Strategies for Integrating Capacity with Demand in Service Networks

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Abstract

Service managers face the problem of simultaneously developing and implementing both capacity and demand management strategies. Often they must choose between marketing options, for shifting or increasing demand, or operations management options such as adding additional capacity via more equipment or employees. The interaction of these two functional area strategies can have surprising, unintended, and often detrimental outcomes from a profit perspective. This article looks at the outcomes of various combinations of these decisions in a service network, a service with multiple activities within one site. We develop and apply an integrative model for determining the profit-maximizing capacity management strategy for a service network. We implement the model by combining a conjoint analysis-based optimal product design model from marketing with a simulation model investigating capacity and demand management strategies from operations management. We tested the model using data from an actual service network, a ski resort. Our results indicated that queue information signage was the most effective strategy for improving profitability. We also found that a decision that management believed would increase revenues—changing the customer class mix—actually decreased profitability substantially.

Keywords: capacity; choice models; ski resorts; hospitality; integrated models

When a manager of a ski resort observes hour-long lift lines at specific chair lifts, should he or she solve the problem by replacing those chairs with new equipment having higher capacity and speed or design a lift ticket program that promotes skiing on off-peak days? Should a fitness center with insufficient exercise machine and pool capacity during 6 to 9 a.m. and 4 to 8 p.m. buy more machines and install an additional pool or sell restricted off-peak gym passes at a 25% discount? At what point is it worthwhile for theme parks to install real-time waiting line information for different rides so that customers can choose to wait for popular rides or go to less crowded areas?

These are the decisions that service managers face when addressing the problem of simultaneously developing and implementing both capacity and demand management strategies. Often they must choose both marketing options for shifting or increasing demand and operations management options such as adding additional capacity through new equipment or scheduling more employees. The interaction of these two functional area strategies can have surprising, unintended, and often detrimental outcomes from a profit perspective. This problem is particularly salient in a service network, a service with multiple activities within one site where there are many opportunities for shifting demand and capacity. Service network examples include location-based entertainment (e.g., entertainment centers, theme parks, Las Vegas casinos, and cruise ships), ski resorts, automobile repair shops, airline in-flight multimedia entertainment systems, exercise facilities, and testing facilities at hospitals and clinics. In service networks, customers usually pay a basic fee to enter the system, may visit each facility perhaps multiple times or may not visit it at all, and usually pay additional fees for certain facilities. Service networks face even more complex capacity management decisions than services with a single service offering. This complexity occurs due to intra-facility demand variation, the number of servers available at any given and physical constraints such as space limitations.

Once the customer enters a service network, the individual either chooses or is instructed (e.g., hospital testing) to participate in any number of activities within the system. Stochastic service environments have unpredictable customer arrival times and service times. In these situations, the service system relies on queuing networks to inventory demand for each of the set of m service facilities. As a result, lengthy waits can occur at each facility depending on the service rate. For example, at a ski resort, the lift technology determines its uphill service rate (e.g., traditional two-person chairs versus high-speed “quad” or four-person chair systems). Usually those lifts with high uphill service rates have shorter queue times than those with lower service rates.

Service networks have unique opportunities for matching capacity to demand because these attributes can be changed, both for the overall system and within the system at certain facilities, that is, capacity changes at one facility affect the queuing performance at all other facilities. For example, increasing the service rate of one chair lift at a ski resort will potentially affect the performance of the whole system. Assuming that management has some influence over external demand on the system through its marketing efforts, the operations area is typically responsible for reallocating demand within the system and matching supply to demand on a real-time basis. Although it is possible to effectively manage capacity through a single strategy or perspective, an optimal strategy would require an integrated set of strategies representing both demand and supply perspectives. Additionally, the overall measure of performance may be measured in terms such as peak daily waiting time for the majority of customers.

As a typical service network, ski resorts have multiple facilities—ski lifts, shops, and restaurants—and their corresponding queues. The resorts are particularly challenged by huge capital investments to adjust capacity. As resort ticket prices continue to escalate, customers have increasing expectations for their ski experience, especially as regard waiting time for ski lifts and quality of facilities. In the United States overall, skier-days (number of customers skiing or snowboarding in 1 day) have increased approximately 6% between the 1980s and the 1990s, but skier-days in the Rocky Mountain region have increased 16% over that same period (National Ski Areas Association 2001). As a typical example, Utah experienced an average of5%skier growth annually from 1979 through 2001, with a shift from a locally dominated population to an increasingly national and international ski population. Snowboarding has significantly affected ski resort demand and now accounts for almost one third of all ticket sales. McCune (1994) and NSAA (2001) indicated that the ski industry recognizes that long-term, sustainable growth is strongly tied to drawing and retaining entry level “snow-sliders” as baby boomers drop out of skiing and are replaced by young adults and kids and previously untapped markets such as older skiers. According to McCune’s research, marketing efforts toward these groups have affected the operational costs at those resorts because the ski terrain must be better maintained (snow parks, half pipes, and constantly groomed runs) for these new groups. For example, resort owners indicate that skiers over 50 years of age have more frequent visits and spend more money per visit than other groups but require more and better quality services and amenities (Parker 1998). In addition, increased pricing incentives, kids, family, and season pass purchases have caused the overall ticket yields (percentage of a full-priced weekend adult ticket) to drop 10% over the past 10 years.

Most resorts face various constraints on capacity owing to environmental regulations that limit their acreage and parking areas. These constraints include surrounding public lands, natural rugged terrain, and water for snowmaking. On the other hand, to be a contender in this market, a resort must continually improve the facility by installing chair lifts, adding trails, and keeping up with the latest snow-making technology (McCune 1994). One of the seven contenders in the Northern Utah market is a resort we shall refer to as Powder Valley (PV). PV had consistently lost market share for 5 years to its rivals. Management attributed PV’s declining ticket sales during this time period to their competitors’ facility improvements and marketing efforts. Based on our initial discussions with PV management, the marketing and operations groups were considering many different strategies for improving PV's profit performance. The marketing group proposed several solutions to either improve revenues on slow days or increase the revenue per customer. At the same time, the operations group was considering several different facility improvements. In the past, new lifts were placed in new locations, or existing lifts were replaced with higher capacity lifts where large queues occurred. Although these decisions significantly affect a resort's profit performance, planners have been slow to adapt contemporary marketing or operations research techniques for testing the implications of different proposed strategies. This reluctance stems from the lack of skilled modelers designing support systems for this industry, the challenge of data collection, and the complexity of evaluating service networks in general.

In this article, we develop and apply an integrative profit model to address this problem. We combine a conjoint analysis-based optimal product design model from marketing with a simulation model investigating capacity and demand management strategies from operations management to determine a profit-maximizing service network. The model extends optimal product design models to services by specifically modeling the interactive relationship between potential attractiveness of a service, the capacity of the service, and customer waiting times. Additionally, the model extends current capacity-demand operations models by modeling the impacts of different capacity/demand matching strategies in a competitive market. Combining these two perspectives provides a more direct link between customer perceptions of various service attributes, including waiting time and profitability.

