18
Golf Course Revenue Management

Lila Rasekh and Yihua Li

Introduction

Golf is one of the greatest sports of the world and is played in many countries. It is enthusiastically followed by millions more on television who, though they have never teed off nor sunk a putt themselves, can still appreciate the game from the comfort of their home.

Golf was established in Great Britain by the seventeenth century. In 1860 the first British Open was played. Soon after, the first golf club in North America – Canada's Royal Montreal Club – was founded in 1873. The first course in the USA was the Chicago Golf Club and this was founded near Wheaton in 1893. The leading association for current golf tournaments, the Professional Golf Association of America (PGA), was founded in 1916. Tournament golf had become a well-established sport in the USA by the 1920s and has been gaining popularity ever since. In 2006, there were 16,052 facilities in the USA with 11,680 open to the public. A facility is a complex containing at least one golf course. According to the National Golf Foundation, the number of people in the USA in 2005 who played golf 25 times or more per year was 4.6 million, with 26 million claiming that they had played golf at some time over the same period (Vitello, 2008).

Considering the large number of players and golf courses, in recent years, many golf management companies like Troon Golf – the world's leading luxury golf course management introduced a Golf Revenue Management System that allows each Troon Golf facility to more efficiently manage tee time inventory and maximize revenues (http://www.golftransactions.com).

Golf course tee-time assignment is a typical Revenue Management problem. Golf course operations are identified with perishable inventory, predictable demand, limited capacity and varying customer price sensitivity (Kimes and Schruben, 2002). The tremendous growth of the demand in the service industry in recent years has brought the term product perishability to their attentions. In the case of the golf course, an available capacity that is not sold on a specific tee-time cannot be inventoried for future sale, it merely vanishes. Coupled with the perishability problem, golf courses face capacity constraint. Perishable inventory and fixed capacity are characteristic of the available room type inventory in hotels and seat inventory in the airline industry. For example, in the hotel industry the number of available rooms for a particular service day is fixed. Similarly, for the airlines, the number of seats for a particular flight is fixed. Given a fixed capacity, we have the classic challenge of Revenue Management, which American Airlines defined as "maximize passenger revenue by selling the right seats to the right customers at the right time," and "for the right price." Therefore the challenge to golf course Revenue Management is to maximize revenue by selling the right tee-time to the right customer at the right time and for the right price within a price discrimination model.

Moreover, varying customer price sensitivity in the golf course industry enables market segmentation. The scientific foundation of pricing relies on segmenting the customers and deals by price sensitivity, and using each price segment's unique sensitivity to set prices on future deals. This in golf management can be interpreted as less price-sensitive players generally play in the early morning at a regular price. On the other hand, more price-sensitive players may wait for a later time of day or special discounts. Therefore, in this Revenue Management problem, time of day and rate category at which the reservation is made segments the potential customers.

With respect to this revenue problem, a set of tee-times are predetermined for each golf course. The maximum capacity for each tee-time is four, and the number of demand for each tee-time can be forecasted. Each demand type has potential revenue for the golf course. Demand is assumed to come from groups or individuals, the size of which ranges from one to four. The objective in solving this problem is to assign the demand to tee-times so as to maximize the total revenue.

The goal of the golf course Revenue Management system is to maximize profits by developing the best reservation policy. In this chapter, we assume such a reservation policy, for which the booking limit for a particular tee-time/discount category is periodically evaluated. Each time a new reservation occurs, the algorithm is applied once assuming the demand forecast is made ready at that moment. These booking limits can be used as the maximum number of booking requests to accept for each tee-time and rate category during the booking period. The algorithm we introduce is based on a linear deterministic model that balances the supply and demand. This linear model is repeatedly applied over time, and provides an update of booking limits as demand is being realized. This model is a typical Revenue Management method used in practice by the airlines and other industries, the essence of which is to optimally allocate rate buckets to the discount categories. Therefore, the fundamental Revenue Management decision would be to accept or reject a reservation.

