PRICING IN A CONGESTIBLE SERVICE INDUSTRY
WITH A FOCUS ON THE SKI INDUSTRY

by

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ABSTRACT

In 2003, the Centre for Operations Excellence at the University of British Columbia’s Sauder School of Business worked on a project for a company in the resort industry. The project was an initial attempt to develop and implement a pricing management practice for the ski lift ticket business of that company. Our main deliverable was the development of an Excel-based tool with a user-friendly interface that could help the company in their budgeting of the ski lift ticket business.

After completing the project, we did some further investigation relative to pricing management techniques that could be applied to this sort of business, namely a congestible service industry. In this thesis we argue that a revenue management system could bring substantial benefits if implemented in this industry. We also identify the requirements and main features of a revenue management system applied to congestible service industries.

Although revenue management is a very popular system in fields such as the airline, hotel and car rental industry, none of them can be classified as congestible industries. The ski lift ticket industry and similar industries possess one characteristic that differentiates them from the ones previously mentioned, there is no fixed capacity. This is the reason why we considered important to study the application of revenue management in congestible service industries.
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CHAPTER I INTRODUCTION

1.1 Context
This thesis attempts to identify the requirements and capabilities of a revenue management system in a congestible service industry. It is primarily focused on the ski lift ticket business of the ski resort industry, but an extension to similar congestible industries is also discussed.

Chapter I gives some important definitions, including a detailed explanation of congestible industries. The second chapter of the thesis describes a two-phase project that was the basis for this thesis. This project was done on behalf of the Centre for Operations Excellence (COE) at the University of British Columbia’s Sauder School of Business. The project was an initial attempt to develop and implement a pricing management practice for a company in the leisure industry. The data used was mainly provided by its biggest ski resort. In order to respect the confidentiality of the company, we used modified data in this thesis. Sections 2.2 and 2.3 describe the objectives of each of the two phases of the project.

Chapter III is a review of the available literature that deals with similar problems. The fourth chapter describes the challenges of applying a revenue management system in the ski lift ticket industry and in similar congestible industries. In Chapter V we define the data requirements of such a system. The sixth and last chapter has some closing comments and recommendations, and gives a brief description of areas for further investigation.

1.2 Definitions
As defined by Cross (1997), revenue management is “the art and science of predicting real-time customer demand at the micro market level and optimizing the price and availability of products” or services. Its purpose is to achieve revenue gains by uncovering hidden revenue-generating opportunities. Revenue or yield management was initially developed in the airline industry. Since the 1980’s revenue management “has
been extended to applications in the lodging, rental car, health care, and restaurant sectors” (Perdue 2002).

1.2.1 Private and public goods
One important characteristic of the industries in which revenue management has already been applied is that they have fixed capacity. Once a car rental firm has rented out all its cars for the day, further demand cannot be met. Or once a hotel has assigned all its rooms for the day, additional customers looking for a room to spend the night in will have to be turned down. A second important fact is that the goods that they offer can be defined as private goods. As defined by Karsten (1995), private goods are those which “can be easily withheld from those who are unwilling or unable to pay for them (exclusion property),” and whose consumption by one person avoids other people from simultaneously consuming the same good (rivalry property). Naturally, two distinct customers would not agree to share the same car or hotel room (rival consumption), and by setting a price on these goods, suppliers can control who will benefit from them (excludable consumption).

In contrast to private goods, public goods are those that display the following two characteristics: non-rivalry, meaning that consumption by one person does not reduce the availability for others, and non-excludability, meaning that once the good is provided it is impossible to stop people consuming it even if they have not paid. Some examples of public goods are firework displays and the protection provided by the military.

1.2.2 Club goods and congestible industries
A third category of goods is club goods. According to Barro and Romer (1991), club goods are excludable and partially non-rival. Many people can use a club good at the same time, but the quality of the benefit provided to each person decreases as the total number of people using the club good increases. This reduction in benefits is normally called congestion. Ski areas are usually classified as club goods, thus we can also say that

1 www.bized.ac.uk/virtual/economy/library/glossary/
a ski area is an example of a congestible industry. Some other examples of congestible industries are zoos, museums, and amusement parks.