In 1994, the U.S. Forest Service and researchers from the University of Utah undertook a large choice modeling study to evaluate what customers wanted in the region's ski resorts (Louviere and Anderson 1994). These data were available in the public domain and could be used to estimate how operational changes affect market share among the seven competitors in the market. With this information, the research team proposed a two-phase project to address an integrative profitability approach to PV's management. First, the team would build a simulation model of the existing resort and evaluate all proposed improvement strategies in terms of capacity measures. Second, the team would integrate the results of the simulation model in conjunction with the choice modeling data to determine the overall profitability of each of the proposed strategies or combination of strategies. The results of this combined effort would help identify those alternatives that provided the best profit solutions.

This article summarizes the results of the analysis carried out by the research team. The first section describes the capacity/demand strategies. The second section presents the simulation experiment, model validity, proposed changes to the system, and results of the experiment. The third section describes the choice model experiment and integration of the two experiments. The fourth section gives the resulting profit estimates and discussion of these results. The fifth section describes the team's recommendations, and the final section contains concluding remarks. The appendix presents our integrative profitability model in a mathematical form.

THE CAPACITY/DEMAND STRATEGIES

In the following section, we cover the five different strategies and their impact on service profit. We chose these specific strategies and respective levels because they are commonly considered by service network managers (and specifically by the ski resort management as feasible and potential solutions). This illustrative, but not necessarily exhaustive, list of strategies is used to determine the profit maximizing configuration.

Effects of Different Demand/Capacity Strategies on Profit

Strategy 1. Price can be varied in an attempt to level demand, such as offering lower off-peak rates. In exchange for lower prices, customers are restricted from using peak times. Service businesses using this strategy include golf courses, restaurants, and telecommunications providers. Using this strategy, one sets the price in traditionally peak periods higher than the price in traditionally nonpeak periods. By doing so, one expects a decrease in the number of customers at peak periods and an increase in the number of customers in the off-peak periods.

Strategy 2. Customer class variation strategies can promote different aspects of the service to different customer segments to shift people from over-utilized to under-utilized portions of the service. Service businesses using this strategy, sometimes in concert with Strategy 1, include airlines and hotels targeting travel time–insensitive customers. This type of strategy can impact service profits in two ways. First, increased promotion costs could affect fixed costs of the service. Second, the different customer mix potentially changes the contribution margin.

Strategy 3. Information can be provided about less crowded periods or shorter waiting times to encourage customers to move temporally. Some customer service telephone support lines implement strategies like this. Similar to Strategy 2, investments in information technology could increase fixed costs and/or variable costs. Strategy 3 could be dependent on the time period, such as hiring people to guide customers into the shorter waiting lines (often seen at toll booths and airline check-ins), or independent of time, such as investing in signage or audio technology to indicate current wait times at different locations.

Strategy 4. Capacity expansion refers to investments in additional fixed capacity to reduce waiting time. Expansions usually require capital investments such as purchasing or leasing new-terrain and adding more uphill capacity. In the profit equation, new capital investments increase fixed costs, which are usually converted to an amortized payment for the appropriate time frame.

Strategy 5. Whereas Strategy 4 covered expanding capacity from some baseline amount (i.e., additional square footage or additional seats), capacity upgrades improve the existing capacity structure. For example, the same transportation system runs more frequently, faster, or adds more seats to an existing car. This type of decision affects the fixed cost but in a less costly manner than full expansion.

INSERT FIGURE 1 HERE

Equation (A1) from the model in the appendix can be maximized through complete enumeration or heuristic search over feasible attribute combinations, where a feasible attribute combination means selecting at most one of each type of strategy (as imposed by Equation A2 in the appendix). For either solution approach, the search is conducted over all attributes except service time. Service time cannot be specified independently because it is a function of capacity, relative attractiveness of the facility, and overall demand for the service class (total demand for the competitive set). However, because service time is an increasing function of the number of customers and the number of customers is a decreasing function of service time, the unique solution can be approximated to a degree of desired accuracy through numerical search. The approach for integrating the waiting time with potential number of customers attracted to a particular attribute combination is outlined in Section 3.

THE SIMULATION MODEL

To evaluate demand and capacity management strategies in the ski resort, we developed a simulation model. In this case, we chose the simulation approach because it allows us to model the real system and track its behavior, rather than simply approximating the behavior as would be required with other methodologies. Several other researchers have developed alternative methods for evaluating the profit implications of different capacity or demand strategies. Rust, Kahorik, and Keiningham (1995) developed a generalizable model for determining return on quality investments. Similarly, Collier (1994) suggested methods for evaluating service quality improvements. More specifically, Pullman, Goodale, and Verma (2000); Pullman, Verma, and Goodale (2001); and Easton and Pullman (2001) developed and applied integrative models to evaluate service capacity in food service environments.

For the service network problem, key considerations for simulation model development and solution were threefold. First, real-world service networks, such as ski areas, consist of complex conditions. Second, we wanted to avoid making assumptions about steady system states because the customer arrival rate varies substantially throughout the day. Third, we needed to measure each individual’s peak waiting time across his or her entire service experience.

Data Collection

The data for this study were collected at PV. PV has a system of eight ski lifts where queuing occurs; movement between queues is probabilistic based on customer class, or in this case, ski terrain ability levels. At most resorts, terrain is classified as beginner, intermediate, and advanced. Figure 1 shows an illustration of the ski resort network configuration. The data collection phase involved several steps: (a) estimation of daily demand, (b) determination of feasible demand-smoothing options and capacity improvements, (c) determination of existing service time for each lift, (d) daily arrival rates λ_{mt} for customers at lift m during time period t, (e) daily network flow patterns for different customer classes, (f) time for travel between lifts as a function of customer class, and (g) data for validation of the existing configuration simulation.

To generate forecasts of daily demand, PV provided the past 10 years of historic data, which included daily customer tallies, snow depth, new snow fall, month, and day type (weekend, weekday, or non-weekend holiday). Additionally, PV management described feasible capacity improvements and available technology for these improvements. These improvements include new chair lifts with higher speeds and doubled seating capacity to replace existing chair lifts and/or expansion into new terrain with a new lift and new runs. PV management had proposed a restricted weekday ticket that they estimated would shift 10% of the weekend skiers equally among the weekdays. The managers also estimated that demand could potentially increase with technology improvements and media attention from the 2002 Winter Olympics. This could range from 5% to 20% from existing demand.

PV management had several alternatives to shift demand within the network. Using an information system, PV could post electronic displays of the estimated waiting times at various lifts. With this feature, a certain proportion of the customers would shift to a lift with lower waiting time. The chosen lift would depend on their customer class. Another option would be promotional efforts for other customer classes. At the time of data gathering, PV was dominated by customers from higher ability classes, though management had begun efforts to increase the proportion of lower ability customers (families and young people). Changes in the ability class proportions could potentially affect the demand for different terrain.

