

Modeling no-shows, cancellations, overbooking, and walk-ins in restaurant revenue management

Tony S. M. Tse^a and Yiu-Tung Poon^b

^aSchool of Hotel and Tourism Management, The Hong Kong Polytechnic University, Kowloon, Hong Kong; ^bDepartment of Mathematics, Iowa State University, Ames, IA, USA

ABSTRACT

Few studies have examined overbooking in the restaurant industry. The authors observed the business situation in a restaurant in Hong Kong over 2 years, noted how demand exceeded supply on a regular basis, and analyzed the reservation data. The reservation data were used to estimate the no-show/cancellation probability and walk-ins for lunch and dinner on different days of the week, to illustrate the model, and to arrive at the optimal booking limits. A conceptual model was developed which would take into consideration the business situation, no-shows, cancellations, and walk-ins to determine the booking limit for maximizing the expected total revenue.

KEYWORDS

Cancellations; no-shows; overbooking; restaurant revenue management; walk-ins

Introduction

Overbooking is a common phenomenon and an accepted practice in the hotel and airline industries. Hotels and airlines engage in protective overbooking, whereby reservations are taken in excess of capacity to overcome the problem of no-shows and late cancellations (Toh, 1986). It is argued that overbooking enhances operating efficiencies by making good use of perishable room nights and airline seats, which might otherwise be wasted. Such advantages of overbooking outweigh the occasional inconveniences to guests and passengers, who can be turned away when checking in. Overbooking in the hotel industry and the airline industry has been well studied (Corney, 1984; Coughlan, 1999; Enghagen & Healy, 1996; Gosavii, Bandla, & Das, 2002; Hwang & Wen, 2009; Lambert, Lambert, & Cullen, 1989; Lefever, 1988; Noone & Lee, 2011; Rothstein, 1971, 1974, 1985; Toh, 1985, 1986; Toh & DeKay, 2002; Weatherford & Bodily, 1992). These previous studies have covered the topic from different angles, including revenue management, human resource management, operational research, and ethics. Although the restaurant business is similar to the hotel and airline businesses in that restaurant tables, room nights, and airline seats are all perishable inventory

and fixed in capacity, there are significant differences between the industries, and fewer studies have examined overbooking in the restaurant industry.

It has been noted that a hotel or airline is likely to be fully booked for only a short period of time during the high season, and overbooking will only occur briefly during periods of very heavy demand. In the restaurant industry, unlike the hotel and airline industries, overbooking occurs in specific restaurants as standard practice over extensive periods of time. Some highly popular restaurants can require advance reservations at all times of year—examples include the French Laundry in California, Le Jules Verne in Paris, The Catbird Seat in Nashville, Noma in Copenhagen, The Fat Duck in Berkshire, and Attica in Melbourne. The demand for some of these restaurants is so high that they are open for reservations months in advance. In Hong Kong, a restaurant known as The Market at Hotel ICON requires reservations several months in advance (All About Hong Kong, 2012). Restaurants requiring these advance reservations are of such high quality that people are prepared to wait months to get a seat. It is, however, not unusual for some people to change their minds during the intervening months and cancel their reservations or simply not show up on the day. For this reason, some of these restaurants also engage in protective overbooking to maximize revenue.

The case of overbooking in restaurants is quite different to the case of overbooking in hotels and airlines due to differences in the nature of the businesses and in industry practices. While an abundant literature exists on overbooking in the hotel and airline industries, very little research has occurred on overbooking in the restaurant industry. The aim of this article is to fill the knowledge gap in restaurant revenue management with the following specific objectives: (1) to analyze the differences between the restaurant, hotel, and airline industries in the way they cope with no-shows and late cancellations, (2) to develop a model for determining the optimal overbooking rate in restaurants, (3) to illustrate the overbooking model with restaurant reservation data, and (4) to suggest ways to cope with no-shows, late cancellations, and walk-ins.

Overbooking in airline, hotel, and restaurant industries

Weatherford and Bodily (1992) identified a number of possible management objectives in the airline industry: maximize profit, maximize capacity utilization, maximize average revenue, maximize revenue, minimize lost customer good will, maximize net present value, and extract each customer's maximum price. An airline could achieve the objectives by managing its constraints and costs. An airline has fixed number of seats, and when an airline overbooks in order to maximize profit and capacity utilization, it has a number of possible ways to handle "disappointed" passengers. The airline can offer to upgrade

passengers in the same flight, or offer seats on another flight with compensation such as cash, meals, or hotel accommodation. It is not uncommon for an airline to invite some passengers to volunteer to be “bumped” in exchange for such compensation so that some seats are released. Weatherford and Bodily (1992) stated that when overbooking occurs, an appropriate penalty should be applied for lost customer good will. The authors also noted that airlines cater to the full-price segment and the discount-price segment, and their behaviors are different in terms of willingness to pay and probability of showing up. In dealing with airline revenue management, Gosavi, Bandla, and Das (2002) argued that a realistic optimization model should consider multiple fare classes, overbooking, concurrent demand arrivals of passengers from the different fare classes, and cancellations. The idea of segmenting customers and assigning different probabilities of showing up to different segments will be incorporated in the analysis of overbooking in the restaurant industry later.