Club goods are partially non-rival because as the number of users increases, the benefits enjoyed by those users decreases due to congestion. But there is no fixed capacity on the availability of this good. A ski area can sell an unlimited number of lift tickets. Congestion will worsen, queues will become longer, but the mountain (including all the facilities on it) will never reach a hard limit of capacity. The same is true for other congestible facilities. In a zoo as a whole, there is no hard limit on the number of people that can benefit from it at the same time. Some visitors could be crowding the reptile gallery, others could be just walking around the open areas of the zoo, and some other ones could be taking a break on the benches scattered around the place. As more people arrive at the facility, the quality of the benefits enjoyed by the visitors will decrease.

It is true that if we consider certain elements of the ski area individually, those elements can be classified as private goods. For example, a ski resort normally has several different runs on the mountain, serviced by a number of ski lifts. On the mountain we can also find different facilities, like restaurants, snack-shacks, washrooms, and retail shops. The ski lifts are private goods, since there are a specific number of chairs or gondolas on each ski lift and each one of those has either a fixed number of seats or a safety maximum load. At any time $t$, those ski lifts can only carry up to a maximum number of people $C_t$. The same is true for the washrooms, where there is a limited number of people that can use the facilities at the same time. But as a whole, the ski area is not a private good. The runs in the mountain get congested as more visitors join in, and queuing occurs at the ski lifts and restaurants. Something that adds to the complexity of what we just said is the fuzziness of the lift ticket usage. When a customer buys a lift ticket for the day, s/he is not forced to use it right away, nor is s/he assigned to one specific unit of capacity. A customer cannot be assigned to a fixed place on the mountain or to a specific seat on a ski lift. Moreover, a customer can use the ticket intermittently, therefore s/he would not contribute to the congestion of the area during the whole period. For example s/he could ski for a couple of hours in the morning, take a break for a while off the mountain
(decreasing the overall congestion by one unit), and then go back up the mountain to use the facilities for some more time.

In this thesis we look at how revenue management can be applied for club goods and congestible industries, such as the ski lift ticket industry, zoos, museums, and amusement parks.
The main goal of the project was to develop the foundations for a revenue management system applied to the ski lift ticket industry. We wanted to develop a systematic approach and identify the data requirements for establishing a pricing strategy.

2.1 Background of the project
The company we did the project for is one of the leading developers and operators of village-centered destination resorts across North America. Its network of resorts includes ski resorts, golf courses and beach resorts, the majority of them being ski resorts. We focused our project on the ski lift ticket business of their ski resorts. As previously mentioned, the project was divided into two phases. In the first phase of the project we did primarily data analysis. During the second phase of the project we developed a software tool, which was the main deliverable for the company. More detail on each phase can be found in sections 2.2 and 2.3.

2.2 First phase of the project
Our project was focused on the usage of the mountain slopes. Since we were not familiar with all the issues affecting the ski lift ticket business, the objective of the first phase of the project was to get a general understanding of how the ski business worked. We first found the peak days of each resort, i.e., the days with the most visitors. We also analyzed the utilization of each resort and the product mix throughout the season. Finally, we analyzed the relationship between visitation, revenue and yield, a concept that will be described in section 2.2.4.

2.2.1 Peak days
First we analyzed how many visitors the resorts had every day of the ski season. We were interested in finding on which days did customers prefer to go skiing/snowboarding. As expected, finding the ten days with the most visitors for each resort, we found that people

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2 Whenever we say “visitors” or “guests” we refer to people with access to the slopes only, i.e., skiers, snowboarders or sightseers.
prefer to go during holidays (like Christmas season, Martin Luther King weekend, Presidents Day weekend or Spring Break) or regular weekends. Virtually none of the resorts had a regular weekday (non-holiday) in their top-ten list of days with the most visitors. Additionally, we found that the difference in number of visitors between the first and the tenth day in terms of guests could be very large. On some of the resorts, the number of visitors on the tenth day of that top-ten list represented less than 70% of the number of visitors on the first day of the same list. We can safely assume that this effect can be seen not only in the resorts of the company that we analyzed, but also for every other ski resort. We just need to visit any ski resort during the Christmas season and we will see that the congestion during that period is far greater than the congestion on a non-peak day.

