several aspects that affect it and that are appropriate (and in some cases necessary) to monitor.

The creation of this price depends on several key factors [68–72], which can be summarized in the following:

- Length of stay (LOS);
- Occupancy (Occ);
- Working days/weekends;
- Time from reservation to service implementation;
- Current competitive prices;
- Other services offered;
- Other attributes (e.g., ongoing events).

Many previous studies omit the following: (1) LOS, (2) current occupancy and (3) booking lead time. Therefore, this paper, in the part on specific reservation pricing, focuses on those attributes that influence the price and determine the theoretical model. The principle applies to the length of stay (1) that it is possible to achieve a lower average price of consummated accommodation with its growth. However, to be able to use this element,

it is always necessary to respect the cost aspect in particular. The total cost of consummated accommodation can be determined for a suitable presentation as the sum of the fixed and variable costs expressed as unit quantities (usually on a daily basis), as follows:

$$ATC_b = \frac{FC}{\sum_{b=1}^b Q_b} + \frac{VC}{\sum_{b=1}^b Q_b}, \quad (11)$$

where index b indicates a specific reservation and Q_b indicates the “order” of a given reservation in terms of the number of used capacities. It is always necessary to focus on the marginal revenue and marginal costs resulting from the next added unit of length of stay (usually one night/room). Indeed, a possible reduction in the price per unit of length of stay is possible only under the following conditions:

$$MC_b \leq MR_b, \quad (12)$$

where index b again indicates one added unit length of stay for reservation. The specific setting of a possible price reduction is, therefore, always individual and again it is necessary to reflect the current situation of the accommodation facility.

In the context of the above, it is possible to determine the specific possible level of price reduction based on a comparison of the unit total costs of the reservation and the revenues achieved from it. When denoting the possible discount level as PR_b (Price Reduction), then its value can be determined by a simple calculation such as the following:

$$PR_b = BAR - ATC_b. \quad (13)$$

For the sake of completeness, it is of course necessary to mention that if the value of the PR_b is negative, the average price can no longer be reduced. For proper work with the length of stay, it is, therefore, first necessary to determine the correct cost, on which the concept of marginal costs is based. These must be compared with the marginal revenues (or revenues) from the realized reservation.

For the current occupancy (2), the mutual relation applies that with the growth of the current occupancy of the accommodation facility, there is more room for increasing the price, and as the price increases, the quantity demanded decreases. Within the model in this publication, this element is incorporated in an extended model working with the so-called booking limits, which does not adjust the price, but just sets a limit for the maximum offered quantity for a given segment. Nevertheless, it is possible and appropriate, when setting the price, to incorporate the current occupancy into the decision-making and this element can serve as a partial adjustment of the currently offered price, even while respecting the set booking limits.

However, the issue to be determined at this point is the level of the maximum price for that segment. This can be determined using the logic of price elasticity. If in the previous step, the general level of price elasticity of demand was determined, it is possible in this step to determine the maximum possible price level at which the reservation could be offered in the event of the availability of free capacities. The procedure, thus, actually sets the condition of the maximum price, which is used in determining the price of a particular reservation at the end of this paper section. The graphical interpretation (see Figure 3) of the given problem then better shows the provided possibilities and connections.

Henceforth, three basic strategies can be applied that present the given problem in general. In the case of a neutral strategy, the value of the occupancy mark up could have an expression that corresponds to the following function, where the mark up is denoted as MUp (Occ) (Mark Up based on Occupancy):

$$MUp(Occ) = (a \times ExOcc + P_{min}) - P_{ref}, \quad (14)$$

If a minimum price (P_{min}) is based on the basic cost analysis, then the set reference price (P_{ref}) (i.e., the price to which we expect an increase) can be based on BAR and, therefore, it can be argued that the value of the mark up is a coefficient of growth rate.

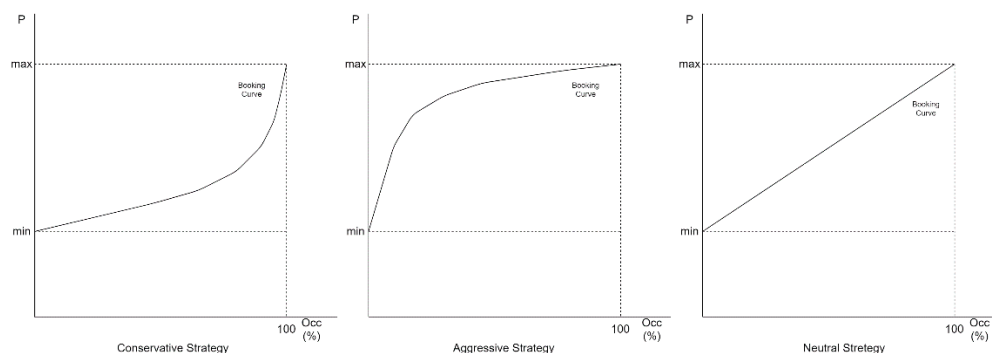


Figure 3. Booking curves.