A hotel also has a fixed inventory, and when a hotel overbooks, it must be prepared to “disappoint” and “walk” guests who approach the hotel check-in counter after all rooms have been allocated. Other than offering an apology to the guest, the hotel has two options to cope with the situation. The hotel can offer an upgrade to the guest or offer transportation to another hotel of similar standard and pay for the difference in room charges. Toh (1985) treated overbooking as an inventory problem of fixed supply and variable demand and proposed a statistically derived inventory depletion model that judiciously balances the opportunity cost of empty rooms with adverse consequences of oversales, allowing hotel managers to systematically establish an optimal booking level. Toh (1986) also noted that American hotels generally have done a much better job than airlines in reducing the incidence of no-shows and late cancellations, and collecting no-show penalties. Hotels are able to cross-check through their reservations systems to detect any multiple/speculative bookings. In addition, hotels monitor demand of and booking by large groups to avoid being caught by surprise late cancellations. According to Lambert et al. (1989), overbooking is the most widely used management tactic to minimize financial loss due to cancellations and no-shows, and they advocated using simulation to study complex, real-world systems that cannot be adequately described by other analytical methods. The first step in simulation is constructing a realistic model by including all relevant components, and then, using historical data from the specific hotel, probability distributions are calculated, and the model is exercised through simulation. Such a simulation model is a relatively inexpensive means of improving management decision making in the area of reservations policies. Use of a simulation model compels management to define and formulate the problem and to articulate such variables as the cost of walking a guest. Jones and Hamilton (1992) also realize that historical data are an

important source of information for clarifying overbooking policies and determining overbooking percentages. The idea of constructing a realistic model by including all relevant components and then using historical data from a specific outlet to calculate probability distributions is later adopted in this study of no-shows, cancellations, overbooking, and walk-ins in a restaurant setting.

It is a wide belief and common practice that overbooking occurs with compensation, and it is this notion of compensation which contributes to the positive perception of overbooking being fair. Close to 44 percent of the respondents in a study consider overbooking in hotels to be unfair (Hwang & Wen, 2009). The authors stressed the importance of perceived fairness toward a hotel's overbooking and compensation policies and stated that ensuring perceived fairness would be an effective strategy for increasing positive word-of-mouth and customer loyalty. This notion of compensation, or penalty, is also taken into consideration in the modeling of cancellations, overbooking, and walk-ins in a restaurant setting later in the discussion.

The literature is not entirely supportive of overbooking. Enghagen and Healy (1996) made the case against overbooking when considering factors such as customer satisfaction, employee satisfaction, profitability, ethics, marketing, and legality. The authors pointed out that there are six direct costs associated with overbooking in hotel management: (1) labor costs in finding guests alternative accommodation; (2) transportation cost in relocating guests to new hotels; (3) the actual cost of providing alternative accommodations; (4) the cost of preparing goodwill letters; (5) the cost of premiums and coupons given out as a means of gaining customer appeasement, and (6) the personnel training costs that may likely be incurred in educating front-desk staff as to the handling of such delicate matters (Corney, 1984, as cited in Enghagen and Healy, 1996). Overbooking has profound marketing implications, especially when considering the promises of guest satisfaction and the costs associated with the delivery of quality service. The practice of overbooking comes into direct conflict with the mission of meeting guests' needs; a promised room, after all, is the most paramount of guests' needs. One may also argue that a hotel has the legal and moral obligations to honor confirmed room reservations. The literature review leads to the necessity and importance of including the cost and penalty components in the modeling of overbooking in the restaurant business in order to be realistic.

Although restaurants also have capacity limits, they rarely "walk" or "bump" customers as in the hotel and airline industries. A restaurant has some flexibility in stretching the seating capacity by re-arranging tables or fitting one or two more seats at a table. In some cases, customers may be asked if they mind taking up a table in a disadvantaged location, or if they could wait while a table is cleared and prepared for them. In other words, a restaurant may have two

capacity limits: (1) a desirable seating capacity and (2) a stretched seating capacity. The desirable seating capacity is the officially designated seating limit, a limit which customers would find comfortable. The stretched seating capacity is a higher seating limit that the restaurant could manage and that customers would put up with. While a hotel may have to “walk” guests and an airline may have to “bump” passengers, a restaurant may “squeeze in” customers to a stretched capacity. A restaurant would have to turn away customers if they continue to arrive beyond the stretched capacity.

The implication of having two seating capacity levels is that a restaurant manager has to be flexible in dealing with customers. Patronage above the desirable seating capacity carries a “cost” associated with the additional revenue in terms of inconvenience to customers, pressure on restaurant staff, and loss of goodwill. This “cost” may increase as the patronage increases and approaches the stretched capacity. Patronage above the stretched capacity would result in turning away customers, as it would become physically impossible to accommodate more guests. For a restaurant, the “penalty” of turning away customers usually involves apology and perhaps a substantial discount for the disappointed customers on their next visit.

Hotels usually follow an industry practice of keeping a room until 6:00 PM for a guest who has made a reservation. Airlines have departure schedules that they must adhere to, and they rarely wait for passengers. Restaurants do not have industry practices as strict as those of hotels and airlines, but they may remind customers that tables are kept for, say, 15 minutes, if they are late. In practice, the table remains available after the holding period unless it has been assigned to another party. Hotels and airlines usually have some form of credit card payment guarantee honored either directly by guests and passengers or by travel agencies. If a guest does not turn up after reserving a room, the hotel can charge the guest for at least one night. If a passenger does not show up after reserving a flight, the airline can penalize the passenger according to the conditions of their ticket type. In the case of a non-endorsable, non-refundable ticket, the passenger may end up forfeiting the entire ticket amount. Although a few very popular restaurants with small numbers of seats do ask for a credit card guarantee, such practices are not widespread in the restaurant industry. People who have made a restaurant reservation and cancel the booking or do not show up are rarely penalized. The fact that most people could walk away without honoring their reservations is believed to be one of the reasons why no-shows and cancellations are more common in the restaurant industry than in the hotel or airline industries.