Service time data were collected by observation of all lifts. We measured the cycle time for each chair lift and interviewed the lift supervisor to determine the frequency and reasons of stoppages for the lift. The network consists of eight different chair lifts with different seating capacity, lift speed, and ride duration. All lifts suffer from occasional random stoppages, which increase proportionally with (a) increased demand on the facility and (b) number of beginners using the facility. To model the probability of a lift stopping, the current wait time at the lift is used as a proxy for demand level. The probability of a stop is assumed to be a linear function of the current wait time and percentage of beginners in the lift line.

Validation data for waiting statistics at each lift were collected by observation of an entire day for 2 sample days. An observer was stationed at a lift and recorded the number of people in line and the waiting time for the last person entering the line. The waiting time is the difference between the point when the person joins the queue and the point when the person enters or sits on the lift. These statistics were collected at each lift every 30 minutes for the entire day. The resort collects data on the total number of customers entering the system each day. The simulation results for the peak wait statistics at each lift should correspond to the actual statistics gathered for a certain number of customers entering the system.

The travel time between service facilities was collected on 10 different days during the ski season. The observers averaged 10 observations per day for a total of 100 observations. Skiers were observed on two of the eight possible lifts each day. The observer randomly selected a customer departing a lift and followed the customer until arrival at the next lift. The observer noted skier ability (beginner to advanced), run choice, weather, ski terrain conditions, and time for travel between facilities. On the days sampled, all runs and lifts were open. Additionally, a group of expert skiers provided information on the minimum times possible between facilities. To determine the probability of customers going between facilities as a function of their ability or customer class, a survey was administered to skiers during their lunch break or after skiing. The survey asked skiers to outline their previous choices of lifts and connecting runs for either the morning or the afternoon period. This information was summarized to develop an empirical frequency distribution matrix for the existing resort. For the improvement scenarios, the probability of a customer choosing an upgraded lift equals the probability of the original lift. If capacity is expanded, the probability of choosing a new lift is set equal to a comparable lift in terms of location and type of terrain, then all the probabilities are reweighed to sum to 1.

The instrument also asked skiers to estimate (a) their ski ability and (b) their arrival, departure, break, and lunch times, and to provide (c) other demographic information. This information was used in the simulation to generate normal distributions for each customer's ski time until lunch, lunch duration and location, and ski duration until departure.

Experimental Process

The experiment has six significant steps. First, set up the simulation of the resort according to the existing configuration. Second, generate the daily conditions and generate a customer demand pattern for the day. Third, run the simulation for the entire day and collect queuing statistics. Fourth, run daily simulations for 10 hypothetical years. Fifth, compare the existing configuration waiting line results with actual data. If necessary, adjust existing configuration model assumptions until model results are comparable to actual. Finally, change the experimental factor level and repeat Steps 2 through 4 for each configuration.

The network has many possible configurations of capacity and demand management alternatives shown in Table 1. The baseline configuration is the existing network and demand patterns. The combination of strategies compared in the experimental design are classified as endogenous variables, those directly influenced by management or within management's control, and exogenous variables, those indirectly influenced by management or outside of management's control. The endogenous variables include lift capacity upgrades, terrain expansion, demand smoothing via ticket pricing alternatives, and queue information efforts. Exogenous variables consist of demand growth and customer class mix variations. Capacity is increased to three possible levels using lift upgrades to newer technology and/or one additional level of terrain expansion. Information effort has three levels: the no information scenario, assuming customers ignore previous wait experience when selecting their next lift; personal wait knowledge scenario, assuming customers do not immediately repeat the previous lift if their wait was longer than their average wait; and resort queue information scenario, customers having a 50% chance of using queue information from signage and moving to the shortest lift line of the feasible lift choices. Feasible lifts are those lifts that are accessible from the current location. All of these

INSERT TABLE 1 HERE

managerial decisions occur under three levels of industry growth (none, 5%, and 20% from existing demand, assuming that each test year has the same growth), demand smoothing with two different alternatives of ticket pricing, and two levels of customer class mix (existing mix and desired mix). For a full factorial experimental design, 4 × 2 × 3 × 3 × 2 × 2 or 288 different scenarios exist.

Multiple regression analysis was used to forecast the number of customers arriving on a given day. The regression equation is based on 250 days of historic data, randomly selected from the past 10 years. Although the original demand model included the previous and current day's inches of new snow, these variables were found not to be statistically significant. Therefore, the daily demand is given by

$$\text{Skiers on Day d} = 1349.4828 + 7.0941 \quad (1)$$

* Cumulative Snow Pack on Day d + 805.7960 * [1, if day d is on a weekend; 0, otherwise] + 661.6250 * [1, if day d is a holiday; 0, otherwise] + error.

For example, a Saturday over President's weekend gets a 1 for both weekend and holiday. With an adjusted R^2 of .368, the explained variance is relatively low; thus, the standard error term in Equation 1 provides a relatively high amount of variation to the daily demand.

Figure 2 outlines the routine that determines the snow conditions and number of skiers who arrive on a given day. Starting with the third Wednesday in November, DAY 1, the program randomly generates an existing snowpack and day's weather based on a normal distribution of historic conditions for that day. The program then determines if the conditions are appropriate to open the resort, that is, snow pack must be above a predetermined minimum. If the resort cannot open, the preceding steps are continued until the snowpack builds up to an appropriate depth. The day number incrementally increases with each repetition. Snow pack increases with new snow fall and decreases 1.5% each day otherwise owing to settling. When the snowpack is adequate, the program determines if the day type is appropriate to open for the season. The opening day must be a holiday or weekend day. Additionally, this stage of the routine determines if the resort should be closed at the end of the season based on snowpack. The routine also reduces demand to 30% of the original value if too much snow falls, for example, greater than 24 inches of snowfall in 1 day. If the resort is open, the program determines how many skiers will arrive during the day and the a.m./p.m. proportions of skiers. The daily simulation is run, and queue statistics are collected for the complete day, after which the statistic counters are reset. Again, the day number, month, and day type are updated for a new day along with new weather conditions.

The arrival times for the ski resort are determined from an exponential inter-arrival Poisson process with a nonstationary mean. The arrival process has two major rises in arrival rate: the first, from 8:00 a.m. until 9:30 a.m., and the second, from 11:30 a.m. until 1:00 p.m. Three baseline daily arrival patterns were collected on 3 sampling days, 2 weekends, and 1 weekday. To determine the arrival pattern, the number of customers walking through the resort entrance was counted for 5-minute

INSERT FIGURE 2 HERE

intervals every 15 minutes, starting 15 minutes before the opening of the ticket sales window. The arrival patterns were compared to the total number of skiers for the day and day type (weekend or weekday). Based on the observed arrival patterns and discussion with managers, we generated arrival rates as follows: For a typical day, generate a normal random variate N ~ N (20, 2) for the percentage of afternoon (after 11:30 a.m.) skiers. If the day is a holiday, weekend day, spring day, or if more than a foot of new snow has fallen in the past 24 hours, the percentage of afternoon skiers is a normal N ~ N (30, 6) random variate.

