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Comparing Customer-Oriented and Revenue-Oriented Overbooking Strategies in Dynamic Pricing Environments

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Abstract

This study aims to construct a strategic decision map, referred to as a revenue matrix, to support pricing strategies and the decision to implement overbooking (OB) in hotels, based on the optimal policies derived from a dynamic pricing (DP) model that incorporates OB. In particular, we examine the determination of OB levels from two perspectives: a customer-oriented approach that emphasizes the probability of service denial due to OB, and a revenue-oriented approach that prioritizes profit maximization. We use real hotel reservation data to estimate key parameters such as demand volume and cancellation rates in order to construct a revenue matrix through numerical computation and determine the optimal pricing and OB levels. The revenue matrix reveals the following characteristics: a fixed pricing strategy is effective when the number of potential customers is low. When the number of potential customers is high and the no-show rate is low, dynamic pricing (DP) without overbooking (OB) is preferable. Conversely, when the no-show rate is high, combining DP with OB yields superior results. Furthermore, when capacity and demand are nearly equal and no-shows are expected, even the customer-oriented strategy can lead to revenue maximization. These findings would provide practical insights for hotel managers in developing flexible sales strategies that balance customer satisfaction and revenue optimization under demand uncertainty.

Keywords

Overbooking, Dynamic Pricing, Revenue Management, Hotel Data Analysis

1. Introduction

As the global economy continues to recover from the COVID-19 pandemic, Japan's tourism industry is also experiencing a revival, notably driven by a sharp increase in accommodation demand from inbound travelers. However, this rapid increase in foreign visitors has brought new challenges. One of the most critical issues is the rise in reservation cancellations associated with the growing use of Online Travel Agencies (OTAs). According to a study by Tussyadiah and Pesonen (2016), reservations made through OTAs exhibit approximately 13 percentage points higher cancellation rates than those made through traditional travel agencies, and about 5 percentage points higher than direct bookings through hotel websites. This trend is attributed to more lenient cancellation policies and the higher likelihood of plan changes due to early bookings on OTA platforms. Consequently, reservation cancellations and no-shows have become a common occurrence, posing a significant risk of revenue loss. Implementing effective countermeasures to mitigate these losses has become an urgent priority in the hospitality industry.

Historically, overbooking (OB) has been used in the hotel industry as a strategy to address cancellations and no-shows. More recently, dynamic pricing (DP) has also been adopted. OB refers to the practice of accepting bookings beyond actual capacity in anticipation of a certain cancellation rate, with the aim of maximizing actual occupancy and revenue. Dynamic pricing (DP), on the other hand, adjusts room rates in response to fluctuations in demand and booking status, aiming to optimize revenue while accounting for cancellation risks. By combining these two strategies, hotels can mitigate the negative impacts of cancellations and no-shows and enhance profitability. Overbooking is an effective strategy for maximizing occupancy and revenue by reducing the risk of vacant rooms due to cancellations or no-shows. However, it also carries the significant risk of service denial when actual arrivals exceed expectations, potentially resulting in decreased customer satisfaction, damage to the brand's image, and additional costs for compensation or arranging alternative accommodations. DP can help suppress cancellations and smooth out demand by adjusting prices based on demand trends and cancellation behaviors. Nonetheless, it alone cannot absorb all cancellation risks, particularly in cases of sudden demand shifts caused by unforeseen events. Therefore, combining OB with DP is considered an effective strategy that leverages the strengths of both. DP can suppress most cancellation risks, while OB can absorb residual uncertainties, maintaining occupancy without resorting to excessive overbooking. This integrated approach enables more sophisticated revenue management, balancing profitability and customer satisfaction.

In practice, some hotels are reluctant to implement OB due to the difficulty of securing backup rooms when overbooking occurs. If affiliated or partner facilities are nearby, hotels may share availability to avoid service denial. However, in the absence of such alternatives, hotels may be forced to refuse service to guests, leading to reputational damage and reduced customer satisfaction. In such cases, it may be more desirable to rely solely on DP for demand management.

This study aims to clarify under what operational conditions DP and OB should be adopted. In particular, we develop a strategic decision map that allows hotel managers to visually assess whether OB should be implemented based on demand intensity and the no-show rate. We propose two approaches for determining OB levels: a customer-oriented approach, which sets OB levels to satisfy a manager-specified acceptable probability of service denial, and a revenue-oriented approach, which maximizes the expected total revenue. To construct the strategic decision map, we formulate a finite-horizon stochastic dynamic programming model for revenue maximization that accounts for cancellations and no-shows. The model parameters, such as arrival rates and cancellation rates, are calibrated using actual hotel booking and cancellation data from Japan, thereby reflecting realistic sales environments in the decision-making process. The numerical experiments revealed the following insights. First, fixed pricing is effective when the number of potential customers is low. Second, when demand is high and the no-show rate is low, DP without OB is preferable. Third, when the no-show rate is high, the combination of DP and OB leads to better revenue performance. Additionally, even when capacity and demand are nearly balanced and no-shows are frequent, adopting a customer-oriented OB strategy can still achieve revenue maximization. These findings offer practical insights for designing flexible sales strategies that balance customer satisfaction and revenue optimization under demand uncertainty.

The remainder of this paper is organized as follows: Section 2 presents a literature review and positions this study. Section 3 defines the mathematical model for revenue maximization. Section 4 describes the calibration method based on actual hotel data. Section 5 analyzes the strategic map derived from numerical simulations. Finally, Section 6 concludes the paper and outlines future research directions.