An additional explanation may help to better articulate the problem. Optimization is conducted by using the forecasted demand – the demand for each tee-time interval between 7:30 am and 3:00 pm. Three rate categories are available for the tee-times, depending on the time of the day, for example, early morning tee-times are more expensive. The prices in each rate category include discount and regular prices, which are used to differentiate the demand with different profit potentials. The Revenue Management System is focused on forecasting, optimization and pricing. It ignores overbooking.

In our studies we consider several golf courses under the same management. The forecast model predicts the demand for each individual golf course. Then it is redistributed to the demand for different times of the day, different rate categories and variable party sizes. There is price discrimination among the following time windows during a day: 7:30 am–9:00 am, 9:00 am–1:00 pm and 1:00 pm–3:00 pm. Therefore, the forecasted demand is distributed to the demand for each of the three time windows. Moreover, within each time window the forecasted demand is distributed as regular and discounted categories. In the last level of the forecast the demand is distributed to party size, which ranges from one to four.

Literature review

Currently, Revenue Management is applied extensively to transportation, hotel, media, restaurant and hospital management. Generally speaking, the methodologies can be classified into two classes according to dynamic (Feng and Xiao, 2000) versus static (Bertsimas and Popescu, 2003) or single leg (Liang, 1999) versus network of two or more legs (Barnhart et al., 2002; Barnhart et al., 2009; Wang and Meng, 2008). Usually, static models treat demand deterministically and resort to a repeated application of a static capacity allocation model called "out rollout policy" (Bertsimas and Popescu, 2003). Optimal models are generally dynamic and dictate the threshold price change whenever the remaining inventory changes or a substantial amount of time elapses. An interesting paper by Gallego and van Ryzin (1997) shows that a repeated application of a simple linear programming (LP) model gives an asymptotically optimal policy on a network. Bertsimas and Popescu (2003) also discuss the performance of repeatedly using the LP model in the airlines' network seat inventory control. We follow a similar process to develop LP models for golf course Revenue Management. Particularly, for the first time, our models address the special features of this Revenue Management problem in the golf course industry.

Similar approaches to the early practices used for Revenue Management in the airline industry were also developed for hotel Revenue Management to balance the expected revenue from sold rooms and the cost of "walking away" customers who fail to honor their reservations (Bitran and Gilbert, 1996; Bitran and Mondschein, 1995). In a recent paper by (Li et al. 2010) the authors used a similar approach to address the table top reservation in a restaurant. Their innovative model enables table combinations to satisfy demand from large groups in restaurants. The management of golf course tee-time reservations through assigning a set of sequential reservations shares similarities with the problem of vehicle routing using time windows. Vehicle routing and scheduling problems with time windows are time-constrained network optimization problems in which a set of trips satisfying demand requirements are assigned to a set of vehicles. The cost of assignment is the total cost on all the routes. The objective is to minimize the assignment cost (Hadjer et al., 2006). Similarly, in the golf course assignment problem, a set of sequential reservations – each covering the entire time period of a service day – are assigned to a set of tee-times. Each golf course serves a sequence of reservations in a day. The objective is to maximize the assignment revenue. In this sense, the golf course reservation management problem shares great similarity with the vehicle routing and scheduling problem. In a general sense, the golf course reservation management falls into a large class of assignment problems, such as the assignment of jobs to machines. The assignment problem can address complex problems from the traveling salesman problem (Held and Karp, 1970) to vehicle routing problems (Li and Wang, 2005; Li et al., 2009).

The remainder of this chapter is organized as follows: the next section describes the problem formulation for the golf course assignment problem; this is followed by a section which presents the numerical results; and the final section is devoted to our concluding remarks.

Problem formulation

As demand increases, the golf course management must make decisions about how to optimally allocate their resources for future demand. The Golf Revenue Optimization (GRO) model is an assignment problem to optimally allocate the reservations for tee-times. GRO is a revenue maximization problem that takes into account the business rules and constraints defined by regular golf courses.