Restaurant revenue management

Literature on restaurant revenue management is limited compared to the literature in hotel and airline industries. Thompson (2010), in his review of

the restaurant revenue management literature, identified two emergent themes: capacity management and customer experiences. A major focus of capacity management studies has been the mix of tables in restaurants; by better matching capacity to demand through different table combinations, a restaurant can increase its effective capacity (Kimes, 2004; Kimes & Thompson, 2004; Thompson, 2002, 2003; Vidotto, Brown, & Beck, 2007). The second theme, customer experiences, deals with how restaurant guests react to different pricing policies, how customer seating affects the amount of money spent, service recovery, and customer sensitivity toward different reservation policies (Kimes & Robson, 2004; Kimes & Wirtz, 2002; Mattila, 1999; McGuire & Kimes, 2006). According to Thompson (2010), two strategic levers exist for restaurant revenue management: price and meal duration (Kimes, 2004; Kimes & Wirtz, 2002). A restaurant manager could offer different menu prices based on higher and lower demand periods. Duration management includes reducing the uncertainty of arrival times, reducing the uncertainty of meal durations, and reducing the time between meals. Thompson (2010) identified the following characteristics of customer demand that are relevant to managing restaurant profitability: number of parties, party size, party composition, items purchased, meal duration, and time dependency. Thompson (2010) also raised a number of research questions to be answered for restaurant revenue management, including questions concerning customers' reactions to different reservation policies as follows: What are the conditions under which reservations should be offered? If reservations are to be offered, what is the ideal ratio of reservations to walk-ins? What are the benefits of taking reservations online? What affects the waiting tolerances of walk-in customers? How should waiting time be estimated? Should the wait estimates quoted to customers be biased or unbiased? There are, in fact, many questions to be answered in the area of reservations policies in restaurant management, and there is hardly any study conducted on no-shows, cancellations, walk-ins, and overbooking. This research will fill the knowledge gap regarding the particular area of overbooking policies in restaurant revenue management.

Research method

In order to study overbooking in the restaurant industry, we observed the business situation in The Market at Hotel ICON for over 2 years, noted how demand exceeded supply on a regular basis, and obtained and analyzed the reservation data. The data include daily numbers of reservations, no-shows, cancellations, and walk-ins for lunch and dinner every day for the 27 months from April 2012 to June 2014. We developed a conceptual model, based on some assumptions, which would take into consideration the business situation, no-shows, cancellations, and walk-ins, in order to

determine the booking limit for maximizing the expected total revenue. We then used the reservation data to estimate the no-show/cancellation probability and walk-ins for lunch and dinner on different days of the week, to illustrate the model, and to arrive at the optimal booking limits. In this sense, the research method is both conceptual and empirical in nature.

Assumptions and modeling of no-shows, late cancellations, and penalties in a restaurant

In an ideal situation, a restaurant manager will maintain patronage up to capacity. In the real world however, as he expects no-shows and cancellations, he overbooks up to a certain level. If the manager overbooks too much, a chance exists that a customer could arrive and be unable to be “squeezed in” because the restaurant will have already reached its stretched capacity. If the manager overbooks too little, a chance exists that empty seats will remain, leaving patronage below the desirable capacity. The question is by how much should the manager overbook?

In restaurant revenue management, no-shows and late cancellations can be treated as having the same effect, in that both result in an empty seat. If the combined probability of no-shows and late cancellations is p , in a case with 100 seats reserved, on average, $100p$ persons either do not show up or make last-minute cancellations. To maximize revenue, the restaurant would want to overbook by a certain percentage to fill the empty seats. Simple mathematics indicates that if the manager overbooks by p to $C/(1 - p)$ persons, where C = restaurant capacity, then the expected number of customers who show up is equal to C , the restaurant capacity. However, this overbooking limit may not maximize revenue, as it does not take into consideration the existence of the two seating capacity limits in the restaurant setting, and the “cost” and “penalty” when the number of customers exceeds the capacity limits. In addition, the probability of no-shows and late cancellations may vary from day to day, and the restaurant needs to grapple with the volatility of the situation.

To deal with the dual capacity limits and the volatility of no-shows and cancellations, let us make the following notations and assumptions.

Notations

N = maximum number of bookings to be accepted by a restaurant (the booking limit to be set by the restaurant)

p = probability of no-show or late cancellation of a reservation

M_1 = desirable seating capacity (the officially designated seating limit which customers would find comfortable)

M_2 = stretched seating capacity (a higher seating limit that a restaurant could manage and that customers would put up with)

x = number of customers with reservation who actually show up

$F_1(x)$ = reduced revenue when $M_1 < x \leq M_2$

$F_2(x)$ = overbook penalty when $M_2 < x \leq N$

r = average bill per customer

$R(N)$ = expected revenue when the booking limit is set at N

Assumptions

Each reservation has two possible outcomes: either honoring the reservation or not honoring the reservation. Therefore, we can assume that the number of no-shows or cancellations follows a binomial distribution. As the probability of a customer showing up is $1 - p$, the number of customers who actually show up is a random variable x that follows a binomial distribution, $\text{Binomial}(N, 1 - p)$.

Modeling

The purpose of this modeling is to find the booking limit N that will maximize the expected total revenue. We note that there are three components in $R(N)$. The first component is the revenue when the number of customers who honor reservations is lower than or equal to the desirable seating capacity, that is, when $0 \leq k \leq M_1$. The second component is the revenue when the number of customers who honor reservations is higher than the desirable seating capacity but lower than or equal to the stretched seating capacity, that is, when $M_1 + 1 \leq k \leq M_2$. As discussed earlier, in such a situation, the total revenue is reduced due to nominal “cost” associated with the additional revenue in terms of inconvenience to customers, pressure on restaurant staff, and loss of goodwill. The third component is the total penalty when the number of customers who honor reservations is higher than the stretched seating capacity, that is, when $M_2 < k$. As discussed earlier, in such a situation, the restaurant will have to turn away customers and allow for a penalty.

For the first component, when $0 \leq k \leq M_1$, the revenue is kr .

For the second component when $M_1 + 1 \leq k \leq M_2$, the reduced revenue is $F_1(k)$.

For the third component when $M_2 < k$, the overbook penalty is $F_2(k)$.