In the case of an aggressive strategy or a conservative strategy, the value of such a mark up would be based on an exponential function.

For booking lead time (3), this is the period that begins from the time of booking to the time of the execution of the service itself, in the case of accommodation services, i.e., until the time of accommodation. There are only a few empirical studies that address this issue. Moreover, these approaches are often not based on any economic model or other interpretation that would lead to the optimization of the issue. Therefore, at least the basic outputs that can be found in the professional literature are presented. The link between booking lead time (BLT) and marketing tools is presented by the authors of [73], who conclude that, in the long run, tools that are based on the assumption of price increases while gradually filling accommodation capacities work relatively well. However, this effect was not observed for short-term BLTs. Interesting conclusions are presented by an empirical study by Falk and Vieru [74], which comes to the clear conclusion that with the growth of the BLT, the price of a given reservation also increases. The lowest prices are then offered in the BLT interval of 10 to 24 days. The importance of BLT for the final price of a reservation is also mentioned in another industry, for example, in rail transport [75]. The significance of a cancellation that affects BLT is reported in a study focusing on the Asian space [74]. It is, therefore, an element that must always be set individually, taking into account the individual accommodation facility. In general, four basic approaches can be envisaged that look at the link between price and BLT. This output can be illustrated in the Figure 4.

However, these are only basic approaches, which probably need to be combined in different situations. To complete the whole issue, it is, therefore, appropriate to first state the basic theoretical framework that will define what decision-making is desirable in relation to the BLT in determining the price. First, it is necessary to realize what situations can theoretically occur in the case of the implementation of the reservation before the actual implementation of the service. Therefore, if the BLT has a positive value, the following three basic situations can arise in terms of economic optimization:

1. Cancellation of reservation
2. The price on the day of implementation on the market will be higher
3. The price on the day of implementation on the market will be lower

The above three basic points need to be modified into economic concepts. Cancellation of a reservation represents additional costs (or marginal loss), which are associated with the fact that there is a certain probability that this free capacity will not be consummated (it is, therefore, a possibility of additional foregone profits). This variant will be marked as ML cancellation (marginal loss when making a reservation cancellation). The second situation, which is identified as the possibility that the price on the day of realization will be higher

on the market, means that the company collects a marginal loss caused by the difference between the initial reservation price and the current price (at which this reservation could theoretically be offered on the market). This variant will be referred to as the MLMPH, denoting the marginal loss (ML) in the situation of a higher market price (Market Price Higher; MPH). The third situation represents the opposite, i.e., the possibility that the price on the day of implementation will be lower on the market and, thus, it can be described as a marginal profit, which is due to the fact that under the current conditions at the time of the service, this reservation would no longer be for sale at the initial price. This option will be referred to as the MPML, i.e., the Marginal Profit (MP) option at a lower market price (Market Price Lower, MPL).

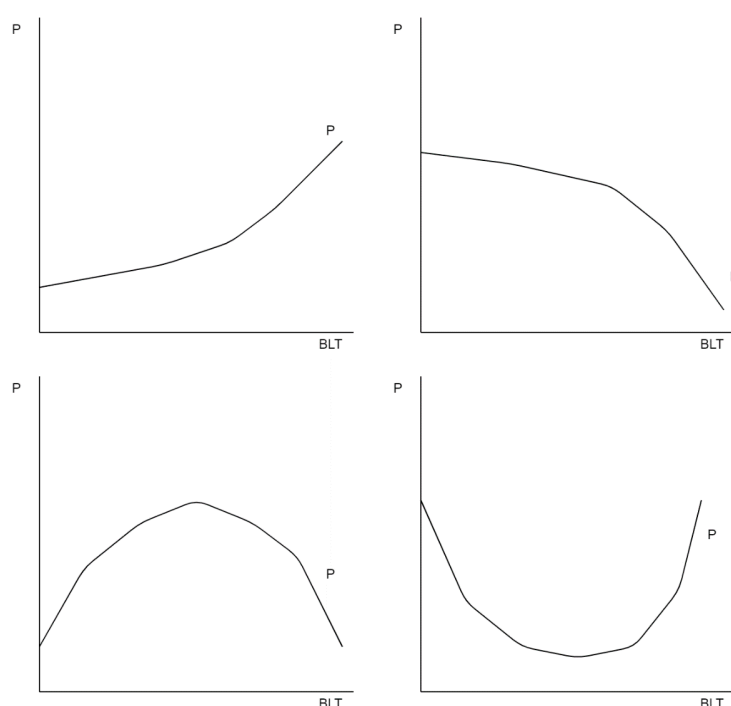


Figure 4. Booking lead time and price changing.