In this problem, a set of tee-times is deterministic at each golf course. The maximum capacity for each tee-time is four, and the number of reservations (demands) for each tee-time each day is forecastable. Each demand type has a deterministic potential with respect to the revenue of the golf course. Demand is assumed to come as groups or individuals, the size of which ranges from one to four. The objective in this problem is to assign the reservations to tee-times so to maximize the total revenue.

Here x_{ij} is defined as a binary variable where $x_{ij} = 1$ if reservation i is assigned to tee-time j; 0, otherwise. Similarly $z_j = 1$ if there is at least one reservation assigned to tee-time j; 0, otherwise. The variable z_j is defined so that the model assigns as many reservations to a tee-time as possible. For example, this strategy forces three parties of size one to reserve one tee-time instead of three different tee-times. The variables y_i^+ and y_i^- are integer variables indicating the time deviation from the customer's requested tee-time T_i. Therefore, the mathematical model for the GRO can be formulated as:

$$[\text{GRO}]\text{Maximize} \sum_{i\in I}\sum_{j\in T} r_{ij}x_{ij} - \sum_{j\in T} c_j z_j - \sum_{i\in I} p_i^+ y_i^+ - \sum_{i\in I} p_i^- y_i^-$$

subject to:

$$\sum_{j\in T} x_{ij} \le 1 \quad \forall i \in I \tag{18.1}$$

$$\sum_{i\in I} s_i x_{ij} \le 4 \quad \forall j \in T \tag{18.2}$$

$$t_j \cdot x_{ij} \ge t_{is} \quad \forall i \in I, \quad \forall j \in T \tag{18.3}$$

$$t_j \cdot x_{ij} \le t_{ie} \quad \forall i \in I, \quad \forall j \in T \tag{18.4}$$

$$z_j \ge x_{ij} \quad \forall j \in T \tag{18.5}$$

$$t_j \cdot x_{ij} + y_i^+ - y_i^- = T_i \quad \forall i \in I, \quad \forall j \in T \tag{18.6}$$

$$x_{ij}, z_j = 0, 1 \quad \forall i \in I, \forall j \in T \tag{18.7}$$

$$y_i^+, y_i^- \ge 0, \quad \text{Integer} \quad \forall i \in I, \forall j \in T \tag{18.8}$$

where

- I is the set of all reservations (parties)
- T is the set of all tee-time intervals in a day
- s_i is the size of party
- r_{ij} is a revenue associated with booking i assigned to tee-time j
- p_i^+ and p_i^- are the penalties associated with the time deviation from the customer's requested tee-time
- c_j is the cost associated with tee-time j, if there is any assignment to this tee-time
- t_j is the time at tee-time j
- party i is allowed to be assigned to a tee-time j in a time window between t_{is} and t_{ie}
- T_i is the tee-time requested by a customer
- $x_{ij} = 1$ if reservation i is assigned to tee-time j; otherwise, the value = 0
- $z_j = 1$ if at least one reservation is assigned to tee-time j; otherwise, the value = 0
- y_i^+ is time-deviation up to 1 hour after the customer's requested tee-time
- y_i^- is time-deviation up to 1 hour before the customer's requested tee-time.

In GRO, constraint (18.1) specifies that each party can be covered at most once. Constraint (18.2) refers to the capacity constraint for each tee-time. The constraints (18.3) and (18.4) specify that a reservation for a requested tee-time must occur within a specified time window. Constraint (18.5) enforces the model to have as many reservations as possible in one tee-time. Note that constraint (18.5) forces variable z_j to be one if there is an assignment to tee-time j. Constraint (18.6) minimizes the time-deviation from the customer's requested tee-time T_i by penalizing the deviation in the objective function. In our experiments, we considered 2 hours as the time window for a reservation, which is up to 1 hour before or 1 hour after the requested time. For example, if a customer asks for an 8:48 am tee-time, GRO allows the assignment of this request to occur at a tee-time between 7:48 am and 9:48 am. Meanwhile constraint (18.6) guarantees a minimum time-deviation from requested 8:48 am tee-time.