2. Literature Review

In recent years, the Japanese hotel industry has faced a sharp increase in reservation cancellations and no-shows due to the surge in inbound tourists, which has negatively impacted hotel revenues. To address this issue while maintaining or improving profitability, various strategies have been studied from the perspective of revenue management.

As countermeasures against no-shows for hotel reservations, the introduction of advance deposits and cancellation fees are common strategies. Reports indicate that credit card guarantees have reduced the average no-show rate for hotels from the conventional 5–15% to approximately 5%, confirming their effectiveness (Ko 2022). However, the strictness of cancellation policies influences customer reservation behavior. Overly lenient policies encourage strategic cancellations, where customers book first and then continue searching for better options, leading to an increase in last-minute cancellations (Chen et al. 2011). On the other hand, excessively strict policies may discourage reservations altogether, thus reducing demand. In this regard, Altin et al. (2023) demonstrated through theoretical modeling and large-scale data analysis that setting cancellation fees at a moderate level yields the best financial performance for hotels.

Dynamic pricing (DP) is a core method in hotel revenue management, and numerous optimization models have been proposed alongside recent advancements in information technology. For example, Zhang and Weatherford (2017) proposed a network-based dynamic pricing optimization model accommodating multi-day hotel stays and demonstrated that it outperforms conventional fixed pricing strategies. Their model sequentially calculates optimal prices for each day and customer segment based on stochastic dynamic programming. Furthermore, research integrating demand forecasting and machine learning to optimize prices is progressing, and AI-driven revenue management systems capable of implementing real-time price adjustments are becoming increasingly widespread in the market (Zhai et al. 2023).

Since the 1990s, research has actively explored applying overbooking (OB) methods, originally established in the airline industry, to hotels. Appropriate OB prevents lost sales opportunities, but excessive overbooking carries the risk of oversales, resulting in "bumping" guests to other facilities. To manage this trade-off, many studies have proposed models for determining optimal OB levels. Bitran and Mondschein (1995) developed a yield management model for hotels considering multi-night stays and proposed reservation control methods for different stay patterns. Hadjinicola and Panayi (1997) examined optimal OB levels when group bookings via overseas tour operators are included, reporting methods to adjust OB levels by customer segment. Badinelli (1998) solved hotel revenue management problems, including OB, using dynamic optimization and presented a model indicating optimal policies. More recently, data-driven models utilizing machine learning have emerged. Zhai et al. (2023) developed a model that predicts each reservation's no-show probability using machine learning and determines the daily OB allowance based on those estimates. This model accurately estimates each customer's no-show probability without assuming a prior demand distribution, resulting in higher profits and demonstrating effectiveness in real data experiments.

Building upon these insights, this study formulates the hotel sales optimization problem including cancellations and no-shows within a finite horizon as a stochastic dynamic programming model. By calibrating the model parameters using actual hotel data from Japan, this study constructs a strategic decision map that serves as a decision support tool with realistic parameter settings.

3. The Model

3.1 Dynamic Pricing Model

This section formulates a dynamic pricing (DP) model for accommodation facilities. Consider the sales profit for one night at a hotel with a total capacity of C rooms. The sales period is divided into T periods, where t represents the remaining sales period until the stay date; specifically, $t = T$ at the start of sales and $t = 0$ on the stay date.

In each period, it is assumed that at most one customer visits the hotel's website either to make a purchase or to cancel an existing booking, and the arrival rate is denoted by m_t. If the visiting customer does not intend to cancel, they decide whether to purchase at price p_t or not. If the customer intends to cancel, a portion of the booking amount is refunded. The probability that a customer arrives with the intention to cancel is denoted by ρ_t, and when the customer does not intend to cancel, the probability of purchasing at price p_t is denoted by $d(p_t)$. Therefore, the probability that a purchase occurs in a period is given by $m_t(1-\rho_t)d(p_t)$, while the probability that no purchase occurs is $m_t(1-\rho_t)(1-d(p_t))$. The probability that a cancellation occurs is $m_t\rho_t$, and the probability that no customer arrives is $1-m_t$. Therefore, the maximum expected total revenue from period t onwards, given that the remaining room inventory is x, can be formulated as:

$$\begin{aligned} V_t(x) = \max_{p_t>0} \big[& m_t(1-\rho_t)d(p_t)\{p_t' + V_{t-1}(x-1)\} \\ & + m_t\rho_t V_{t-1}(x+1) \\ & + m_t(1-\rho_t)\big(1-d(p_t)\big)V_{t-1}(x) \\ & + (1-m_t)V_{t-1}(x)\big], \qquad t \geq 1, x = 0,1,\dots,C+\alpha. \end{aligned} \tag{1}$$

Here, the maximum value of the room inventory x is C plus the overbooking amount α, that is, $C+\alpha$. When the remaining room inventory is $x = 0$, no sales are conducted to customers and only cancellations can occur; therefore, p is set to infinity and the purchase probability is set to $d(p_t) = 0$. Conversely, when the remaining room inventory is $x = C + \alpha$, there are no purchasers accepted, and thus the cancellation probability is set to $\rho_t = 0$. In the first term of equation (1), the marginal profit p'_t is recorded when a purchase is made. This value represents the purchase revenue p_t minus the expected refund amount due to possible future cancellations. By incorporating the expected refund at the time of purchase in this way, it becomes unnecessary to retain the information of purchased customers as states, which avoids an increase in the number of states and prevents exponential growth in computation time. Similar approaches have been adopted in previous studies such as Sato and Sawaki (2011) and Aydın et al. (2017). The refund-adjusted profit p'_t is given by the following equation:

$$p'_t = p_t \left(1 - \sum_{i=0}^{t} q_i g_i\right), \tag{2}$$

where q_i represents the probability that a purchase made in period t is canceled in period i, and g_i represents the refund rate when a cancellation occurs in period i.