Based on the conducted expert interviews, it is then possible to present the general concept of these three situations graphically in the following Figure 5, where the limit value indicates the value of one of the three situations listed above.

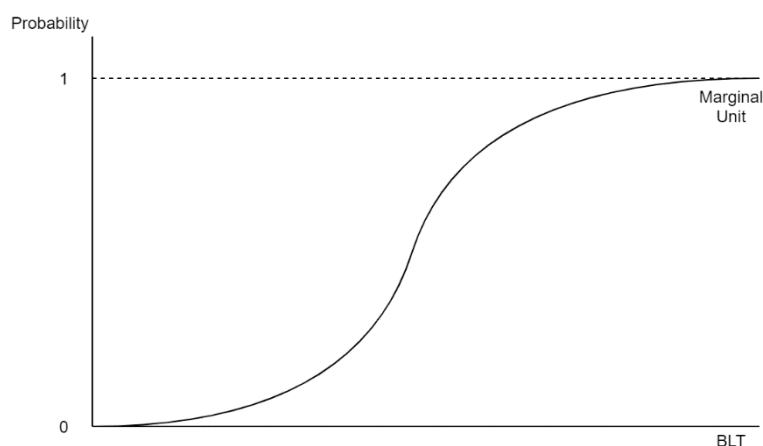


Figure 5. BLT probability curve.

The Figure 5 shows that with an increasing BLT, the probability that one of the above situations will occur and that, therefore, a marginal loss, marginal profit or marginal cost in the form of lost profits when cancelling a reservation will be achieved also increases. However, growth is not linear. This probability in the infinity of BLT approaches the limit of one. Nevertheless, it should be noted that this is only a theoretical framework, which must always be properly grasped in specific market conditions.

To make the result more complex, it is important to mention that the problem of booking cancellation can be described in detail in case of time-varying and cancellation predicting. A good predicting model for the consumer behavior related to the cancellation can be used as an approach based on the artificial neural network (see [18]). Even if this model assumes to put the value of $ML_{cancellation}$ at a specific moment, the whole value can change over time.

If we assume a rational-minded manager, it is obvious that she/he will try to minimize the possible marginal loss and maximize the possible marginal profit. The whole application then makes sense under the conditions when the following applies:

$$p_{cancellation} \times ML_{cancellation} + p_{MPH} \times ML_{MPH} \leq p_{MPL} \times MP_{MPL}, \quad (15)$$

where p denotes the probability of individual events. Probability represents a function of the BLT variable, and its course may correspond to some probability function of traditional distribution. It follows from the above that the distribution may correspond, for example, to the normal distribution for $0 \leq BLT \leq +\infty$. In the case of the transformation of the above problem into an optimization approach, it is possible to state that we are optimizing the following function within the task of nonlinear programming in order to find its minimum:

$$OPT(BLT) = \left(\int_0^{BLT} \frac{1}{\sigma \times \sqrt{2\pi}} e^{-\frac{(BLT-\mu)^2}{2\sigma^2}} dBLT \right) \times ML_{cancellation} + \left(\int_0^{BLT} \frac{1}{\sigma \times \sqrt{2\pi}} e^{-\frac{(BLT-\mu)^2}{2\sigma^2}} dBLT \right) \times ML_{MPH} - \left(\int_0^{BLT} \frac{1}{\sigma \times \sqrt{2\pi}} e^{-\frac{(BLT-\mu)^2}{2\sigma^2}} dBLT \right) \times MP_{MPL} = 0 \rightarrow \min, \quad (16)$$

The above solution is possible under the following conditions of non-negativity:

$$BLT \geq 0.$$

4. Summary

This paper introduced a model of price optimization that can be used in the area of accommodation services. The whole model is focusing on price optimization only and creates a two-step approach that is based on a stochastic assumption of consumer behavior (measured by the coefficient of price elasticity). The first step is to set the general price for different segments. Before the first step, it is necessary to make valid segmentation and to determine the coefficient of price elasticity. If the firm knows those attributes, an optimization process that is based on nonlinear programming and the Monte Carlo simulation approach can be carried out. The second step in the whole process of setting the price is focused on the price of the current reservation. It is necessary to incorporate all the attributes that can influence the final price. The whole process of setting the price is dynamic and, therefore, can be changed based on the current condition of the market. The model created in this paper describes the theoretical application of three main attributes that influence the price of the current reservation (the second step in the whole process). The first attribute is length of stay (LOS), the second is current occupancy (Occ) and the third is the booking lead time (BLT). All those attributes influence the price and the managers who set the price should act following the optimization and recommendation that is described in the text.