The objective function in GRO maximizes the total revenue from the assignment of parties to a tee-time, and minimizes the number of tee-times that are not at full capacity. Moreover, it minimizes the time-deviation from the customer's requested tee-time. The minimization is a secondary priority for this objective function of GRO. Therefore, the value of parameter c_j, p_i^+, and p_i^- should be very small compared to r_{ij}. This cost can be an arbitrarily small value associated with variable z_j, y_i^+, and y_i^-. In our test, the value of c_j is empirically set at \$5. Similarly, p_i^+ and p_i^- are set at \$3.

Three rate categories exist for the tee-times, depending on the time of day; for example, early morning tee-times are more expensive. The prices in each rate category include discount and regular prices, which are used to differentiate the demand with different profit potentials. Therefore, the 2 hours time window allows the GRO to move the discount category to the tee-times with a lower rate or a lower demand.

Solution approach

The GRO model is a linear model. This model can be directly solved by the branch-and-bound (B&B) algorithm. However, our empirical results show that the direct application of B&B to this problem takes about 10 hours for each run – due to the large size of the problem – using a built-in algorithm of the B&B in the SAS-OR software. To reduce the computational time, we propose a heuristic to find an initial feasible solution to the GRO. The rationale is that the computational efficiency of the B&B algorithms can be greatly improved by having a quality initial solution (Geoffrion and Marsten, 1972).

In the following algorithm, we introduce the proposed heuristic in the form of a pseudo code. Its solution is used in the B&B method as a lower bound called Algorithm one.

Algorithm one: golf tee-time assignment

Initialization

Sort reservations in a non-decreasing order of arrival for tee-time and a decreasing order of party size;

Set all $x_{ij} = 0$. ($x_{ij} = 1$ if booking i is assigned to tee time j; otherwise the value = 0).

Iterations

Step one: Find a feasible assignment, x_{ij}, with the maximum revenue; if a feasible assignment is not identified, go to *Step two*; and then go to *Step three*.

Step two: Set $x_{ij} = 1$ and go back to *Step one*.

Step three: Stop when an integer-feasible solution of the assignment is found.

Step four: Enter the solution as a low bounder to a Mixed Integer Programming (MIP) solver to obtain an optimal solution for the problem.

The resulting solution obtained from Algorithm one is used as a lower bound to GRO during the B&B process. This lower bound reduces the CPU time from hours to a few minutes.

Computational results

For the computational experiments, we implemented the GRO on SAS Enterprise Guide 4.0 software. We conducted the experiments using forecasted demand for a typical golf course with 9-minute tee-time intervals, which allows for approximately 60 different tee-times between 7:30 am and 3:00 pm. The one-day problem size for this particular golf course contains 46,500 variables and 1081 constraints. Our empirical results show that the direct application of B&B to this problem takes about 10 hours for each run (due to the large problem size) using a built-in algorithm of B&B in the SAS-OR software. For the 60-day forecast, we performed the assignments daily for 60 days in the advance base. Therefore, the 10-hour optimization is impractical for the industry.

Later, we used the heuristic explained in Algorithm one to find the initial integer-feasible solution to the GRO. This initial solution improved the performance of the algorithm and cut the CPU time to a few minutes. Table 18.1 shows that for a particular set of data, the heuristic solution assigned 69 reservations to the tee-times and generated \$15,857 of revenue. By using this lower bound in the GRO, Table 18.2 presents the optimal solution with 88 assignment and \$17,267 of revenue.

The demand data of different sized parties are established from the simulated historical data. The demand is forecast for all incremental time

Table 18.1 Heuristic solution

Total revenue	Assigned demand
$15,857	69

Table 18.2 Optimal solution

Total revenue	Assigned demand
$17,267	88

Table 18.3 Forecasted demands

Index No.	Party size	Forecasted demand	Capacity	Tee-time
1	1	1	4	7:36
2	2	2	4	7:36
3	1	1	4	7:45
4	2	2	4	7:45
5	1	1	4	7:54
6	2	2	4	7:54
7	1	1	4	8:03
8	2	2	4	8:03
9	1	1	4	8:12
10	2	2	4	8:12
11	1	1	4	8:21
12	2	2	4	8:21
13	1	1	4	8:30
14	2	2	4	8:30
15	2	3	4	8:39
16	2	3	4	8:48
....	....	....	....	....
456	4	1	4	13:54

intervals (tee-time intervals) of 9 minutes, according to the party size as shown in Table 18.3. The first row of Table 18.3 shows that the demand forecast for a party of size one at 7:36 am is one. Similarly, the forecast for a party of size two at 7:36 am is two.