On the stay date ($t = 0$), no-shows occur. When the remaining room inventory is x, let the number of purchasers up to $t = 0$ be $C + \alpha - x$, and let b denote the no-show rate. The number of no-shows, represented by the random variable X, follows a binomial distribution with parameters $(C + \alpha - x, b)$. Accordingly, the number of show-ups is given by $Y(x) = C + \alpha - x - X$. If the number of guests Y is less than the number of rooms C, then vacancies occur, and a vacancy cost of π_1 is incurred for each vacant room, amounting to $C - Y(x)$ in total. On the other hand, if the number of guests $Y(x)$ exceeds the number of rooms C, bumping occurs, and a bumping cost of π_2 is incurred for each bumped guest, amounting to $Y(x) - C$ in total. Therefore, the maximum expected revenue at $t = 0$ can be expressed as

$$V_0(x) = \begin{cases} -\mathbb{E}[\pi_1(C - Y(x))], \text{ if } C \geq Y(x), \\ -\mathbb{E}[\pi_2(Y(x) - C)], \text{ if } C \leq Y(x). \end{cases} \tag{3}$$

3.2 Determination of Overbooking Levels

In this section, we first introduce a method for determining the overbooking level using the customer-oriented approach. Vajpai (2018) treats the number of no-shows, under-stays (early check-outs before the originally booked number of nights), and late cancellations (cancellations made shortly before the stay) occurring within a certain period as random variables following a Poisson distribution, and calculates the optimal OB level based on the associated probabilities. In this study, we adopt Vajpai's (2018) method as the customer-oriented approach and determine the OB level by considering the possibility of no-shows. The manager sets the OB level at the start of the sales period. At that time, the number of purchasers on the stay date, denoted by $Z(\leq C + \alpha)$, as well as the number of no-shows, denoted by X, are both unknown. Therefore, Z is assumed to be a random variable following a Poisson distribution, and X is assumed to follow a binomial distribution, as follows:

$$Z \sim \text{Poisson}(md(p)(1 - \rho)T), \tag{4}$$

and

$$X \sim \text{Bino}(\min\{C + \alpha\,, Z\}, b). \tag{5}$$

In this context, the accommodation availability probability S is defined as the probability that the number of no-shows X is greater than or equal to the smaller of the OB level α and the number of accepted guests exceeding the total room capacity, which is $Z - C$, that is,

$$\alpha_C^* = \{\alpha > 0 | \mathrm{P}(X \geq \min\{\alpha, Z - C\}) \geq S \text{ and } \mathrm{P}(X < \min\{\alpha + 1, Z - C\}) < \mathrm{S}\}. \tag{6}$$

Considering factors such as customer satisfaction, the manager sets the desired accommodation availability probability S and determines the OB level α_C^* that satisfies equation (6).

In the revenue-oriented approach, the optimal OB level is determined by finding the value α that maximizes the maximum expected revenue given by equation (1). Specifically, if the maximum expected revenue under OB level α at the start of sales ($t = T$) is denoted by $V_T^\alpha(C)$, then the optimal OB level can be defined as follows:

$$\alpha_R^* = \underset{\alpha \geq 0}{\operatorname{argmax}} V_T^\alpha(C). \tag{7}$$

4. Estimation of Model Parameters

In this section, we estimate parameters for customer arrival rates and cancellation rates using reservation and cancellation data from a single accommodation facility in Japan. The analysis uses a total of 2,867 records from periods excluding the COVID-19 pandemic, specifically from April 1, 2019, to November 30, 2019, and from April 1, 2022, to May 31, 2024. Although the target facility offers multiple room types, we use the data from the single room type with capacity $C = 10$. In cases where a single purchase included multiple guests, the total amount of payment was divided to calculate the per-person price, and each purchase was treated as a single-person purchase record. To conduct the analysis, we set the analysis horizon to $T = 200$, as the earliest booking in the dataset was observed 209 days prior to the check-in date.

This setting minimizes data loss while ensuring consistency and computational efficiency in the model implementation. The cancellation policy of the target hotel is shown in Table 1. Based on this policy, the refund rate g_i is set as follows: $g_i = 0.2$ on the day of stay ($t = 0$); g_i = 0.5 for cancellations made 1 to 2 days before the stay ($1 \leq i \leq 2$); g_i= 0.8 for cancellations made 3 days prior to the stay ($i = 3$); and g_i= 1.0 for cancellations made 4 or more days in advance.

Table 1. Cancellation Policy

Cancellation date	Refund rate
Day of stay	20%
1~2 days before	50%
3days before	80%
4 days to before	100%

4.1 Estimation of Arrival and Cancellation Event Rates

The number of reservations and cancellations for each reservation lead time was aggregated from the actual data, and their sum was calculated as the number of arrival events. Figure 1 illustrates the distribution of arrival events by lead time, where the horizontal axis represents the lead time and the vertical axis indicates the relative frequency of arrivals. In the figure, the blue bars represent reservation events, while the yellow bars represent cancellation events. The figure shows a tendency for both reservations and cancellations to increase as the date of stay approaches. The arrival rate is approximated using the log-normal distribution shown in Equation (8). Based on the actual data, the parameters of Equation (8) are as follows: the standard deviation after logarithmic transformation $\sigma = 1.2041$, and the median before transformation $\phi = 13.577$.

$$m_t = \frac{1}{t\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln t - \varphi)^2}{2\sigma^2}\right) \tag{8}$$