2.2.2 Resort utilization

Although the ski lift ticket business cannot be classified as a fixed capacity industry, we wanted to see if the different resorts were being well utilized. In order to do this, we needed a definition of capacity. We defined the maximum capacity of each resort to be the number of visitors on the day with the fifth largest amount of visitors during the 02/03 season. We chose this number for two reasons. The first one is because we considered that the first day in terms of visitors should not be considered as the maximum capacity of the resort (i.e., what the resorts should be aiming at), given that skiing can become a very unpleasant experience with too many people on the mountain. The second reason is that the first day for some resorts was often an outlier. By selecting the fifth day, we made sure that the value in consideration for every resort was not an outlier.

After finding what we considered to be the full capacity of each resort, we then calculated how many days of the ski season were between that value and 50% of it. Finally we calculated how many days fell below 50% of the full capacity. We chose that value as a benchmark to compare across the different resorts. It is not very high, so the smaller or more regional resorts should not be in disadvantage when compared against the bigger resorts and it is not very low, so it still is a good number to compare to. We noticed that few resorts are very popular throughout the whole ski season, while the rest are mainly
visited during the holidays and some selected weekends. Table 1 shows the number of days in each of the tiers previously defined for the best resort when classified according to our utilization criterion. While only some resorts are highly utilized, the majority of them have a significant amount of spare capacity.

<table>
<thead>
<tr>
<th>2002-2003 Winter Ski Season, Resort A</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visitors on 5th highest day</td>
</tr>
<tr>
<td>Days with visits between 5th highest</td>
</tr>
<tr>
<td>day and 50% of it</td>
</tr>
<tr>
<td>Days with visits below 50% of the 5th</td>
</tr>
<tr>
<td>highest day</td>
</tr>
<tr>
<td>Total number of days</td>
</tr>
<tr>
<td><strong>Percentage of days below 50%</strong></td>
</tr>
</tbody>
</table>

Table 1: Utilization of a sample resort

2.2.3 Product mix

Then we analyzed not only how many visitors the resort had every day, but also what kind of lift tickets were used to access the slopes. One may think that the number of different products, or lift tickets, available at the resorts is not very large. However, every resort has at least 200 different products. Some resorts can have up to 1,000 or even more products or SKU’s.

There are several features that define a different product. For example:

- The number of days the lift ticket is valid for:
  A one-day lift ticket can have a different price on a per day basis as a three-day lift ticket, thus forcing it to be a different product.

- The channel through which the product is sold:
  A lift ticket that one buys at the ticket window at the resort is different from a lift ticket that one buys online (through a web site).

- Whether the ticket is part of a package:
People can buy a package that includes a ski lesson, the rental of the ski equipment for a day and a one-day lift ticket. Or they can ask for a package that includes lift tickets for several days together with lodging at the resort.

- The age of the product user:
  In most cases, ski resorts establish different prices for lift tickets for adults, youths, seniors and children.

- The level of loyalty/commitment from the user to the resort:
  Usually these are products directed to customers intending to visit the resort several times during the season, both on consecutive and non-consecutive days, like Season Passes and Frequency Cards.

Naturally, this is just a sample of the different products any given resort can offer. New products are introduced all the time. It is easy to see that a resort can have more than 200 different products. For example, if a resort has lift tickets from one day up to fifteen days, and they are classified by age category (children, youth, adult and senior), and every one of them is sold through four different channels (online, grocery store, ticket window and pre-booked by phone), we would end up with 240 different products (15*4*4).

All the different products a resort has can be grouped into categories and subcategories. Figure 1 shows a simple example of this grouping with two main categories (“Lift & Lodging” and “Day”), one having four products and the other one having eight products, grouped into two sub-categories (“Window” and “Pre-booked”).