Table 18.4 shows the assigned reservations for the tee-times. The capacity for each tee-time is a maximum of four reservations. Therefore, for each tee-time, we are able to take up to four reservations as is shown in Table 18.4. For example, this means that at 7:36 am, three reservations are assigned – one with ID B001D1S2 and the other two with reservation ID B003D1S2.

Table 18.4 Tee-time assignments

Tee-Time	Booking1	Booking 2	Booking 3	Booking 4
7:36	B001D1S2	B003D1S2	B003D1S2	
7:45	B002D1S2			
7:54	B004D1S2			
8:03	B017D1S2	B017D1S2	B017D1S2	
8:12	B008D1S2			
8:21				
8:30	B015D1S2			
8:39	B006D1S2	B006D12S2		
8:48	B010D1S2	B010D1S2		
8:57	B021D1S2	B021D1S2		
13:27	B085D1S4	B096D1S4		
13:36	B099D1S4			
13:45	B101D1S4			
13:54	B103D1S4			
13:27	B085D1S4	B096D1S4		
13:36	B099D1S4			
13:45	B101D1S4			
13:54	B103D1S4			

Conclusion

Golf courses sell the same tee-times to different players at different prices. The price discrimination is either due to the time of day, for example, early morning tee-times are more expensive; or it is due to discount and promotional prices. While the golf course management would like to sell the tee-time to highly profitable players as much as possible, it is necessary to allow the lower profitable players to prevent tee-times from remaining vacant. Allocating the tee-times to the right combinations of players such that the revenues are maximized is the topic of Revenue Management. The history of Revenue Management goes back to major airlines in the USA. The early effort in reservation control in the air industry is focused on overbooking. The overbooking is computed based on the forecast of bookings, passengers' cancellation, no-shows and go-shows. A similar approach to overbooking for hotel Revenue Management balances the expected loss of revenue from unsold rooms against the cost of "walking" the customer by failing to honor the reservation. Later the development of the Revenue Management system extends to four key areas including forecasting, overbooking, seat (room) inventory and pricing. In our golf Revenue Management system we ignored the overbooking and focused on forecasting, tee-time inventory and pricing. This could be interpreted as a decision on what inventory should be sold at what price.

The forecast model predicts the demand for each golf course/time of day/rate category/party size. The optimization part provides a linear model that optimally allocates booking limits to a specific golf course/time of the day/rate category/party size. These booking limits can be used as the maximum number of booking requests to accept for each tee-time and rate category during the booking period. This model is a typical Revenue Management method used in practice by the airline and other industries, the essence of which is to optimally allocate rate buckets to the discount categories. Therefore, the fundamental Revenue Management decision would be to accept or reject a reservation.

In this chapter, we studied a special Revenue Management problem in the golf course industry, as compared to the Revenue Management problems in the airline and hotel industries. A unique feature of this golf reservation problem is that the resources are provided in blocks; for example, a golf tee-time with a capacity of maximum four. This resource block can accommodate up to four reservations (if all the reservations are of size one). These unique features distinguish this problem from those in the hotel and airline industries. We propose an Mixed Integer Programming (MIP) model to solve this problem.

With respect to the methodologies adopted in this study, the linear models in the GRO can be implemented directly and solve the problem with the B&B algorithm. To overcome the complexity of the algorithm and to solve the problem more efficiently, we propose a heuristic algorithm to find a quality-feasible solution that can serve as a lower bound in the B&B algorithm. This heuristic solution substantially reduces the CPU time for solving the problem.

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