We use the Binomial distribution from probability theory to determine the probability that the number of customers who honor reservations is k , as follows:

$$\text{Probability } (x = k) = \binom{N}{k} (1-p)^k p^{N-k}, \text{ where } \binom{N}{k} = \frac{N!}{k!(N-k)!} \text{ is the}$$

binomial coefficient.

Therefore, the expected value of the total revenue is the sum of the three components as follows:

$$\begin{aligned} R(N) = & \sum_{k=0}^{M_1} \binom{N}{k} (1-p)^k p^{N-k} k r + \sum_{k=M_1+1}^{M_2} \binom{N}{k} (1-p)^k p^{N-k} F_1(k) \\ & + \sum_{k=M_2+1}^N \binom{N}{k} (1-p)^k p^{N-k} (F_1(M_2) - F_2(k)). \end{aligned}$$

The optimal booking limit N^* is the value of N that maximizes $R(N)$. The value depends on the average bill per customer r , functions F_1 and F_2 , and probability p .

The modeling so far has not taken walk-in customers into consideration. Sometimes they could help fill some of the empty seats due to no-shows and cancellations. In order to have a more realistic model, we also take the walk-in customers into consideration in the modeling and further modify the above optimization process. When vacancies exist due to no-shows or cancellations, the seats can be released to walk-in customers. Suppose there are k customers who honor reservations and m walk-in customers. The actual number of customers that the restaurant can accommodate would be the minimum of $(k + m)$ and M_2 , the stretched seating capacity. Including this consideration, $R(N)$ has four components, which are described below:

For the component when $0 \leq k \leq M_1 - m$, the revenue is $(k + m)r$.

For the component when $M_1 - m + 1 \leq k \leq M_2 - m$, the reduced revenue is $F_1(k + m)$.

For the component when $M_2 - m + 1 \leq k \leq M_2$, the reduced revenue is $F_1(M_2)$.

For the component when $M_2 < k$, the overbook penalty is $F_2(k)$.

Therefore, the expected value of the total revenue is the sum of the four components, as follows:

$$\begin{aligned}
 R(N) = & \sum_{k=0}^{M_1-m} \binom{N}{k} (1-p)^k p^{N-k} (k+m)r \\
 & + \sum_{k=M_1-m+1}^{M_2-m} \binom{N}{k} (1-p)^k p^{N-k} F_1(k+m) \\
 & + \sum_{k=M_2-m+1}^{M_2} \binom{N}{k} (1-p)^k p^{N-k} F_1(M_2) + \sum_{k=M_2+1}^N \binom{N}{k} (1-p)^k \\
 & p^{N-k} (F_1(M_2) - F_2(k))
 \end{aligned}$$

Finding the booking limit N^* to maximize $R(N)$ is a discrete optimization problem. The problem can only be solved by direct evaluation of $R(N)$ for different values of N , because N^* cannot be written in a closed form of p . This will be illustrated by the data analysis in the next section.

Data analysis

We applied the above modeling to the reservation data of The Market at Hotel ICON. We used the reservation data (including daily numbers of reservations, no-shows, cancellations, and walk-ins for lunch and dinner) for the 27 months from April 2012 to June 2014. After removing the data from weeks in which deposits were required, we have reservation data corresponding to 749 lunches and 749 dinners in 107 weeks. (There are festive periods, such as Christmas, when the restaurant requires deposits for accepted reservations.) We first used a maximum-likelihood estimation method to estimate the no-show/cancellation probability, p , for lunch and dinner on different days of the week and then analyzed whether the no-show/cancellation rates on different days of the week are significantly different.

Table 1 shows the estimated no-show/cancellation rates for lunch on different days of a week, and Table 2 shows the estimated no-show/cancellation rates for dinner on different days of a week.

It is interesting to note that the estimate for probability of a no-show or late cancellation of a reservation ranges from 9.07% to 12.95%, and it is lowest on Thursday and highest on Saturday for both lunch and dinner. We

Table 1. Lunchtime no show/cancellation rates for each day of the week.

Days of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Estimate for p	10.08%	10.36%	10.52%	9.07%	10.60%	12.95%	10.53%

Table 2. Dinnertime no show/cancellation rates for each day of the week.

Days of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Estimate for p	10.63%	10.84%	10.73%	9.61%	11.35%	11.38%	10.88%

can reasonably conclude from this data analysis that the incidence of no-shows/cancellations is lowest on Thursday and highest on Saturday, for both lunch and dinner. The analysis of the statistical significance of the differences among the no-show/cancellation rates on different days of the week is given next.

To analyze whether there are any significant differences between the no-show/cancellation rates for different days of the week, we let

\hat{p}_i = maximum likelihood estimator for p on day i of the week and

n_i = total number of reservations on day i of the week.

The difference between the values of p for day i and j is significant at level α if

$$Z_{ij} = \frac{|\hat{p}_i - \hat{p}_j|}{\sqrt{\frac{\hat{p}_i(1-\hat{p}_i)}{n_i} + \frac{\hat{p}_j(1-\hat{p}_j)}{n_j}}} > z_{\alpha/2},$$

where $z_{\alpha/2}$ is the standard normal value at $\alpha/2$. For $\alpha = 0.05$, $z_{\alpha/2} = 1.96$.

The values of Z_{ij} for the lunch reservations are given in Table 3 and for the dinner reservations in Table 4. Values of Z_{ij} corresponding to significant differences ($Z_{ij} > 1.96$) are indicated in bold.

Table 3. Values of Z_{ij} for the comparison of the probabilities of no-shows/cancellations in lunch reservations on different days of the week.

	$j = 1$	2	3	4	5	6	7
$i = 1$	0	0.93	1.45	3.48	1.73	9.34	1.55
2	0.93	0	0.50	4.24	0.77	8.08	0.56
3	1.45	0.50	0	4.70	0.25	7.50	0.03
4	3.48	4.24	4.70	0	5.03	12.45	4.97
5	1.73	0.77	0.25	5.03	0	7.34	0.23
6	9.34	8.08	7.50	12.45	7.34	0	7.79
7	1.55	0.56	0.03	4.97	0.23	7.79	0

Note. 1 = Monday, 2 = Tuesday, 3 = Wednesday, 4 = Thursday, 5 = Friday, 6 = Saturday, 7 = Sunday; values of Z_{ij} corresponding to significant differences ($Z_{ij} > 1.96$) are italicized.