As the season progresses, the program checks on the day number and snow pack conditions. If the snow pack falls below a certain minimum or the day number exceeds 155 days, the resort is closed for the season.

The daily conditions routine generated 100 hypothetical seasons of daily demand patterns. Of these 100 patterns, 10 test years were chosen to replicate the entire model. Two represent low-demand years, two represent high-demand years, and six represent average years. Each scenario is run for each day of the 10 test years or approximately 1,550 sample days.

Finally, each day arriving customers are randomly assigned an arrival time according to the arrival routine. Each day of the test year has a specific random number stream so that each capacity/demand scenario has identical arrival patterns and demand for a particular day. Departure time, lunchtime, and ski ability level k for each customer are determined using empirical frequency distributions derived from the customers' surveys.

The program simulates each hypothetical skier's activities for the day. These activities are the following for a skier:

1. The skier arrives and is assigned an ability level k, lunch time, departure time, and departure location.
2. The skier chooses a lift j with a probability p_{ijk} depending on ability level k and current location i.
3. The skier enters the lift line, and waiting line statistics begin. If there is no wait line, the skier enters the lift and is kept on the lift for the appropriate lift travel time. When the skier enters the lift, the program determines if a stoppage occurs. If so, the stoppage time is added to all the lift's loaded customers' transport time.
4. At the end of each lift, the program checks to see if the skier has passed the desired lunchtime or departure time minus 15 minutes. If this occurs, the skier goes to the lunch location or departs. Otherwise, the model finds the next lift j and the skier travels to lift j with time t_{ijk} and repeats Step 3.
5. The duration of lunch, TLUNCH, is determined from randomly sampling from a normal distribution based on empirical data. After lunch, the skier goes to Step 2.

INSERT TABLE 2 HERE

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6. At 3:45 p.m., certain lifts close. Remaining skiers randomly choose an available open lift until all lifts close. When all lifts close, they depart from their last lift choice.

When the customer arrives at a specific facility, he or she joins the line and queuing statistics are collected for him or her and the lift. When the customer departs the facility, the program determines if he or she continues in the network or leaves the network. If the customer continues in the network, the program randomly generates the next lift visited and transit time to the lift based on departure lift and customer class. The next lift decision and transit times are based on an empirical frequency distribution and an exponential distribution, respectively.

If customers are waiting when the chair arrives, they are transported for a constant time. If a breakdown occurs, this stoppage time affects those individuals on the lift and those waiting in line for the lift. Customers do not balk from the stopped lift waiting line. Otherwise, the facility is unoccupied and its next lift event is calculated and put on the event list.

The simulation is run for the whole day, and waiting statistics are collected for all customers and for each facility. The daily routine is repeated for the entire season, and the seasonal routine is repeated for 10 hypothetical seasons. The program collects statistics on the number of days falling in each demand range (c_d < 500, 500 ≤ c_d < 1,000, . . . c_d ≥ 6,500, etc.) and the corresponding peak waiting time ranges for all customers and each lift m (wait < 10 minutes, 10 minutes ≤ wait < 20 minutes, . . . , wait ≥ 50 minutes).

Simulation Validation

The nature of a ski resort makes model validation difficult. To collect a large number of full-day waiting line statistics requires an observer at each of the eight lifts for many entire days. Therefore, the validation of the model has two thrusts. First, the results of the model are compared with opinions of resort managers and a group of frequent skiers who have skied at the resort at least 50 times in the past 5 years. Second, the results of the model are compared against actual observed waiting line data collected at certain lifts during different demand days.

The frequent ski customers and PV managers provided estimates of when and how long peak waits would be for different demand levels. All the individuals agreed that Lift 2 and Lift 4 would experience the longest waits as demand increased. These waits could be as long as 45 to 60 minutes on days with demand exceeding 4,500 skiers. Predicting when peak waits occur is generally not possible, because the time depends on the snow and weather conditions during the day. After running the model for the existing configuration, the season pass customers and PV managers felt the overall model wait time results adequately represented reality.

Results

Tables 2 and 3 present waiting time results from the simulation using three sample growth levels. The analysis behind these tables does not consider competition or customer preferences, just the impact of various facility configurations and demand conditions on waiting time. This might be viewed as an analysis from the perspective of operations management only.

Under the current conditions, most of the excess wait time occurred on weekends or holidays. These delays occurred at the two lifts with easy access to predominately challenging terrain. One of the lifts is a large-capacity enclosed gondola with an 8-minute cycle time, and frequently people have to wait for two cycles before entering. The first two lift replacements access easy terrain, whereas the

INSERT TABLE 3 HERE

third lift replacement adds additional access to difficult terrain. Generally, peak wait times for the large group of expert customers is not reduced until the third lift replacement or if they learn about smaller lines from the information system.

The top left cell of Table 2 shows the proportion of customers experiencing a peak wait of 10 minutes or less under the current configuration. The proportion decreases from74% to 71% to 60% as the demand increases from 0% to 5% to 20%, respectively. These scenarios illustrate that as growth increases, many of the strategy configurations cannot maintain the existing service level. Similarly, Table 3 shows the effect of changing the customer class mix. Without any operational changes, at least 20% more customers will experience waits greater than 10 minutes. Conversely, installing two new lifts and queue information signage, the resort could maintain the high service levels (more than 90% of customers experience less than 10-minute peak waits) through 20% growth. Given historical growth rates in the area, this suggests that by just replacing one lift, the resort will not be able to cope with the demand for more than 4 years.

These analyses indicate that some combination of inter-day smoothing, replacing lifts, and adding signage is optimal if the goal is to maintain or decrease peak waiting time for the maximum number of customers. However, without considering competition, customer preferences, and costs, it is not possible to determine the profit-maximizing strategy.