5. Discussion

Contrary to several studies mentioned in the literature review [27], the proposed optimization model is clearly stating a procedure of price demand elasticity calculation that makes the whole model more applicable, which reflects the findings of Ivanov et al. [21] and Denizci Guillet [23]. One of the proposed methods of price demand elasticity calculation, the log–log linear regression, was used by Petricek et al. [54] with a high level of reliability. This approach can be used to identify the individual behavior of key market segments, while finding the unique values directly linked to the behavior of the clients of a specific hotel.

Similarly to several studies mentioned in the literature review [32,33,35,36,38,39], the proposed model uses a stochastic approach as the pricing and price optimization can be performed automatically using available modern hospitality and business intelligence tools, which can be the solution for the efficiency improvement mentioned by Vives et al. [8]. A stochastic approach allows the researcher and revenue management practitioners to set the variability/distribution of the variables used for optimization and find the most suitable solutions, which is always connected with a certain level of uncertainty.

Another benefit of the proposed approach is in the use of big data in the price demand elasticity calculation. The use of big data can be perceived as one of the drivers of the future success of hotel operators in the competitive market. Where previous research focused on cancellation management [17,18], demand forecasting [19,20] or customer online booking evaluation [76], this study uses the big data to estimate the booking behavior within a predefined market segment using reservation data and also the dynamic pricing and rate optimization based on the stochastic approach, which delivers a more comprehensive solution than the previously mentioned studies.

6. Conclusions

The main aim of this article was to propose a simulation-based methodology of price optimization based on the price elasticity of the demand coefficient calculation, which directly reflects customer behavior that can be applied in the revenue management for the area of accommodation service. The approach that is described in the text is only focused on the price, but it does not mean that the optimization for revenue management should not be based also on the optimization of capacity. In accordance with the current issues in hospitality, future possible work with big data and other possibilities can be more focused toward the development of e-commerce services, although we discussed only price optimization. The price optimization model is missing a full theoretical description if we are focusing solely on the stochastic approach and optimization based on the price elasticity. However, we can argue that the coefficient of the price elasticity of demand is still the key factor that should determine the behavior of accommodation in the case of price setting.

The proposed model reflects the current need for more comprehensive solutions that would reflect more aspects of the customer behavior and will be able to react to the ongoing changes and needs of revenue managers and practitioners. As mentioned before, future research should focus on the simultaneous optimization of the price and the capacity or take into consideration customers other than the flexible online segments (FIT or transient). The distribution strategy commonly consists of yieldable and non-yieldable segments. This dynamic and public pricing mostly focuses on the yieldable online segments and omits other customers, which might be even more beneficial for specific hotels (mostly the business clientele-oriented ones).

The presented model only shows the price optimization. In the case of complex use, it is also important to focus on the part of capacity management. For better results this model can be combined with the approaches using machine learning for quantity demanded prediction or other elements that influence consumer behavior. Those updates and extensions will make the whole approach more robust and helpful for any facility, regardless of its capacity, a number of segments or destinations.

Author Contributions: Conceptualization, M.P. and S.C.; methodology, M.P.; validation, M.P. and S.C.; formal analysis, M.P.; investigation, M.P. and S.C.; resources, M.P.; data curation, M.P. and S.C.; writing—original draft preparation, M.P. and S.C.; writing—review and editing, M.P., S.C. and D.M.; visualization, M.P.; supervision, M.P.; project administration, D.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of The Institute of Hospitality Management (protocol code 2/2018-KR, January 2018).