The cancellation event occurrence rate ρ_t is defined as the proportion of cancellations to total arrival events (i.e., the proportion represented by the yellow area in Figure (1). As the number of data points for arrival events decreases closer to the start of the sales period T, the variability of ρ_t increases. This increased variability leads to instability in the observed values, thereby complicating the reliable estimation of the parameters. Therefore, a weekly moving average is applied when estimating the cancellation event occurrence rate ρ_t. Figure 2 shows the cancellation event occurrence rate for each lead time, with the horizontal axis representing lead time and the vertical axis representing the moving average of the cancellation rate. This cancellation event rate is approximated using the polynomial function in Equation (9). The parameters of Equation (9) are set to $\beta = -0.000001, \gamma = 0.000153, \delta = -0.007073$, and $\varepsilon = 0.399835$.

$$\rho_t = \max\{\beta x^3 + \gamma x^2 + \delta x + \varepsilon, 0\} \tag{9}$$

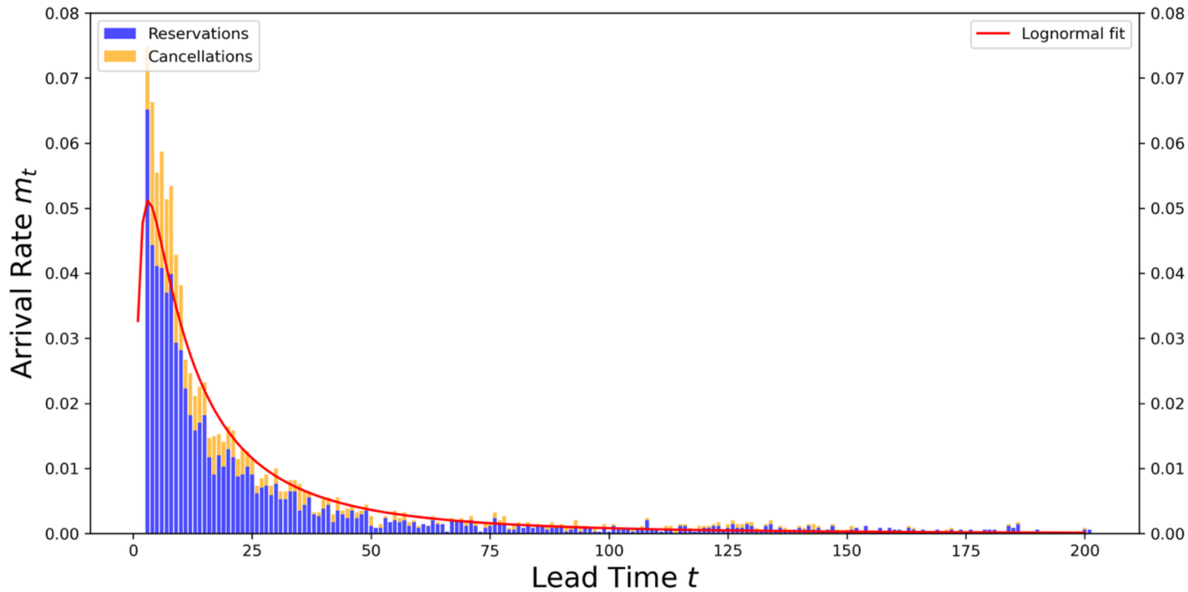


Figure 1. Distribution of reservation and cancellation events by lead time

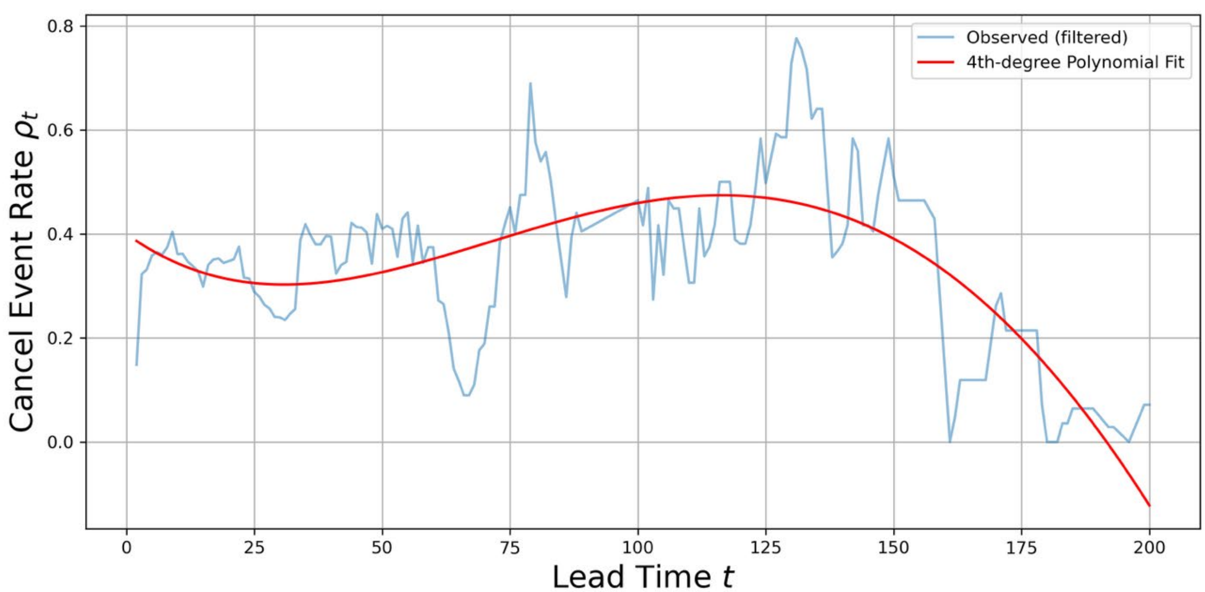


Figure 2. Arrival rate of customers who intend to cancel

4.2 Cancellation Rate

The cancellation rate q_i is defined as the probability that a reservation made t periods before the stay is canceled in period i (where $i \leq t$). Based on the cancellation rate q_i and the refund rate g_i determined by the cancellation policy for each cancellation date, the refund-adjusted profit is calculated using equation (2). In this study, the exponential model proposed by Ito et al. (2024) in equation (10) is employed. This model yields the daily cancellation probability based on the remaining days until the stay, i, and the elapsed days since the reservation, $t - i$.