Table 4. Values of Z_{ij} for the comparison of the probabilities of no-shows/cancellations in dinner reservations on different days of the week.

	$j = 1$	2	3	4	5	6	7
$i = 1$	0	0.72	0.34	3.61	2.46	2.57	0.87
2	0.72	0	0.37	4.30	1.72	1.83	0.14
3	0.34	0.37	0	3.93	2.10	2.21	0.52
4	3.61	4.30	3.93	0	6.05	6.18	4.48
5	2.46	1.72	2.10	6.05	0	0.10	1.60
6	2.57	1.83	2.21	6.18	0.10	0	1.71
7	0.87	0.14	0.52	4.48	1.60	1.71	0

Note. 1 = Monday, 2 = Tuesday, 3 = Wednesday, 4 = Thursday, 5 = Friday, 6 = Saturday, 7 = Sunday; values of Z_{ij} corresponding to significant differences ($Z_{ij} > 1.96$) are italicized.

It is found that the lunch no-show/cancellation rates on Thursday and Saturday are indeed significantly different to the rates on other days of a week. The dinner figure on Thursday is significantly different from the figures on all other days of a week, and on Saturday from 3 days of a week. The incidence of no-shows/cancellations on Thursdays is the lowest probably because most customers have their plans finalized toward the end of a week, and their meal appointments are quite definite, while they might have other activities coming up on Friday, the day before the weekend. The incidence of no-shows/cancellations on Saturdays is highest probably because customers are juggling many leisure activities on the first day of a weekend, and they are more likely to change their plans.

After establishing the no-show/cancellation rates, we proceed to working out the seating capacities. From the data provided and based on the restaurant manager's advice, we set the desirable seating capacity M_1 to 190 and the stretched seating capacity M_2 to 210. For the k th customer above 190, we assume that there is a "cost" associated with the additional business. We depict this "cost" by a linear diminishing function $\frac{2k-1}{40}r$, which means that the "cost" increases as the capacity is stretched further. The "cost" starts to kick in when patronage exceeds M_1 and is quantified as a portion of the average bill per customer r . The portion becomes larger as patronage approaches M_2 , when the "cost" almost cancels out the revenue. Although this "cost" assumption may seem arbitrary, it is up to the restaurant manager to determine the function based on how keen he or she is to "squeeze in" customers.

For $190 < k \leq 210$, the reduced revenue from the k th customer is given by $(1 - \frac{2k-1}{40})r$, as illustrated in Table 5. This "cost" function is chosen to produce a 2.5% drop in the revenue for the 191st customer and an additional reduction of 5% for each additional customer afterward, and the total revenue from the 20 customers above 190 is $10r$, half that from the regular customers.

Thus, for $190 < x \leq 210$,

$$F_1(x) = \left(190 + \sum_{k=191}^x \left(1 - \frac{2k-1}{40} \right) \right) r = \left(x - \frac{1}{40}(x-190)^2 \right) r.$$

For customers above the stretched seating capacity of 210, we assume a penalty of $\frac{x}{2}$ for each customer (whom the restaurant must turn away). Thus, the overbook penalty:

Table 5. Reduced revenue with increasing $k > 190$.

k	191	192	193	...	209	210
Reduced revenue	$0.975r$	$0.925r$	$0.875r$...	$0.075r$	$0.025r$

$$F_2(x) = \left(\frac{x - 210}{2} \right) r.$$

The discrete optimization problem of finding the booking limit N^* to maximize $R(N)$ is solved by direct evaluation of $R(N)$ for different values of N , as N^* cannot be written in a closed form of p . For the purpose of optimization, we can assume $r = 1$.

Considering the example of $p = 9.07\%$ for Thursday lunch, we calculated $R(N)$ for different values of N and identified the value that gives the maximum $R(N)$. Figure 1 shows the different $R(N)$ values from $N = 215$ to $N = 235$. The maximum value of $R(N)$ was found at $N = 228$.

The same direct evaluation of $R(N)$ was carried out for each day of a week and for lunch and dinner. The optimal N for lunch and dinner on different days of a week were calculated, and the values are given in Table 6. The optimal booking limit for lunch ranges from 228 on Thursday to 239 on Saturday. The optimal booking limit for dinner ranges from 230 on Thursday to 234 on both Friday and Saturday.

In order to make the analysis more realistic, we also took the walk-in customers into consideration. We first calculated the sample mean of the number of walk-in customers for each day of the week and rounded them to the nearest whole number. These values were taken as the number of walk-in customers on different days of a week. Table 7 gives the number of walk-in lunch customers on different days of a week, and Table 8 gives the number of walk-in dinner customers on different days of a week. In this case, the

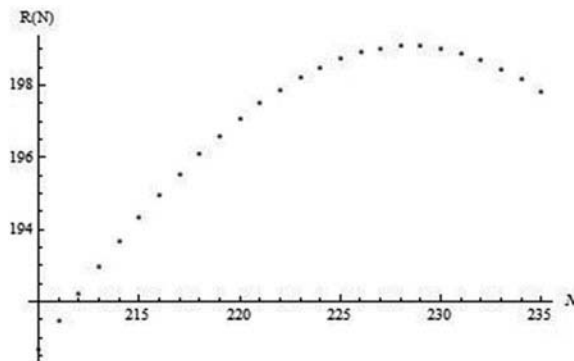


Figure 1. Different values of $R(N)$ corresponding to different values of N for Thursday lunch.

Table 6. Optimal N calculated for lunch and dinner on each day of the week.