CHOICE MODELING

For the study's second phase, attributes that affect customer ski resort choices were developed from focus groups of skiers in the region as part of a U.S. Forest Service study (Louviere and Anderson 1994). Consumers' resort preferences were modeled in terms of 13 attributes: snow base, new snow, physical setting, distance from home, vertical drop, types of runs, size of area, snowboards allowed/not allowed, challenge mix, facilities, ticket price, peak lift line wait, and types of lifts. The questionnaire contained 10 choice sets, as well as perceptions, preferences, past usage, and likely future usage of PV and each of its six competitive resorts. The questionnaire was sent to 1,200 regional skiers. By the cutoff date, 276 completed surveys were returned. From the choice set data, we estimated an aggregate model with LOGIT (Ben-Akiva and Lerman 1991), and the resulting utility weights are provided in Table 4. With the model results, the aggregate customers' overall systematic utility, U_j, is consistent with an additive quadratic function of the utility for price, P_j, service time T_j, and other service attributes, X_{jk} (*k* = 1, . . ., *K*):

$$U_j = \beta_p P_j + \beta_{p^2} P_j^2 + \beta_t T_j + \beta_{t^2} T_j^2 \sum_{k=1}^{K} \beta_k x_{jk}. \tag{2}$$

According to Ben-Akiva and Lerman (1991), if one assumes that the random utility error components are (a) independently distributed, (b) identically distributed, and (c) Gumbel distributed, then the probability that the aggregate group would choose service *j* out of a set of *J* competitive service establishments is

$$\pi_j = \frac{e^{U_j}}{\sum_{j=1}^{J} e^{U_k}}. \tag{3}$$

For each possible attribute combination, the minimum possible waiting time, MWAIT, is assumed and Equations 2 and 3 are used to determine the potential number of customers. The expected

INSERT TABLE 4 HERE

waiting time, EXWAIT, is estimated from a simulation or queuing model based on the number of people expected to visit, their arrival rate, and the capacity of the facility. If EXWAIT ≤ MWAIT (i.e., the expected wait time is less than or equal to the wait used to calculate the market share), this predicted market share is used in the profit objective function. Otherwise, MWAIT is incremented by a small amount and this process is repeated until reaching the equilibrium wait point, where the wait time matches facility demand and capacity.

RESULTS OF OVERALL MODEL

This section provides an example of the procedure and the results for all the different strategies. Because it was infeasible to run all possible growth levels, in cases where we needed to determine the wait time for a growth of 10% or 18%, the appropriate wait is determined from interpolation between known values.

Example of Procedure

In this section, we illustrate how the waiting time simulation results are combined with the choice model results to integrate customer preferences with management's profit objectives.

1. Table 5 provides the resort's prices and costs and assumptions for the different strategies.
2. The model uses the information in Table 4 and the actual attributes of all competitors to predict PV's existing market share.
3. The relationships between strategies and peak waiting times are determined from the simulation results with complete enumeration of the full factorial design as previously discussed. Whereas Tables 2 and 3 show the proportion of customers having 10 minutes wait or less, we have a database of peak waits for all customers used in this procedure.
4. (a) Because the model slightly over-predicted PV's current market share of 12.8%, we used the reweighting scheme proposed by Green and Krieger (1989) to model the effects of changing its facilities. (b) We assign the resort a new configuration: for example, install one new chair lift and set the minimum wait time, MWAIT, at 20 minutes. After modifying the

appropriate attributes for PV and using the utility weights from Table 4, PV's new reweighted market share is 14.13% or a 1.32% increase in market share from the original value. The 1.32% increase in market share corresponds to 39,000 skier-days in an overall regional market of 2,954,690 skier-days. Correspondingly, the 39,000 skier-days increase represents 10.3% growth to the resort itself with 378,641 existing skier-days. (c) After searching the simulation results from Step 3, the expected peak wait time for the new configuration with 10.3% growth, EXWAIT, is 33 minutes. (d) The expected wait, EXWAIT, of 33 minutes is more than MWAIT (20 minutes), the wait time used to calculate the original market share. Therefore, MWAIT is incremented by 1 minute in step (b) (which reduces the expected market share) and the subsequent steps are repeated. When MWAIT reaches 22 minutes, EXWAIT is within 1 minute of MWAIT. At this point, the MWAIT is incremented by tenths of a minute until the difference between MWAIT and EWAIT is within one decimal place (22.2 minutes). At this point, the predicted market share, 13.7%, is the equilibrium value to use in the profit objective function. The new profit for the resort is $10.67 million per year; the facility improvement increased profits by $450,000 from the exiting configuration.

INSERT TABLE 5 HERE

Model Results

Table 6 shows the impact of facilities changes on market share. The heading "No Resort Queue Information" refers to either using no prior info or personal queue knowledge as these assumptions show no significant difference in market share and profit results. Adding new terrain and/or replacing a lift has a direct impact on the attractiveness of the resort owing to the type of lift variable. Both of these changes also have an indirect impact on attractiveness as they are able to reduce waiting time. However, without signage, these changes have a limited impact. Inter-day smoothing has a desirable impact on market share and waiting time only when signage is added and when less than two lifts are replaced.

With current customer mix (first number in Table 6), market share is maximized when signage is installed and at least two lifts are replaced. Expanding into new terrain has little incremental impact on either market share or waiting times once one lift is replaced. Inter-day smoothing decreases waiting times with the current configuration but has little impact once one or more lifts have been replaced. With the desired customer mix of more beginner and intermediate skiers and less expert skiers (second number in Table 6), market share is maximized when either three lifts are replaced or two lifts are replaced and signage is added. Adding one or two lifts without any other strategy has the least impact on share.

High contribution margins (82% for average price and 74% for off-peak price) suggest that (a) profit maximizing configurations may be relatively similar to market share maximizing ones and (b) inter-day smoothing will not be profitable.

Table 7 shows profit solutions for the model found using the procedure described above. From the baseline and current customer class mix, replacing the first lift increases profits $0.45 million, whereas replacing two lifts only increases profits by $0.28 million. Replacing all three lifts marginally increases profits by $0.03 million. Information signage increases profits by an average of about $1 million. New terrain adds virtually nothing, and inter-day smoothing decreases profits about $1.8 million. With the desired customer class mix, the first replacement lift increases profits by an average of $0.3 million, and the next two replacements increase profits by $0.1 million and $.05 million, respectively. Signage increases average profits by $1.4 million, and inter-day smoothing decreases them by $1 million. This analysis shows the importance of including both marketing and operations perspectives. Inter-day smoothing looked like a potential way to decrease waiting time in the analysis of Tables 2 and 3, but it is devastating to profits.

Profits are maximized when the current customer mix is maintained and when the resort installs two new chairs and queue information signage. Although demand increases by more than 25%, the new resort configuration can still reduce service time from 20 minutes to 10 minutes. Thus, that solution is feasible and the resulting yearly profit is approximately $2.08 million above the existing configuration (e.g., $12.30 million vs. $10.22 million).

IMPLICATIONS FOR MANAGEMENT

Should PV management execute all the suggested strategies simultaneously to achieve the highest service level? The answer depends on the costs associated with each strategy level and the desired service level from the customers' perspective. Each alternative involves a considerable capital investment: $1.5 million for an upgraded lift, $2 million for expanded terrain (not including extensive environmental impact reviews), and $0.5 million for queue information signage.