The cancellation rate q_i is given by equation (10), where U denotes the number of exponential terms constructed based on the remaining days until the stay i, V denotes the number of exponential terms based on the elapsed days since the reservation $t-i$, and W indicates whether a constant term is included in the cancellation rate.

$$q_i = C_{U,V,W}(i,t) = \sum_{k=1}^{U} d_k e^{-e_k i} + \sum_{j=1}^{V} f_j \, e^{-r_j(t-i)} + h. \quad (10)$$

The parameter d_k, e_k, f_j, and r_j are estimated using the maximum likelihood estimation (MLE) method based on the observed reservation and cancellation data. Specifically, d_k represents the weight of cancellations with respect to the remaining days i, and e_k indicates the decay speed of the cancellation rate. The parameter f_j represents the weight for the variation in the cancellation rate based on the elapsed days since the reservation $t-i$, and r_j determines how rapidly the cancellation rate decays with respect to $t-i$.

In this study, the cancellation rate q_i is not re-estimated; instead, we employ the parameter values previously estimated by Ito et al. (2024) using historical reservation and cancellation data. Specifically, we adopt the exponential model $C_{(4,2,O)}$, which consists of four exponential terms based on the remaining days until the stay, two exponential terms based on the elapsed days since the reservation, and excludes the constant term (denoted by $Z = O$ for "Omitted"). The cancellation rates are calculated based on this specified model, and all parameters d_k, e_k, f_j and r_j are directly taken from the prior study.

Figure 3 illustrates the transition of the probability that reservations made in period t are canceled by the stay date. The figure shows that the cancellation rate is relatively high immediately after a reservation is made, and gradually decreases over time. However, the rate begins to increase again approximately ten days prior to the stay, and then decreases once more as the stay date approaches. This trend may be explained by two main factors: first, a considerable number of customers tend to cancel shortly after making a reservation; second, many cancellations occur just before the cancellation fee is applied, as customers attempt to avoid incurring additional costs.

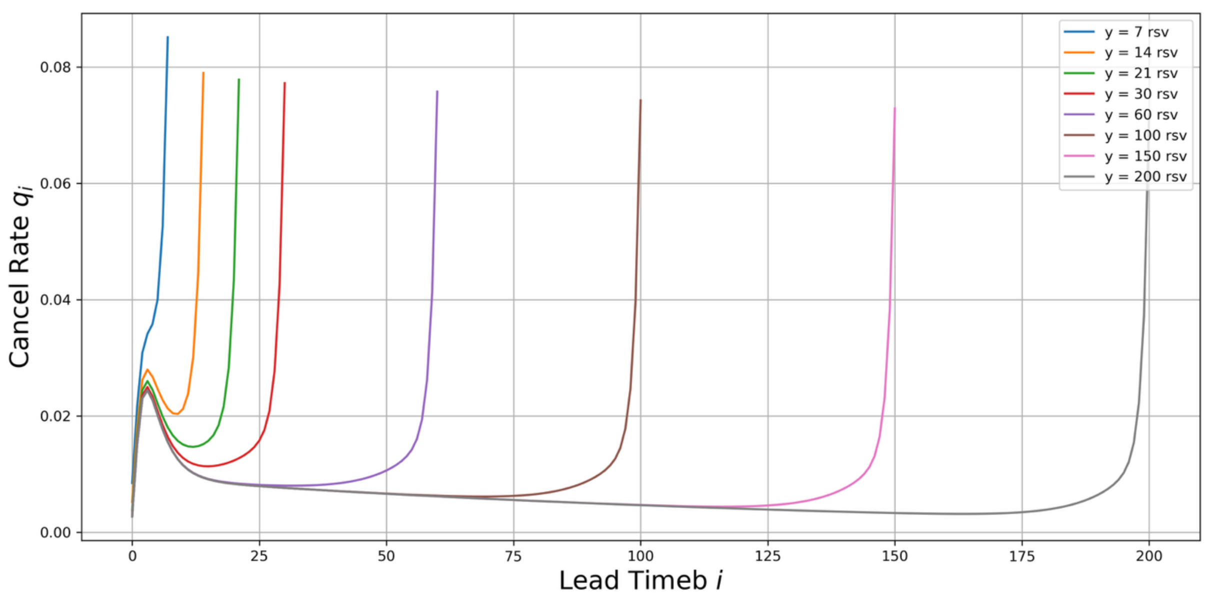


Figure 3. Trends in cancellation rates by reservation lead time

4.3 Estimation of Purchase Probability

Next, we estimate the probability of purchase $d(p_t)$ at price p_t in period t. The distribution of the number of purchases at price p_t is approximated using a lognormal distribution. If $F(p_t)$ denotes the cumulative distribution function of this lognormal distribution, then the purchase probability at price p_t is given by $d(p_t) = 1 - F(p_t)$. The probability density function $f(p_t)$ of the lognormal distribution is given by equation (11). The parameters of this distribution are as follows: the location parameter l = 1826.80, the standard deviation on the log scale θ = 0.134, and the mean on the log scale η =ln$(6523.13) \approx 8.782$. In Figure 4, the bar graph represents the purchase rates observed in the actual data, while the curve indicates the estimated purchase probability $d(p_t)$. When $p_t \leq l$, the purchase probability $d(p_t)$ is defined as zero, based on the assumption that purchases cannot occur below the location parameter.