Days of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Optimal N for lunch	231	232	232	228	232	239	232
Optimal N for dinner	232	233	233	230	234	234	233

Table 7. Number of walk-in lunch customers for each day of the week.

Days of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Sample mean	10	9	11	9	11	10	10

Table 8. Number of walk-in dinner customers for each day of the week.

Days of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Sample mean	14	14	14	15	17	16	15

number of walk-ins is quite consistent, ranging from 9 to 11 during lunch, and 14 to 17 during dinner.

To analyze whether there are significant differences in the number of walk-in customers on different days of the week, we let:

$\hat{\mu}_i$ = sample mean of the number of walk-in customers on day i of the week;
 S_i^2 = sample variance of the number of walk-in customers on day i of the week; and

n_i = sample size for the data on day i of the week.

Based on the walk-in lunch customer data, $n_i = 107$ for all i , and the calculated sample mean and variance are given in Table 9. Based on the walk-in dinner customer data, $n_i = 107$ for all i , and the sample mean and variance are given in Table 10.

The difference between the values of μ for day i and j is then significant at level α if:

$$Z_{ij} = \frac{|\hat{\mu}_i - \hat{\mu}_j|}{\sqrt{\frac{s_i^2}{n_i} + \frac{s_j^2}{n_j}}} > z_{\alpha/2},$$

where $z_{\alpha/2}$ is the standard normal value at $\alpha/2$. For $\alpha = 0.05$, $z_{\alpha/2} = 1.96$. The values of Z_{ij} for lunch and dinner walk-ins are given in Tables 11 and 12 respectively. Values of Z_{ij} corresponding to significant differences ($Z_{ij} > 1.96$) are indicated in bold. It is observed that the incidence of walk-in

Table 9. Calculated sample mean and variance of number of walk-in lunch customers for each day of the week.

Days of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Sample mean	9.82	9.26	10.68	8.92	10.79	9.50	9.73
Sample Variance	27.05	32.65	34.63	29.00	29.13	34.12	37.60

Table 10. Calculated sample mean and variance of number of walk-in dinner customers for each day of the week.

Days of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Sample mean	14.42	13.63	14.16	14.72	17.10	15.72	14.94
Sample Variance	49.83	45.33	50.02	51.98	41.39	43.49	52.66

Table 11. Z_{ij} for the comparison of the probabilities of lunch walk-ins on different days of the week.

	$j = 1$	2	3	4	5	6	7
$i = 1$	0	0.75	1.13	1.25	1.33	0.42	0.12
2	0.75	0	1.79	0.46	<i>2</i>	0.31	0.58
3	1.13	1.79	0	2.29	0.13	1.47	1.16
4	1.25	0.46	2.29	0	<i>2.54</i>	0.77	1.03
5	1.33	<i>2.00</i>	0.13	<i>2.54</i>	0	1.67	1.34
6	0.42	0.31	1.47	0.77	1.67	0	0.27
7	0.12	0.58	1.16	1.03	1.34	0.27	0

Note. 1 = Monday, 2 = Tuesday, 3 = Wednesday, 4 = Thursday, 5 = Friday, 6 = Saturday, 7 = Sunday; values of Z_{ij} corresponding to significant differences ($Z_{ij} > 1.96$) are italicized.

Table 12. Z_{ij} for the comparison of the probabilities of dinner walk-ins on different days of the week.

	$j = 1$	2	3	4	5	6	7
$i = 1$	0	0.84	0.27	0.31	2.9	1.39	0.53
2	0.84	0	0.56	1.15	<i>3.86</i>	2.3	1.38
3	0.27	0.56	0	0.57	<i>3.18</i>	1.67	0.8
4	0.31	1.15	0.57	0	<i>2.55</i>	1.06	0.23
5	2.9	<i>3.86</i>	<i>3.18</i>	<i>2.55</i>	0	1.55	2.3
6	1.39	2.3	1.67	1.06	1.55	0	0.82
7	0.53	1.38	0.23	0.23	2.3	0.82	0

Note. 1 = Monday, 2 = Tuesday, 3 = Wednesday, 4 = Thursday, 5 = Friday, 6 = Saturday, 7 = Sunday; values of Z_{ij} corresponding to significant differences ($Z_{ij} > 1.96$) are italicized.

dinner customers on Friday is higher while there is no clear pattern on the other days.

Using the modeling discussed in the previous section, we calculated the optimal value of N by substituting m with the sample mean of the number of walk-in customers. The optimal N calculated for lunch and dinner on different days of a week are given in Table 13. After adjusting for walk-ins, the optimal booking limit for lunch ranges from 221 on Thursday to 230 on Saturday, and the optimal booking limit for dinner ranges from 220 on Thursday to 224 on Saturday.

It is interesting to note that even when $N > M_2$, the probability of having more customers than the stretched capacity is very low. In fact, for the optimal N values for different days of a week, the probabilities of having $k > M_2$ are less than 1%. In other words, the restaurant manager could afford to take a higher risk of overbooking since the chance of customers turning up and exceeding the stretched capacity is very low. Obviously, the situation may change over time, and it is important to

Table 13. Optimal N calculated for lunch and dinner on each day of the week including walk-ins.

Days of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Optimal N for lunch	223	224	224	221	224	230	224
Optimal N for dinner	223	223	223	220	223	224	223

regularly review the no-show, cancellation, and walk-in situation and to revise the parameters in the modeling equation.

Discussion and conclusion

Notwithstanding the arguments for and against overbooking, this paper has analyzed the differences between the restaurant, hotel, and airline industries in how they cope with no-shows and late cancellations and developed a model for determining the optimal overbooking rate in a restaurant based on past reservation data. While the restaurant business is similar to the hotel and airline businesses in that restaurant tables, room nights, and airline seats are all perishable inventory and fixed in capacity, the industries differ in other ways and in their way of coping with no-shows and cancellations. Restaurants deal with a less well-defined capacity. They may define a desirable seating capacity, which is the officially designated seating limit, and a stretched seating capacity that the restaurant could manage and that customers would put up with. A restaurant may “squeeze in” customers between the desirable capacity and the stretched capacity at a cost. A restaurant would have to turn away customers if they continue to arrive beyond the stretched capacity and incur a penalty.