Of course, different products have different prices, thus the importance of this analysis. The mix of products on any given day can tell us something about the total revenue for that day. For example, since the products in the “Lift & Lodging” category are purchased as a package, the average price of these products should be lower than the average price for the products in the “Day” category. Let us consider a simple case in which we are comparing two days with the same number of visitors but with a different product mix, for example 70% of the visitors belonging to the “Lift & Lodging” category and 30% in the “Day” category for one of the days, and vice versa for the other day. Based on the
product mix, we could assume that the total revenue for the second day would be greater
than the total revenue for the first day. In a few words, the product mix can give us some
hints about what really matters, the total revenue.

The product mix can also help to understand what drives people to the slopes. A certain
product or category could be the one causing the peak days. We could see a higher
percentage of users of one product category during the peak days and a lower percentage
of users of the same product category during the rest of the season. Perhaps the products
in that specific category are the pre-purchased multi-day cards, sold at a lower rate, and
people tend to use those to go skiing during the peak days. Of course, this is only one
possibility. It would require further analysis and experimentation in order to confirm
whether this is causality or simple randomness.

2.2.4 Visitation, revenue and yield
The last thing we did during the first phase of the project was learn about the relationship
between visitation, revenue and yield. Yield is a number used by the resorts to measure
their performance. It is derived from the other two amounts and it is defined as the amount of money the resorts get per visitor. For some of the resorts, we had total daily visits and total daily revenue. From there we calculated daily yield. Comparing two days with more or less the same number of visitors, we find that the total revenue can be very different. The reason for this is found in the yield. One day had a slightly larger yield than the other, thus causing the total revenue to go up. What really matters about the yield is to understand why it varies from day to day. It can be because the prices are different for the same products at different times of the season and/or because the product mix is different from one day to the next one. Having too many visitors holding a cheap ticket would cause the yield, and therefore the revenue, to go down. An example of this can be seen in Figure 2.

![Figure 2: Revenue and yield for two days with the same number of visitors](image)

2.3 Second phase of the project

During the second phase of the project we developed the main deliverable for the company. The objective was to develop an Excel-based tool with a user-friendly interface that could help the resorts in their budgeting of the ski seasons. We called this the Company Budgeting Tool (CBT).

A few months before the start of the ski season, every resort prepares a budget of its lift ticket business. This means budgeting the number of visitors and the revenue generated
by those visitors for every day of the season. But usually every resort has its own way of preparing those budgets, either by using a different methodology or by presenting the information in different ways. And the visitation budgets are regularly prepared on a high level, i.e., the budget specifies how many visitors the resort will get every day of the season but only classified by main category, not by product.

The tool that we developed would standardize the budgeting process across the different resorts of the company. It would also create a budget that follows a bottom-up approach, meaning that the price and the visitation by product would be considered in calculating the revenue, as opposed to calculating the revenue based on average yields.

Additionally, based on our analyses of the first phase of the project, we considered it necessary to develop something new so that all the basic information could be gathered in the same place and so that it could also be easily analyzed. Perhaps the data was already available, but it was not very easily examined due to the fact that it was dispersed in different reports and formats. By combining all the data into one single report, we made it easier to understand what was happening every single day of the season.

2.3.1 Description of the tool
The CBT implements a standard template for generating, displaying and analyzing revenue budgets for the resorts’ lift ticket businesses. It was developed in Excel with a Visual Basic for Applications (VBA) front end, therefore it is easy to work with. Figure 3 shows a screenshot of the main menu of the CBT.

The main menu has three buttons. The last button simply hides the menu so that all the information hidden behind it can be seen (since the tool is designed in Excel, all the menus will have an Excel workbook behind them). Clicking on the second button will access the main capabilities of the tool, which will be described later on. The first button is the first one to be used at the beginning of every season. Since every year is different, the first thing that should be done with the tool is to “create” a new season, i.e., set up the start and end date of the season, as well as the number of weeks per month.
With the data provided by the user, CBT will create a standard template. The model will be set up and worksheets will be prepared for data entry. Weekly (Monday to Sunday) and monthly summaries are also set up, therefore, some standardization is required. This standardization is described in the next paragraph.