$$f(p) = \frac{1}{(p-l)\theta\sqrt{2\pi}}\exp\left(-\frac{(\ln(p-l)-\eta)^2}{2\theta^2}\right),\ \ p > l \tag{11}$$

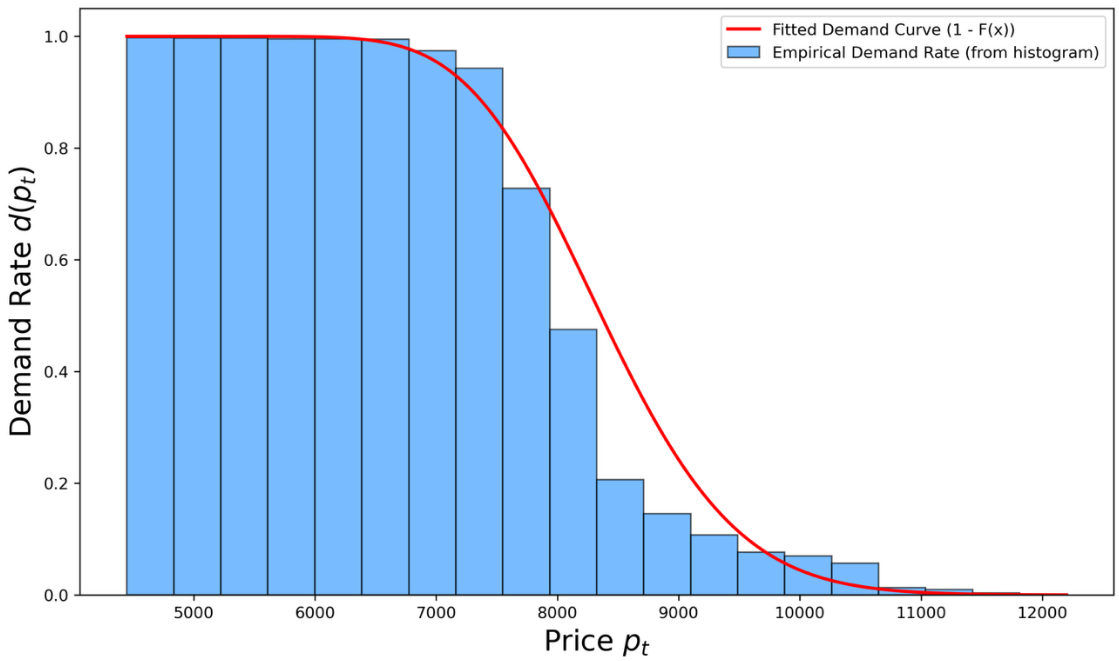


Figure 4. Demand rate with respect to price

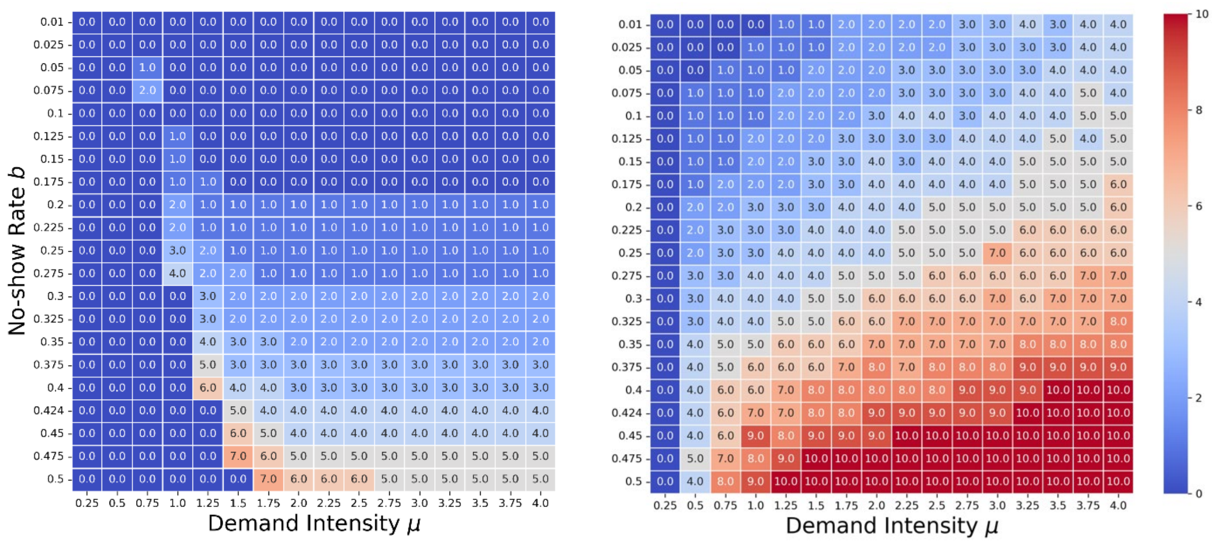
5. Revenue Matrix

5.1 Result of Determining the Amount of Overbooking Level

In this section, the OB levels determined by the customer-oriented approach and the revenue-oriented approach are presented using the parameters set in Section 4. Figure 5 shows the OB levels for each demand intensity μ and no-show rate b, with the vertical axis representing the no-show rate and the horizontal axis representing the demand intensity. The values within each cell indicate the OB level. Here, demand intensity refers to the multiplier applied to the potential number of customers m, meaning that a higher demand intensity implies a larger number of potential customers on the stay date, representing a busy day. In calculating the optimal prices and OB levels, μm was used instead of m in equations (1) and (4). We set The accommodation availability probability is set to $S = 0.9$, with the OB levels range $0 \leq \alpha \leq 10$, vacancy cost $\pi_1 = 0$, and bumping cost π_2 =30000.