An overbooking model was developed based on the above assumptions to calculate the optimal overbooking limit which delivers the maximum revenue. The case of The Market has been used to illustrate the model and how no-shows, cancellations, and walk-ins may differ significantly between different days of a week for lunch and dinner. It is important to note that the no-show, cancellation, and walk-in patterns are specific to a particular restaurant, and therefore, it is necessary to analyze an individual restaurant's historical reservation data in order to establish the patterns and calculate the estimates. This article has illustrated the method to analyze such patterns and calculate the estimates.

The model suggests that if a restaurant needs to engage in protective overbooking, whereby reservations are taken in excess of capacity to overcome the problem of no-shows and late cancellations, it could work out the optimal overbooking limit by using its past reservation data of no-shows, late cancellations, and walk-in customers. To cope with no-shows and late cancellations, a restaurant should determine its own desirable seating capacity and stretched seating capacity based on table setting arrangements and its own standard of service. In addition, the restaurant should determine the cost incurred when customers are squeezed in above the desirable capacity but below the stretched capacity in terms of inconvenience to customers, pressure on restaurant staff, and loss of goodwill. The restaurant should also determine the penalty associated with turning away customers above the stretched capacity in terms of apology, loss of goodwill, or perhaps promising a substantial discount for disappointed

customers on their next visit. The restaurant manager should allow high cost and penalty in the modeling if he or she wants to maintain a high level of service and disappoint fewer customers. The restaurant manager could allow low cost and penalty in the modeling if he or she wants to take the risk of squeezing in and disappointing more customers in order to achieve higher revenue. The restaurant manager should also take note of how walk-in customers may fill the empty seats made available due to no-shows and late cancellations.

The overbooking model developed in this paper has several limitations. First, unlike in airlines and hotels where seats and rooms are sold in such a way that they are completely filled, a restaurant will sometimes fill a table with customers below the table capacity. Six or seven customers might be seated at an eight-seat table. Therefore, a grey area exists, and it creates uncertainty in how full a restaurant is even when the number of reservations is known. If tables can be configured to accommodate the exact number of customers, that would be very helpful. However, this may not be possible on every occasion. To ensure that the modeling is accurate, it may be necessary to record both the number of customers assigned to a table and the seating capacity of that table to ensure that the record reflects the true seating capacity of the restaurant.

Second, the current model does not take into consideration group size when considering reservations and cancellations. There may be a case for considering the probability of no-shows and cancellations in relation to group size. It is noted that some restaurants require deposits for reservations of large groups, and this industry practice suggests that restaurant managers may have some sense of the risk of cancellations by large groups and the implications of requiring a deposit. It would also be helpful to study the relationship between group size and the no-show/cancellation rate. This may help provide a more accurate estimate of the probability of no-shows and cancellations for groups of different sizes.

Third, the restaurant considered in the current study offers fixed-price buffet meals, which may not be the case in most restaurants. Further research is needed for restaurants offering an à la carte menu where bills vary for different customers. In connection with the discussion in the previous paragraph, it may also be worthwhile to study the average spending per customer for groups of different sizes.

The importance of information and communication technologies (ICT) in restaurant operations has been discussed in recent years, and Ruiz-Molina, Gil-Saura, and Berenguer-Contrí (2014) emphasized the need to explore in greater depth how ICT should be designed and implemented. It seems that restaurants could use database ICT to enhance their forecasts in overbooking, cancellations, and walk-ins and strengthen revenue management. Bujisic, Hutchinson, and Bilgihan (2014) cautioned that managers, in implementing revenue management strategies, remind them to be sensitive to the potential negative reactions

among their customers. The researchers allege that more research is needed regarding price sensitivity, and future studies should focus on the perceived fairness of revenue management principles and recommend strategies to optimize costs and prices without negatively affecting customer satisfaction. Sigala (2003) believed that creating a customer-centric ICT and organizational infrastructure in restaurants could help create an adaptable organization responsive to customer needs and patterns. Different types of restaurants might use customer databases for predicting demand so as to better personalize customer experiences. Future research should investigate how businesses in different restaurant sectors can best deploy ICT and align them with corporate strategies. Using ICT to model restaurant situations such as those investigated in this research, for example, could help managers cope with the dynamic changes in demand and customers arriving at different times and staying for different durations of time.

References

- All About Hong Kong. (2012). *The Market@ Hotel ICON*, Tsim Sha Tsui. Retrieved from <http://forum.allabouthongkong.com/index.php?/blog/6/entry-473-the-market-hotel-icon-tsim-sha-tsui/>
- Bujisic, M., Hutchinson, J., & Bilgihan, A. (2014). The application of revenue management in beverage operations. *Journal of Foodservice Business Research*, 17(4), 336–352. doi:10.1080/15378020.2014.945892
- Corney, W. J. (1984). The use of computer spreadsheets for overbooking optimization and analysis. *International Journal of Hospitality Management*, 3(4), 153–157. doi:10.1016/0278-4319(84)90016-1
- Coughlan, J. (1999). Airline overbooking in the multi-class case. *Journal of the Operational Research*, 50, 1098–1103.
- Enghagen, L. K., & Healey, E. (1996). The case against overbooking. *Journal of Hospitality and Leisure Marketing*, 4(1), 51–62.
- Gosavii, A., Bandla, N., & Das, T. K. (2002). A reinforcement learning approach to a single leg airline revenue management problem with multiple fare classes and overbooking. *IIE Transactions*, 34, 729–742. doi:10.1080/07408170208928908
- Hwang, J., & Wen, L. (2009). The effect of perceived fairness toward hotel overbooking and compensation practices on customer loyalty. *International Journal of Contemporary Hospitality Management*, 21(6), 659–675. doi:10.1108/09596110910975945
- Jones, P., & Hamilton, D. (1992). Yield management: Putting people in the big picture. *Cornell Hotel and Restaurant Administration Quarterly*, 33(1), 89–95.
- Kimes, S. (2004). Restaurant revenue management: Implementation at Chevys Arrowhead. *The Cornell Hotel and Restaurant Administration Quarterly*, 45(1), 52–67. doi:10.1177/0010880403260107
- Kimes, S., & Robson, S. (2004). The impact of restaurant table characteristics on meal duration and spending. *Cornell Hotel and Restaurant Administration Quarterly*, 45(4), 333–346. doi:10.1177/0010880404270063
- Kimes, S., & Thompson, G. (2004). Restaurant revenue management at Chevys: Determining the best table mix. *Decision Sciences*, 35(3), 371–392. doi:10.1111/deci.2004.35.issue-3