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Srinivasan, S.S.; Anderson, R.; Ponnnavolu, K. Customer loyalty in e-commerce: An exploration of its antecedents and consequences. *J. Retail.* **2002**, *78*, 41–50. [\[CrossRef\]](#)
2. Hemmington, N.; Kim, P.B.; Wang, C. Benchmarking hotel service quality using two-dimensional importance-performance benchmark vectors (IPBV). *J. Serv. Theory Pract.* **2018**, *28*, 2–25. [\[CrossRef\]](#)
3. Yang, T.; Xun, J.; He, X. British SMEs' e-commerce technological investments and firm performance: An RBV perspective. *Technol. Anal. Strat. Manag.* **2015**, *27*, 586–603. [\[CrossRef\]](#)
4. Huang, H.; Liu, Y.; Lu, D. Proposing a model for evaluating market efficiency of OTAs: Theoretical approach. *Tour. Econ.* **2019**, *26*, 958–975. [\[CrossRef\]](#)
5. Sánchez-Lozano, G.; Pereira, L.; Chávez-Miranda, E. Exploring online prices with an advance booking horizon on Booking.com. *Eur. J. Tour. Res.* **2020**, *26*, 2606.
6. Abrate, G.; Nicolau, J.L.; Viglia, G. The impact of dynamic price variability on revenue maximization. *Tour. Manag.* **2019**, *74*, 224–233. [\[CrossRef\]](#)
7. Kimes, S.E. The Basics of Yield Management. *Cornell Hotel Restaur. Adm. Q.* **1989**, *30*, 14–19. [\[CrossRef\]](#)
8. Vives, A.; Jacob, M.; Payeras, M. Revenue management and price optimization techniques in the hotel sector. *Tour. Econ.* **2018**, *24*, 720–752. [\[CrossRef\]](#)
9. Gao, G.-X.; Bi, J.-W. Hotel booking through online travel agency: Optimal Stackelberg strategies under customer-centric payment service. *Ann. Tour. Res.* **2021**, *86*, 103074. [\[CrossRef\]](#)
10. Leoni, V.; Nilsson, W. Dynamic pricing and revenues of Airbnb listings: Estimating heterogeneous causal effects. *Int. J. Hosp. Manag.* **2021**, *95*, 102914. [\[CrossRef\]](#)
11. Masiero, L.; Viglia, G.; Nieto-Garcia, M. Strategic consumer behavior in online hotel booking. *Ann. Tour. Res.* **2020**, *83*, 102947. [\[CrossRef\]](#)
12. Mitra, S.K. An analysis of asymmetry in dynamic pricing of hospitality industry. *Int. J. Hosp. Manag.* **2020**, *89*, 102406. [\[CrossRef\]](#)
13. Abrate, G.; Fraquelli, G.; Viglia, G. Dynamic pricing strategies: Evidence from European hotels. *Int. J. Hosp. Manag.* **2012**, *31*, 160–168. [\[CrossRef\]](#)
14. Koushik, D.; Higbie, J.A.; Eister, C. Retail Price Optimization at InterContinental Hotels Group. *Interfaces* **2012**, *42*, 45–57. [\[CrossRef\]](#)
15. Weaver, A. Tourism, big data, and a crisis of analysis. *Ann. Tour. Res.* **2021**, *88*, 103158. [\[CrossRef\]](#)
16. Talón-Ballester, P.; González-Serrano, L.; Soguero-Ruiz, C.; Muñoz-Romero, S.; Rojo-Álvarez, J.L. Using big data from Customer Relationship Management information systems to determine the client profile in the hotel sector. *Tour. Manag.* **2018**, *68*, 187–197. [\[CrossRef\]](#)
17. Antonio, N.; de Almeida, A.M.; Nunes, L. Big Data in Hotel Revenue Management: Exploring Cancellation Drivers to Gain Insights into Booking Cancellation Behavior. *Cornell Hosp. Q.* **2019**, *60*, 298–319. [\[CrossRef\]](#)
18. Sánchez-Medina, A.J.; C.-Sánchez, E. Using machine learning and big data for efficient forecasting of hotel booking cancellations. *Int. J. Hosp. Manag.* **2020**, *89*, 102546. [\[CrossRef\]](#)
19. Guizzardi, A.; Pons, F.M.E.; Angelini, G.; Ranieri, E. Big data from dynamic pricing: A smart approach to tourism demand forecasting. *Int. J. Forecast.* **2020**. [\[CrossRef\]](#)
20. Stylos, N.; Zwiendelaar, J.; Buhalis, D. Big data empowered agility for dynamic, volatile, and time-sensitive service industries: The case of tourism sector. *Int. J. Contemp. Hosp. Manag.* **2021**, *33*, 1015–1036. [\[CrossRef\]](#)
21. Ivanov, S.; Del Chiappa, G.; Heyes, A. The research-practice gap in hotel revenue management: Insights from Italy. *Int. J. Hosp. Manag.* **2021**, *95*, 102924. [\[CrossRef\]](#)
22. Guillet, B.D. An evolutionary analysis of revenue management research in hospitality and tourism. *Int. J. Contemp. Hosp. Manag.* **2020**, *32*, 560–587. [\[CrossRef\]](#)