Figure 5(a) shows the OB levels determined by the customer-oriented approach. It can be observed that as the no-show rate increases, the OB level also increases. Additionally, when the demand intensity is $\mu > 2$, no significant change in OB level is observed. This is characteristic of the customer-oriented approach, as it does not increase the OB level unnecessarily even when the number of potential customers is high, in order to satisfy the constraint of the accommodation availability probability S =0.9. Furthermore, in the calculation based on equation (6), when the expected number of staying guests is small and the accommodation availability probability P exceeds the threshold S for all levels of overbooking, it is considered that overbooking is unnecessary. In such cases, the OB level α is set to zero. Figure 5(b) presents the OB levels determined by the revenue-oriented approach. It can be seen that both higher no-show rates b and higher demand intensities μ tend to result in higher OB levels.

A comparison between Figure 5(a) and Figure 5(b) reveals that the revenue-oriented approach shown in Figure 5(b) results in higher OB levels. This is because the revenue-oriented approach places less emphasis on the negative impact of customer bumping. As a result, when the expected revenue gain from overbooking exceeds the expected loss from potential bumping, the model tends to allow for higher levels of overbooking.



(a) Customer-oriented approach.

(b) Revenue-oriented approach

Figure 5. OB levels for the customer-oriented and revenue-oriented approaches

5.2 Expected Rate of Change in Revenue

Next, we demonstrate the effectiveness of DP and OB under different sales environments by comparing the expected revenues obtained from four pricing methods. The four pricing methods are: fixed pricing (FP), where a constant price is maintained throughout the sales period; dynamic pricing (DP) without overbooking; and two overbooking-based approaches, namely a customer-oriented approach and a revenue-oriented approach. For fixed pricing policy, the optimal price is determined using the solution to the following problem:

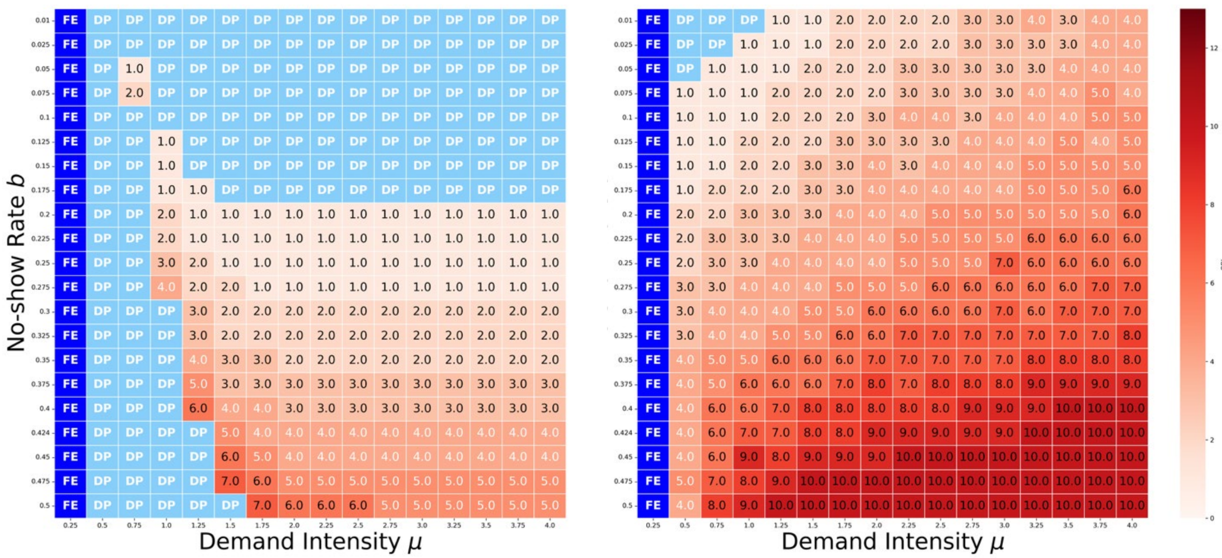
$$\max_{p} \ v_T(C, p_t) \quad \text{s.t. } p_t = p, t = 1, \dots, T, \tag{12}$$

where $v_T(\cdot,\cdot)$ appears within the square brackets in equation (1) and represents the total expected revenue. In other words, this problem aims to determine a constant optimal price at the beginning of the sales period that maximizes the total expected revenue over the entire horizon T. When overbooking is not applied (refer to as DP0), the optimal pricing policy can be obtained by solving equation (1) with $\alpha = 0$.

Figure 6(a) presents a strategic map (Revenue matrix) summarizing the sales strategy with the highest expected revenue among fixed pricing (FP), DP0 and the customer-oriented approach for each combination of no-show rate b and demand intensity μ. For the customer-oriented approach, the OB level is also indicated. When the expected revenues of the strategies are equal, the strategy that is simplest to implement and imposes the lowest operational burden is prioritized. The operational burden increases in the order of FP, DP0, and the customer-oriented approach. From Figure 6(a), it can be observed that when the demand intensity μ is extremely low at 0.25, fixed pricing is effective. This is because supply always exceeds demand, and thus there is no need to increase prices based on scarcity. Additionally, when the no-show rate is low, it is not necessary to implement OB, and price adjustments using DP can reduce vacant rooms by balancing supply and demand.