- Kimes, S., & Wirtz, J. (2002). Perceived fairness of demand-based pricing for restaurants. *The Cornell Hotel and Restaurant Administration Quarterly*, 43(1), 31–37. doi:[10.1016/S0010-8804\(02\)80006-4](https://doi.org/10.1016/S0010-8804(02)80006-4)
- Lambert, C., Lambert, J., & Cullen, T. (1989). The overbooking question: A simulation. *Cornell Hotel and Restaurant Administration Quarterly*, 30(2), 14–20. doi:[10.1177/001088048903000206](https://doi.org/10.1177/001088048903000206)
- Lefever, M. (1988). The gentle art of overbooking. *Cornell Hotel and Restaurant Administration Quarterly*, 29(3), 7–8. doi:[10.1177/001088048802900305](https://doi.org/10.1177/001088048802900305)
- Mattila, A. (1999). An examination of factors affecting service recovery in a restaurant setting. *Journal of Hospitality & Tourism Research*, 23(3), 284–298. doi:[10.1177/109634809902300304](https://doi.org/10.1177/109634809902300304)
- McGuire, K., & Kimes, S. (2006). The perceived fairness of waitlist management techniques for restaurants. *Cornell Hotel and Restaurant Administration Quarterly*, 47(2), 121–134. doi:[10.1177/0010880405284212](https://doi.org/10.1177/0010880405284212)
- Noone, B. M. and Lee, C. H. (2011). Hotel overbooking. The effect of overcompensation on customers' reactions denied service. *Journal of Hospitality & Tourism Research*, 35(3), 334–357.
- Rothstein, M. (1971). An airline overbooking model. *Transportation Science*, 5, 180–192. doi:[10.1287/trsc.5.2.180](https://doi.org/10.1287/trsc.5.2.180)
- Rothstein, M. (1974). Hotel overbooking as a Markovian sequential decision process. *Decision Sciences*, 5, 389–404. doi:[10.1111/deci.1974.5.issue-3](https://doi.org/10.1111/deci.1974.5.issue-3)
- Rothstein, M. (1985). OR forum—OR and the airline overbooking problem. *Operations Research*, 33, 237–248. doi:[10.1287/opre.33.2.237](https://doi.org/10.1287/opre.33.2.237)
- Ruiz-Molina, M., Gil-Saura, I., & Berenguer-Contrí, G. (2014). Information and communication technology as a differentiation tool in restaurants. *Journal of Foodservice Business Research*, 17(5), 410–428. doi:[10.1080/15378020.2014.967639](https://doi.org/10.1080/15378020.2014.967639)
- Sigala, M. (2003). Integrating and exploiting information and communication technologies (ICT) in restaurant operations. *Journal of Foodservice Business Research*, 6(3), 55–76. doi:[10.1300/J369v06n03_05](https://doi.org/10.1300/J369v06n03_05)
- Thompson, G. (2002). Optimizing a restaurant's seating capacity: Use dedicated or combinable tables? *Cornell Hotel and Restaurant Administration Quarterly*, 43(3), 48–57.
- Thompson, G. (2003). Optimizing restaurant-table configurations: Specifying combinable tables. *The Cornell Hotel and Restaurant Administration Quarterly*, 44(1), 53–60. doi:[10.1016/S0010-8804\(03\)90046-2](https://doi.org/10.1016/S0010-8804(03)90046-2)
- Thompson, G. (2010). Restaurant profitability management: The evolution of restaurant revenue management. *Cornell Hospitality Quarterly*, 51(3), 308–322. doi:[10.1177/1938965510368653](https://doi.org/10.1177/1938965510368653)
- Toh, R. S. (1985). An inventory depletion overbooking model for the hotel industry. *Journal of Travel Research*, 23(4), 24–30.
- Toh, R. S. (1986). Coping with no-shows, late cancellations and oversales: American hotels out-do the airlines. *International Journal of Hospitality Management*, 5(3), 121–125. doi:[10.1016/0278-4319\(86\)90004-6](https://doi.org/10.1016/0278-4319(86)90004-6)
- Toh, R. S. and DeKay, F. (2002). Hotel room-inventory management: An overbooking model. *Cornell Hotel and Restaurant Administration Quarterly*, 43(4), 79–90.
- Vidotto, A., Brown, K., & Beck, C. (2007). Managing restaurant tables using constraints. *Knowledge-Based Systems*, 20, 160–169. doi:[10.1016/j.knosys.2006.11.002](https://doi.org/10.1016/j.knosys.2006.11.002)
- Weatherford, L., & Bodily, S. (1992). A taxonomy and research overview of perishable-asset revenue management: Yield management, overbooking, and pricing. *Operations Research*, 40(5), 831–844. doi:[10.1287/opre.40.5.831](https://doi.org/10.1287/opre.40.5.831)