23. Rodríguez-Algeciras, A.; Talón-Ballester, P. An empirical analysis of the effectiveness of hotel Revenue Management in five-star hotels in Barcelona, Spain. *J. Hosp. Tour. Manag.* **2017**, *32*, 24–34. [\[CrossRef\]](#)
24. Talluri, K.; Van Ryzin, G. Revenue Management Under a General Discrete Choice Model of Consumer Behavior. *Manag. Sci.* **2004**, *50*, 15–33. [\[CrossRef\]](#)
25. Binesh, F.; Belarmino, A.; Raab, C. A meta-analysis of hotel revenue management. *J. Revenue Pricing Manag.* **2021**, 1–13. [\[CrossRef\]](#)
26. Baker, T.K.; Collier, D.A. A Comparative Revenue Analysis of Hotel Yield Management Heuristics. *Decis. Sci.* **1999**, *30*, 239–263. [\[CrossRef\]](#)
27. Pekgün, P.; Menich, R.P.; Acharya, S.; Finch, P.G.; Deschamps, F.; Mallery, K.; Van Sistine, J.; Christianson, K.; Fuller, J. Carlson Rezidor Hotel Group Maximizes Revenue Through Improved Demand Management and Price Optimization. *Interfaces* **2013**, *43*, 21–36. [\[CrossRef\]](#)
28. Pimentel, V.; Aizezikali, A.; Baker, T. Hotel revenue management: Benefits of simultaneous overbooking and allocation problem formulation in price optimization. *Comput. Ind. Eng.* **2019**, *137*, 106073. [\[CrossRef\]](#)
29. Pimentel, V.; Aizezikali, A.; Baker, T. An evaluation of the bid price and nested network revenue management allocation methods. *Comput. Ind. Eng.* **2018**, *115*, 100–108. [\[CrossRef\]](#)
30. Goldman, P.; Freling, R.; Pak, K.; Piersma, N. Models and techniques for hotel revenue management using a rolling horizon. *J. Revenue Pricing Manag.* **2002**, *1*, 207–219. [\[CrossRef\]](#)
31. Weatherford, L.R. Length of stay heuristics Do they really make a difference? *Cornell Hotel. Restaur. Adm. Q.* **1995**, *36*, 70–79. [\[CrossRef\]](#)
32. De Boer, S.V.; Freling, R.; Piersma, N. Stochastic Programming for Multiple-Leg Network Revenue Management (No. EI 9935/A). Econometric Institute Research Papers. Erasmus University Rotterdam, Erasmus School of Economics (ESE), Econometric Institute. 1999. Available online: <https://ideas.repec.org/p/ems/eureir/1604.html> (accessed on 20 May 2021).
33. Lai, K.-K.; Ng, W.-L. A stochastic approach to hotel revenue optimization. *Comput. Oper. Res.* **2005**, *32*, 1059–1072. [\[CrossRef\]](#)
34. Liu, S.; Lai, K.; Wang, S. Booking models for hotel revenue management considering multiple-day stays. *Int. J. Revenue Manag.* **2008**, *2*, 78. [\[CrossRef\]](#)
35. Liu, S.; Lai, K.K.; Dong, J.; Wang, S.-Y. A stochastic approach to hotel revenue management considering multiple-day stays. *Int. J. Inf. Technol. Decis. Mak.* **2006**, *5*, 545–556. [\[CrossRef\]](#)
36. Zhuang, W.; Chen, J.; Fu, X. Joint dynamic pricing and capacity control for hotels and rentals with advanced demand information. *Oper. Res. Lett.* **2017**, *45*, 397–402. [\[CrossRef\]](#)
37. Badinelli, R.D. An optimal, dynamic policy for hotel yield management. *Eur. J. Oper. Res.* **2000**, *121*, 476–503. [\[CrossRef\]](#)