INSERT TABLE 6 HERE

INSERT TABLE 7 HERE

If PV management assumes that service level improvements lead to growth and that their marketing efforts eventually change the customer class mix, the results of the simulation dictate the following sequence of improvements. First, PV management should install queue information signage. The signage is both the least expensive investment and offers the largest single improvement in service levels. For the signage to function effectively, the queue data must be updated constantly so that the information is meaningful to the customers. If 50% of the customers use the queue information to make their next lift decision, the resort's lift facilities will be used more efficiently with the indicated service levels. The 50% amount is a fairly optimistic number, and looking at the economics of installing signs and our results, we see that in most cases profits increase at least $1 million. Even if a much smaller percentage of customers act on the queue information, the investment is small relative to the yearly profit improvement. If more than 50% use the queue information, service levels will further increase without additional capital investment. Furthermore, by monitoring queue lengths, management has the ability to keep track of service levels on a continual basis.

Second, PV management should upgrade at least one lift and preferably two lifts. After the two upgrades, they should monitor their customer class mix and overall demand to see if shifts are occurring. A third lift should be upgraded after a 5% increase in demand growth.

Last, further service improvements have marginal benefits compared to the dollars invested. Management should assess the trade-off between the cost of inter-day demand smoothing and expanding into new terrain. The simulation evaluated the effects of shifting 10% of the weekend skiers to the weekdays. This strategy has a cost, and it is unclear what type of price reduction is needed to move different proportions of customers to off-peak days. Obviously, there is a limit to how many people can be shifted to weekdays. Similarly, expanding into new terrain has limited impact because all possible expansion terrain appeals to intermediate and advanced skilled skiers. If the desired customer class mix shifts to lesser skilled skiers, these skiers do not disperse to the new terrain. Because these two strategic objectives are in direct conflict with each other, the expansion strategy contributes very little to the increase in service levels while the desired customer class mix degrades service levels. Clearly, management should carefully evaluate the per capita revenue gains from the desired customer mix versus the service level declines. For example, the family skier segment increases the percentage of beginners and intermediates in the customer class mix and according to market research data spends more money on lessons and amenities than do experts. But, increasing this percentage may degrade service levels for many skiers in the system, potentially affecting long-term profits. Management will need to evaluate the potential impact of poor service levels versus the gains from increased revenues from this segment.

Management Response

These results and recommendations were presented to the management after the project's completion. The owners had spent many years trying to get U.S. Forest Service approval for expansion into new terrain and permission for new lifts. Upon receiving Forest Service approval, they proceeded with the expansion without regard to the results of this study. Over the past few years, the group added two more high-speed lifts and will install information signage this year. Many of the key management team members that participated in this project are no longer at the resort, so current marketing and revenue data are not available.

CONCLUSIONS

This article presented an integrative profit model for determining the optimal capacity management strategy for a service network. The model accounted for both (a) the operations management perspective by including capacity changes and queue management and (b) the marketing perspective by accounting for demand variability, demand smoothing, growth, and segment variation.

In this application, we found several instances where marketing objectives conflicted with operational objectives. For example, changing the customer class mix to increase revenues conflicted with operational objectives by reducing the service levels for customers in the network. Additionally, it is apparent that marketing efforts to shift customers from peak to off-peak periods may not improve the service levels compared to other operational alternatives. Similarly, there was a direct conflict between marketing's strategy for the desired customer class mix and this group's ability to use the existing and potentially expandable terrain. This finding implies that the firm must consider the trade-offs between increased revenues and the costs associated with decreased customer service levels.

We found that reallocating demand within the system using information signage was more effective and potentially more cost-efficient than any other strategy to improve service levels. Because service networks have multiple facilities, the signage system encouraged more customers to move to underutilized facilities. This research suggests that a firm, faced with the objective of maximizing the number of customers entering a system subject to limits on waiting time, should prioritize the efficient use of existing facilities before looking at capacity expansion and external demand management strategies. Disney's use of Fast Pass—a mini-reservation system at each queue—is an example of a similar approach, to achieve a similar outcome, in a different service network. Although we focused on the application of this integrated approach in a ski resort, we expect that a similar methodology could be applied in service networks other than location-based entertainment.

Our research raises several issues that could benefit from further investigation. First, the customer preference data we obtained related their choices to their perceived waiting times. When solving our integrative model, however, we used skiers' actual waiting times. We are not aware of any research addressing the gap between perceived and actual waiting times in the ski industry, but this gap has been shown to exist in other service industries. Second, when solving our integrative profitability model, we are choosing the best strategy based solely on which performed best. We did not, for example, measure the second-order effects, which would enable one to develop confidence intervals for different decisions. Such ability would be useful because it would let one know, for example, whether one's decision was robust. Third, we used various assumptions about customers shifting within the system with sign information and with restricted tickets. The suggested amounts came from the ski industry expert opinions, and both of these strategies resulted in significant impact on the system's performance. Further research should examine how different customer groups respond to waiting information and to restricted ticket incentives. It may be the case that in certain services, strong customer preferences would be of lesser value in shifting demand. Additionally, a significant weekly ticket price decrease could actually increase demand overall rather than just shift people from weekends.

Finally, we applied this model and different strategies to a ski resort. In this case, waiting sign information was the big bang for the buck solution. In ski resorts, customers gather at central information points and can easily head off in a new direction to get to lesser populated lifts. This is not necessarily the case for theme parks, where customers may formulate plans at the beginning of the day and shifting choices may require lengthy walks and backtracking. Hence, further research could examine how different industries and different customer groups would respond to different strategies with different preference levels.

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APPENDIX: INTEGRATIVE PROFITABILITY MODEL

To assess the profit of any strategy, we use a general equation for the profit of service j as illustrated below:

$$\text{Maximize } Z = \sum_{t \in T} \left(N_t \cdot \pi_{jt} \left(\sum_{h \in H} P_{jth} - \sum_{s \in S} v_s \cdot y_s \right) \right) - \sum_{s \in S} f_s \cdot y_s \tag{A1}$$

$$\sum_{h \in H} y_h \leq 1, \sum_{g \in G} y_g \leq 1, \sum_{w \in W} y_w \leq 1, \sum_{e \in E} y_e \leq 1, \sum_{r \in R} y_r \leq 1 \tag{A2}$$

$$\pi_{jt} = f(y_s, J, N_t), \tag{A3}$$

where Indices are

t = time periods

i = potential customers

j = services

h = pricing variation strategies

g = customer class variation strategies

w = waiting line information strategies

e = capacity expansion strategies

r = capacity replacement strategies

s = capacity/demand management strategies

Constants are

f_s = fixed cost of capacity/demand strategy *s*

N_t = number of potential customers in period *t*

p_{jth} = price of service *j* during time period *t*, when using price variation strategy *h*

π_{jt} = probability that a customer selects service *j* from *J* services in period *t*

v_s = per-customer variable cost of capacity/demand strategy s

Sets are

T = time periods

J = competitive set of services

H = pricing variation strategies

G = customer class variation strategies

W = waiting line information strategies

E = capacity expansion strategies

R = capacity replacement strategies

S = capacity/demand management strategies (*S* = *H* ∪ *G* ∪ *W* ∪ *E* ∪ *R*)

Variables are

$$y_s = \begin{cases} 1, \text{if capacity demand / strategy } s \text{ is applied} \\ 0, \text{otherwise} \end{cases}$$

The objective function (A1) multiplies the population by the probability that a customer uses the service and by their unit contribution, sums the result over all time periods, and then subtracts fixed service delivery costs. Equation A2 restricts the model to selecting no more than one of each type of capacity/demand management strategy. Equation A3 provides the relationship between the probability that a customer selects the service and the chosen strategies, the alternative services available to customers, and the total demand in the period.