Next, Figure 6(b) presents a strategic map comparing the expected revenues obtained using the four pricing methods: fixed pricing (FP), DP0, the customer-oriented approach, and the revenue-oriented approach. Similar to Figure 6(a), when the expected revenues are equal among the strategies, we adopt pricing policies in the order of priority: FP, DP0, customer-oriented approach, and revenue-oriented approach.

From Figure 6(b), it can be seen that FP is effective when both the no-show rate and the number of potential customers are low. Furthermore, as both the no-show rate and the number of potential customers increase, the OB level also increases accordingly. When the number of potential customers is high, the selling price is set to balance supply and demand, resulting in higher prices. In such cases, even if costs due to service denial occur, the high sales revenue outweighs these costs, leading to higher OB levels being set. Comparing Figures 6(a) and (b), we see that when the demand intensity μ is 0.75, or when the no-show rate is high, there are ranges where the OB levels are the same.



(a) Customer-oriented approach. (b) Revenue-oriented approach.

Figure 6. Revenue matrix for different OB strategy

5.3 Comparison of Customer- and Revenue-Oriented Approach

Finally, we analyze the revenue decay rate of the customer-oriented approach in comparison with the revenue-oriented approach. Figure 6 replaces the OB levels shown in Figure 5(a) with the revenue reduction rates of the customer-oriented approach relative to the revenue-oriented approach. According to this figure, the revenue decrease ranges from 0% to 4.2%, indicating that the revenue-oriented approach is more effective in terms of maximizing revenue. This can be attributed to the fact that the revenue-oriented approach tends to allow for higher OB levels, as it places less emphasis on avoiding bumping, thereby improving overall revenue performance. Additionally, in the range of demand intensity between 0.75 and 1.5, the revenue decay rate remains relatively low. This implies that when the number of potential customers is close to the hotel's capacity and demand conditions are moderate, it is possible for the hotel to adopt the customer-oriented approach while still achieving near-optimal revenue. Based on this Figure 7, hotel managers can make informed decisions about whether to implement the customer-oriented approach by evaluating the acceptable level of revenue loss.

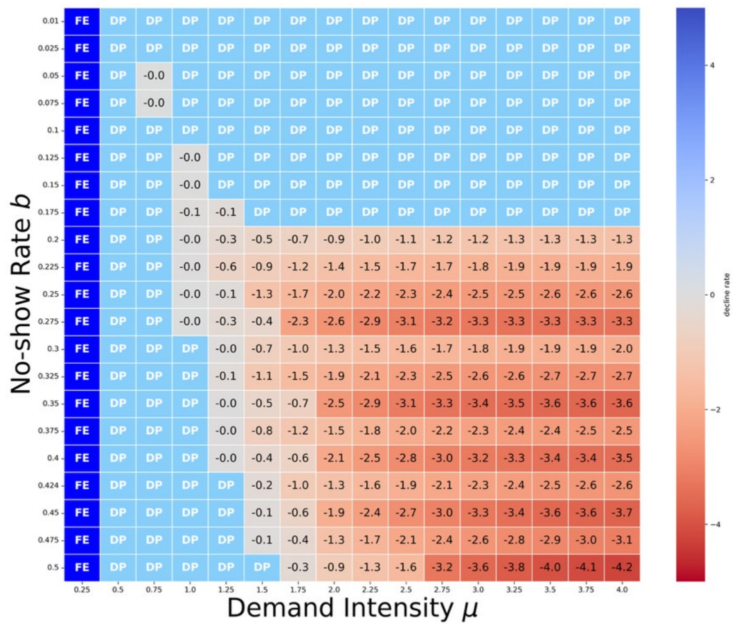


Figure 7. Relative revenue (%) of customer-oriented approach

6. Conclusions and Future Issues

This study developed a revenue maximization model that integrates overbooking (OB) strategies into dynamic pricing (DP) to support decision-making under uncertain demand environments. We proposed the customer-oriented and revenue-oriented approaches. By calibrating model parameters using actual hotel reservation and cancellation data from Japan, we constructed strategic maps to evaluate the effectiveness of each strategy under varying demand intensity and no-show rates.

Numerical experiments revealed several key findings. First, under low potential demand, fixed pricing was the most effective strategy. Second, in cases of high demand and low no-show rates, DP without OB yielded the best performance. Third, when no-show rates were high, combining DP with OB significantly improved revenue. Moreover, even in conditions where capacity and demand were nearly balanced and no-shows were frequent, adopting a customer-oriented OB strategy could still result in revenue maximization. It was also observed that the effect of OB becomes more pronounced as the potential demand increases, but the marginal revenue improvement diminishes beyond a certain level of OB. These findings provide practical insights for hotel managers to determine the most appropriate combination of DP and OB strategies based on their operational context. The strategic maps proposed in this study serve as a decision support tool to flexibly adjust sales strategies in response to fluctuating demand, aiming to balance revenue optimization and customer satisfaction.

Two issues can be identified as future research directions. First, it is necessary to diversify compensation methods in cases of service denial. In actual hotel operations, when customers cannot be accommodated due to OB, there are multiple compensation options, such as offering a free upgrade to a higher room category or arranging alternative accommodations through partnerships with nearby facilities. Future models should incorporate and evaluate these realistic compensation options. Second, it is necessary to consider multiple types of accommodation facilities. In this study, calibration was performed using data from a single accommodation facility, and thus the generalizability of the resulting strategic map may be limited. Future research should adjust model parameters for different types of accommodations, such as business hotels and resort facilities, and verify the applicability of the proposed strategies accordingly.

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