38. Zhang, D.; Weatherford, L. Dynamic Pricing for Network Revenue Management: A New Approach and Application in the Hotel Industry. *Inform. J. Comput.* **2017**, *29*, 18–35. [\[CrossRef\]](#)
39. Guizzardi, A.; Pons, F.M.E.; Ranieri, E. Advance booking and hotel price variability online: Any opportunity for business customers? *Int. J. Hosp. Manag.* **2017**, *64*, 85–93. [\[CrossRef\]](#)
40. Ivanov, S.; Zhechev, V.S. Hotel Revenue Management—A Critical Literature Review. *SSRN Electron. J.* **2011**. [\[CrossRef\]](#)
41. Elmaghraby, W.; Keskinocak, P. Dynamic Pricing in the Presence of Inventory Considerations: Research Overview, Current Practices, and Future Directions. *Manag. Sci.* **2003**, *49*, 1287–1309. [\[CrossRef\]](#)
42. Roper, A.J.; El Haddad, R.; Jones, P. The Impact of Revenue Management Decisions on Customers Attitudes and Behaviours: A Case Study of a Leading UK Budget Hotel Chain. In Proceedings of the EuroCHRIE 2008 Congress, Dubai, UAE, 11–14 October 2017. Available online: <https://epubs.surrey.ac.uk/816229/> (accessed on 20 May 2021).
43. Lee, S.; Garrow, L.; Higbie, J.; Keskinocak, P.; Koushik, D. Do you really know who your customers are? A study of US retail hotel demand. *J. Revenue Pricing Manag.* **2009**, *10*, 73–86. [\[CrossRef\]](#)
44. Ivanov, S.H. Hotel Revenue Management: From Theory to Practice. Available online: <http://search.ebscohost.com/direct.asp?db=hjh&jid=HOIN&scope=site> (accessed on 20 May 2021).
45. Aziz, H.A.; Saleh, M.; Rasmy, M.H.; ElShishiny, H. Dynamic room pricing model for hotel revenue management systems. *Egypt. Inform. J.* **2011**, *12*, 177–183. [\[CrossRef\]](#)
46. El Gayar, N.; Saleh, M.; Atiya, A.; El-Shishiny, H.; Zakhary, A.A.Y.F.; Habib, H.A.A.M. An integrated framework for advanced hotel revenue management. *Int. J. Contemp. Hosp. Manag.* **2011**, *23*, 84–98. [\[CrossRef\]](#)
47. Liu, W.; Guillet, B.D.; Xiao, Q.; Law, R. Globalization or localization of consumer preferences: The case of hotel room booking. *Tour. Manag.* **2014**, *41*, 148–157. [\[CrossRef\]](#)
48. Narangajavana, Y.; Garrigos-Simon, F.J.; García, J.S.; Forgas-Coll, S. Prices, prices and prices: A study in the airline sector. *Tour. Manag.* **2014**, *41*, 28–42. [\[CrossRef\]](#)
49. Coenders, G.; Espinet, J.M.; Saez, M. Predicting Random Level And Seasonality Of Hotel Prices: A Latent Growth Curve Approach. *Tour. Anal.* **2003**, *8*, 15–31. [\[CrossRef\]](#)
50. Balaguer, J.; Pernías, J.C. Relationship between spatial agglomeration and hotel prices. Evidence from business and tourism consumers. *Tour. Manag.* **2013**, *36*, 391–400. [\[CrossRef\]](#)
51. Gallego, G.; Van Ryzin, G. Optimal Dynamic Pricing of Inventories with Stochastic Demand over Finite Horizons. *Manag. Sci.* **1994**, *40*, 999–1020. [\[CrossRef\]](#)
52. Dolnicar, S. Market segmentation analysis in tourism: A perspective paper. *Tour. Rev.* **2019**, *75*, 45–48. [\[CrossRef\]](#)