FIGURE 1
Ski Resort Service Network Configuration

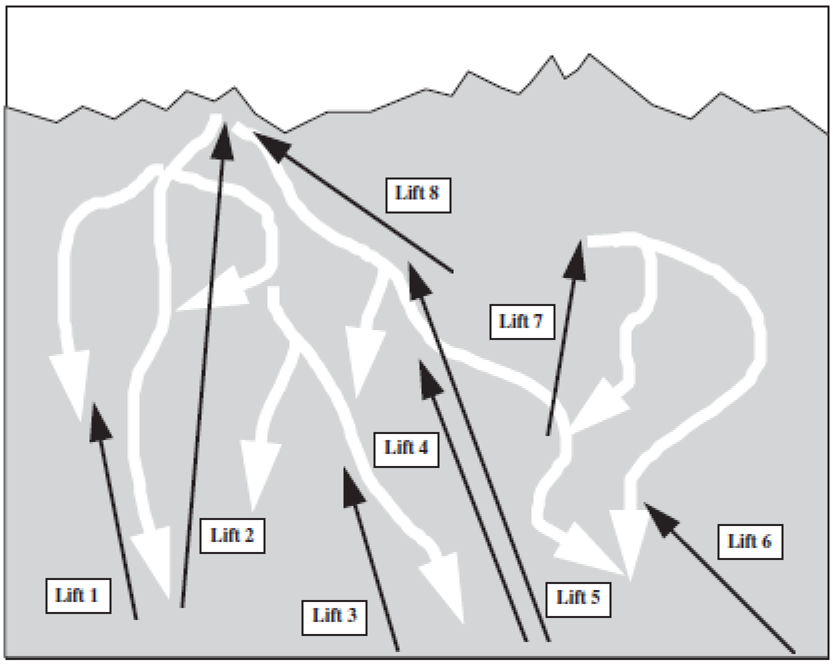

TABLE 1
Experimental Factors

Factor	*Number of Levels*	*Unit of Measure*	*Levels*
Capacity upgrades: improved lifts	4	Uphill capacity: customers/cycle	(1) No change (2) One high-speed quad (3) Two high-speed quads (4) Three high-speed quads
Capacity expansion: additional terrain	2	Uphill capacity: customers/cycle	(1) No change (2) One high-speed quad with new terrain
Information usage	3	Use of prior and current queue information	(1) Customers return to any lift (2) Customers do not return to lift if wait > average (3) 50% customers move to shorter queues
Industry growth	3	Proportion of existing daily demand	(1) No change (2) 5% growth (3) 20% growth
Inter-daily demand smoothing	2	Proportion of weekend demand moved	(1) No change (2) 10% of weekend to weekdays
Class variation	2	Proportion of customer classes	(1) Existing mix (2) Increase beginners and intermediates

FIGURE 2
Conditions Assignments Routine

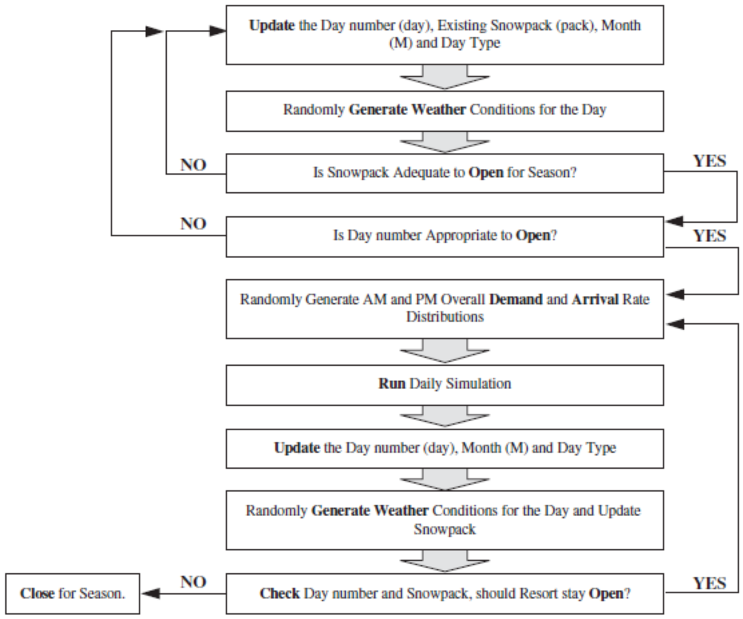

TABLE 2
Service Levels for Minimum Peak Wait With Current Customer Class Mix

		No Inter-Day Demand Smoothing			*Use of Inter-Day Demand Smoothing*		
Capacity Changes		*No Prior Queue Information*	*Personal Queue Knowledge*	*Resort Queue Information*	*No Prior Queue Information*	*Personal Queue Knowledge*	*Resort Queue Information*
No New Terrain	0 new lifts	.74, .71, .60	.77, .73, .61	.87, .84, .71	.75, .72, .60	.79, .74, .63	.90, .86, .73
	1 new lift	.72, .70, .63	.86,. 84, .76	.95, .92, .84	.73, .70, .63	.87, .85, .77	.97, .95, .87
	2 new lifts	.73, .70, .63	.89, .87, .81	.98, .97, .92	.74, .71, .64	.90, .88, .82	.99, .98, .94
	3 new lifts	.89, .86, .79	.90, .88, .83	.99, .98, .93	.90, .88, .80	.91, .89, .83	.99, .98, .95
Expand Terrain	0 new lifts	.75, .71, .61	.86, .83, .76	.92, .89, .79	.77, .73, .62	.87, .84, .77	.94, .92, .82
	1 new lift	.74, .71, .64	.87, .85, .77	.96, .94, .89	.75, .72, .64	.88, .85, .78	.97, .96, .91
	2 new lifts	.75, .73, .65	.89 , .87, .81	.98, .97, .94	.76, .74, .65	.90, .88, .81	.99, .98, .95
	3 new lifts	.90, .88, .80	.90, .88, .82	.99, .98, .95	.91, .88, .81	.91, .89, .83	.99, .99, .96

NOTE: Values are the proportion of customers who experience a peak wait time of 10 minutes or less under this scenario. Triplets represent, respectively, the results with (a) no growth, (b) 5% growth, and (c) 20% growth.

TABLE 3
Service Levels for Minimum Peak Wait With Desired Customer Class Mix

Capacity Changes		No Inter-Day Demand Smoothing			Use of Inter-Day Demand Smoothing		
		No Prior Queue Information	*Personal Queue Knowledge*	*Resort Queue Information*	*No Prior Queue Information*	*Personal Queue Knowledge*	*Resort Queue Information*
No new terrain	0 new lifts	.53, .50, .45	.67, .65, .59	.73, .69, .55	.52, .5, .45	.67, .66, .59	.76, .71, .56
	1 new lift	.46, .45, .42	.69, .67, .61	.81, .77, .67	.46, .44, .41	.69, .67, .61	.83, .79, .68
	2 new lifts	.47, .45, .42	.7, .68, .63	.87, .84, .77	.47, .45, .41	.7, .67, .62	.89, .86, .77
	3 new lifts	.67, .64, .58	.70, .68, .63	.88, .86, .78	.67, .64, .57	.7, .68, .63	.89, .87, .79
Expand terrain	0 new lifts	.53, .50, .45	.67, .65, .60	.78, .75, .65	.52, .50, .45	.67, .65, .60	.79, .76, .66
	1 new lift	.47, .46, .42	.69, .67, .61	.82, .79, .71	.47, .46, .42	.69, .67, .61	.83, .80, .71
	2 new lifts	.49, .46, .42	.69, .68, .63	.87, .85, .78	.48, .46, .42	.70, .67, .62	.89, .86, .78
	3 new lifts	.67, .65, .59	.70, .68, .63	.88, .86, .79	.68, .64, .58	.70, .68, .63	.90, .87, .80

NOTE: Values are the proportion of customers who experience a peak wait time of 10 minutes or less under this scenario. Triplets represent, respectively, the results with (a) no growth, (b) 5% growth, and (c) 20% growth.

TABLE 4
Utility Weights for Ski Resort Attributes

Variable	*Description*	*Weights*	*Variable*	*Description*	*Weights*
Intercept		.2435*	Difficulty Level 2	25% difficult runs	–.0876
Drive time	Minutes drive time to area	–.1414*	Difficulty Level 3	35% difficult runs	–.0464
(Drive Time)^2		–.0172*	Setting Level 1	Rolling terrain	.2080*
Snow Base	Depth of snow base	.0896*	Setting Level 2	Sloping terrain	–.0834
(Snow Base)^2		–.0091	Setting Level 3	Steep terrain	–.0754
Lift Line Wait	Minutes of lift line wait	–.1909*	Terrain Level 1	Groomed trails	–.0167
(Lift Line Wait)^2		–.0037	Terrain Level 2	Trails and bowls	–.0238
New Snow	Inches of new snow	.0308*	Terrain Level 3	Trails and glades	.0433
(New Snow)^2		–.0024*	Facility Level 1	Ski shop and snack bar	–.0492
Vertical Drop	Feet of vertical drop	.0086*	Facility Level 2	& restaurant/bars	.0835
Number Runs	Number of runs	.0068	Facility Level 3	& boutiques & lodging	.0784
(Number Runs)^2		.0001	Lift Types Level 1	Double chairs	.0258
Price	Dollar price of lift ticket	–.0697*	Lift Types Level 2	Mixed doubles and triples	.0279
(Price)^2		–.0004	Lift Types Level 3	Quads, doubles, & triples	.0601
Difficulty Level 1	20% difficult runs	.0463	Snowboarding	Allow = 1; disallow = 0	–.0279

$*p \leq .05$.

TABLE 5
Variable Inputs for Service Profiles

Variable	*Input*
T_1 time periods overutilized	56 days
T_2 time periods underutilized	99 days
P_1 average price	\$33
P_2 off-peak price	\$23
V_1 variable cost/customer (existing customer class mix)	\$6
V_2 variable cost/customer (varied customer class mix)	\$3
Number of people in:	
Segment 1 during T_1	492,448
Segment 2 during T_1	866,709
Segment 3 during T_1	610,636
Segment 1 during T_2	295,470
Segment 2 during T_2	433,354
Segment 3 during T_2	256,073
Cost replacement lift[a]	\$248,117
Cost expansion terrain[a]	\$310,147
Cost information signage[a]	\$62,029
Market overall demand/year	2,954,690 skier-days
Actual resort demand/year	378,641 skier-days
Busy/average day demand ratio	2:1
Other fixed costs	\$0

a. Yearly cost amortized over 15 years at 9% interest.

TABLE 6
Forecast Market Share

Capacity Changes		No Inter-Day Demand Smoothing (%)		Use of Inter-Day Demand Smoothing (%)	
		No Resort Queue Information	*Resort Queue Information*	*No Resort Queue Information*	*Resort Queue Information*
No new terrain	0 new lifts	12.80, 9.50	12.80, 11.30	12.80, 11.30	13.30, 12.30
	1 new lift	13.70, 10.10	14.30, 12.50	13.70, 11.70	14.80, 13.10
	2 new lifts	13.80, 10.10	16.10, 13.10	13.80, 11.70	16.10, 13.70
	3 new lifts	13.80, 11.70	16.10, 13.70	13.80, 11.70	16.10, 13.70
Expand terrain	0 new lifts	13.70, 10.10	13.70, 11.70	13.70, 11.70	14.30, 12.50
	1 new lift	13.70, 10.10	14.90, 12.50	13.70, 11.70	16.00, 13.10
	2 new lifts	13.80, 11.70	16.10, 13.10	13.80, 11.70	16.10, 13.70
	3 new lifts	13.80, 11.70	16.10, 13.70	13.80, 11.70	16.10, 13.70

NOTE: Doublets represent, respectively, the value for (a) the current customer class mix and (b) the desired customer class mix.

TABLE 7
Forecast Profit (in millions of dollars)

		No Inter-Day Demand Smoothing		*Use of Inter-Day Demand Smoothing*	
Capacity Changes		*No Resort Queue Information*	*Resort Queue Information*	*No Resort Queue Information*	*Resort Queue Information*
No new terrain	0 new lifts	10.22, 8.43	10.16, 9.93	8.44, 8.43	8.70, 9.08
	1 new lift	10.67, 8.69	10.34, 10.80	8.77, 8.53	9.43, 9.50
	2 new lifts	10.50, 8.44	12.30, 11.07	8.59, 8.28	10.07, 9.66
	3 new lifts	10.25, 9.66	12.06, 11.32	8.34, 8.04	9.82, 9.41
Expand terrain	0 new lifts	10.60, 8.64	10.53, 10.04	8.70, 8.47	9.05, 8.99
	1 new lift	10.34, 8.41	11.13, 10.48	8.45, 8.22	9.91, 9.19
	2 new lifts	10.18, 9.60	11.87, 10.77	8.27, 7.98	9.66, 9.34
	3 new lifts	9.93, 9.35	11.62, 10.98	8.02, 7.72	9.41, 9.09

NOTE: Doublets represent, respectively, the value for (a) the current customer class mix and (b) the desired customer class mix.