53. Du, F.; Yang, F.; Liang, L.; Yang, M. Do service providers adopting market segmentation need cooperation with third parties? *Int. J. Contemp. Hosp. Manag.* **2016**, *28*, 136–155. [\[CrossRef\]](#)
54. Petricek, M.; Chalupa, S.; Chadt, K. Identification of Consumer Behavior Based on Price Elasticity: A Case Study of the Prague Market of Accommodation Services. *Sustainability* **2020**, *12*, 9452. [\[CrossRef\]](#)
55. Tran, X.V. Effects of Economic Factors on Demand for Luxury Hotel Rooms in the U.S. *Adv. Hosp. Tour. Res.* **2015**, *3*, 1–17.
56. Anderson, C.K.; Xie, N. Dynamic pricing in hospitality: Overview and opportunities. *Int. J. Revenue Manag.* **2016**, *9*, 165. [\[CrossRef\]](#)
57. Ratliff, R.M.; Rao, B.V.; Narayan, C.P.; Yellepeddi, K. A multi-flight recapture heuristic for estimating unconstrained demand from airline bookings. *J. Revenue Pricing Manag.* **2008**, *7*, 153–171. [\[CrossRef\]](#)
58. Rosselló, J.; Aguiló, E.; Riera, A. Modeling Tourism Demand Dynamics. *J. Travel Res.* **2005**, *44*, 111–116. [\[CrossRef\]](#)
59. Damonte, L.T.; Domke-Damonte, D.J.; Morse, S.P. The case for using destination-level price elasticity of demand for lodging services. *Asia Pac. J. Tour. Res.* **1998**, *3*, 19–26. [\[CrossRef\]](#)
60. Canina, L.; Carvell, S. Lodging Demand for Urban Hotels in Major Metropolitan Markets. *J. Hosp. Tour. Res.* **2005**, *29*, 291–311. [\[CrossRef\]](#)
61. Hiemstra, S.J.; Ismail, J.A. Incidence of the Impacts of Room Taxes on the Lodging Industry. *J. Travel Res.* **1993**, *31*, 22–26. [\[CrossRef\]](#)
62. Bayoumi, A.; Saleh, M.; Atiya, A.F.; Aziz, H.A. Dynamic pricing for hotel revenue management using price multipliers. *J. Revenue Pricing Manag.* **2013**, *12*, 271–285. [\[CrossRef\]](#)
63. Zakhary, A.; Atiya, A.F.; El-Shishiny, H.; El Gayar, N. Forecasting hotel arrivals and occupancy using Monte Carlo simulation. *J. Revenue Pricing Manag.* **2009**, *10*, 344–366. [\[CrossRef\]](#)
64. Bitran, G.R.; Gilbert, S.M. Managing Hotel Reservations with Uncertain Arrivals. *Oper. Res.* **1996**, *44*, 35–49. [\[CrossRef\]](#)
65. Marcus, B.; Anderson, C.K. Revenue management for low-cost providers. *Eur. J. Oper. Res.* **2008**, *188*, 258–272. [\[CrossRef\]](#)
66. Petricek, M.; Sochurkova, M. The Use of Monte Carlo Simulation in Hotel Revenue Management. *Czech Hosp. Tour. Pap.* **2015**, *11*, 18–25.
67. Talluri, K.; Castejon, F.; Codina, B.; Magaz, J. Proving the performance of a new revenue management system. *J. Revenue Pricing Manag.* **2010**, *9*, 300–312. [\[CrossRef\]](#)
68. Ivanov, S.H.; Zhechev, V.S. Маркетинг в Хотелиерството (Hotel Marketing) (SSRN Scholarly Paper No. ID 2271307). Rochester, NY: Social Science Research Network. 2011. Available online: <https://papers.ssrn.com/abstract=2271307> (accessed on 20 May 2021).
69. Hung, W.-T.; Shang, J.-K.; Wang, F.-C. Pricing determinants in the hotel industry: Quantile regression analysis. *Int. J. Hosp. Manag.* **2010**, *29*, 378–384. [\[CrossRef\]](#)
70. Lee, M.; Jeong, M.; Shea, L.J. Length of stay control: Is it a fair inventory management strategy in hotel market? *Tour. Econ.* **2021**, *27*, 307–327. [\[CrossRef\]](#)
71. García, M.A.R. Effects of Competition and Quality on Hotel Pricing Policies in an Online Travel Agency. *Tour. Econ.* **2013**, *19*, 63–76. [\[CrossRef\]](#)
72. Portolan, A. Impact of the attributes of private tourist accommodation facilities onto prices: A hedonic price approach | European Journal of Tourism Research. *Eur. J. Tour. Res. Eur. J. Tour. Res.* **2013**, *6*, 74–82.
73. Noone, B.M.; Lin, M.S. Scarcity-Based Price Promotions: How Effective are they in a Revenue Management Environment? *J. Hosp. Tour. Res.* **2020**, *44*, 883–907. [\[CrossRef\]](#)
74. Falk, M.; Vieru, M. Myth of early booking gains. *J. Revenue Pricing Manag.* **2018**, *18*, 52–64. [\[CrossRef\]](#)
75. Sun, Y.; Jiang, Z.; Gu, J.; Zhou, M.; Li, Y.; Zhang, L. Analyzing high speed rail passengers' train choices based on new online booking data in China. *Transp. Res. Part C Emerg. Technol.* **2018**, *97*, 96–113. [\[CrossRef\]](#)
76. Saito, T.; Takahashi, A.; Koide, N.; Ichifuji, Y. Application of online booking data to hotel revenue management. *Int. J. Inf. Manag.* **2019**, *46*, 37–53. [\[CrossRef\]](#)