Using the menu shown in Figure 4, the user first enters the opening and closing dates of the season. If the start date entered is not a Monday, the model will use the first Monday
before that start date as the model’s start date. Similarly, if the closing date entered is not a Sunday, the model will automatically push it ahead to the following Sunday. This is done so that every week in the season has seven days (from Monday to Sunday), making it possible for the weekly and monthly summaries to work properly. The extra days added in the first and last week of the season do not affect the results of the model.

![Figure 5: Menu used to set up the number of weeks per month](image)

Figure 5 shows the menu used to enter the number of weeks for each month. Given the previously explained standardization, for the sake of reporting, every month will have anything from 0 to 35 days, in seven-day increments. This menu is important because, for example, we might want to see five weeks in December 2004, but only four weeks in December 2005. Or if the season starts in November 27, then it is possible that we only want one week for November. It would not make sense to have four or five weeks in November if only half a week will actually hold any data.

Figure 6 gives an example of when we would want four weeks in one month and when we would choose five weeks. In this example, February would have four weeks. For the sake of reporting, the last day of the month would be part of March, which in turn would have five weeks. The first three days of April would also be part of March. Of course, the user is the one who finally decides how many weeks to include in each month, according to his/her own requirements.
After this information is entered, the model starts creating all the necessary worksheets. Figure 7 shows a partial view of a typical worksheet for one month. On the left-hand side of the worksheet we have the list of products. They are organized by categories (bold and uppercase letters) and subcategories (bold and upper and lowercase letters). By pressing the buttons labeled ‘1’, ‘2’ or ‘3’ in the upper-left corner of the worksheet (the ones arranged horizontally), the user can hide the information for the products so that only the data for the subcategories and for the main categories is visible. S/he can also hide the subcategories rows so that only the data for the main categories remains visible.

Figure 7: Partial view of a typical worksheet for one month
On the upper section of the worksheet (rows 5-7) we can see that there are three basic columns for each day of the season: Visits, Price/Yield and Revenue. There is also a group of three columns showing the weekly summaries, and another group of three with the monthly summary (not shown in the figure). At the bottom of the worksheet (not shown here), we have a “Total” row. This row holds the total number of visitors, total yield (revenue divided by visits) and total revenue for each day, week and month of the season. Similarly to what can be done with the list of products, by pressing the other group of buttons labeled ‘1’, ‘2’ and ‘3’, the user can hide the daily data and/or the weekly data.

The column labeled Price/Yield will show the Prices for the products only, and the Yield for the subcategories and main categories. We should keep in mind that only individual products at the day level can have prices. Whenever we talk about a subcategory, a main category or the total for one day, then we are referring to yield. The same happens when we refer to a product across several days, we would be talking about the product’s yield. Of all the information displayed here, the user only controls the prices and visits at the product-day level. Everything else (yields, total daily visitation for a subcategory, total weekly revenue for a product, etc.) is calculated automatically using formulas previously set in the worksheet. This is done so that the budget is built using a bottom-up approach and at the same time it will be consistent with the available data, i.e., the current prices of each product.

In order to protect the integrity of the monthly worksheets and to simplify the task, the user has to enter the prices and the visits at the product-day level using two different worksheets: one worksheet is used for the prices and the other one for the visits.

Figure 8 shows a partial view of the worksheet used to enter the prices for the whole season. We can see that we do not have the weekly and monthly summaries in this worksheet. And we only have one column for each day, instead of the three basic columns in the monthly worksheets. Values can be entered into one cell and then they can be dragged away from the cell, either vertically or horizontally. This is useful when we
want to enter the same price for one product on several days or for one day on several products. The traditional copy-paste methods can also be used.

After all the prices have been entered, an automated function of the model will copy each value into its corresponding place in the monthly worksheets. Entering the visits is done in the same way using a similar worksheet. Forecasting of the visits at the product or SKU level was not within the scope of this project, therefore at this stage we only used historical visitation data in order to fill up this “Visits” worksheet.

The CBT also includes four useful graphs. Three of them are the totals per day: total daily visits, total daily revenue and total daily yield. Figure 9 shows the ‘Total Visits by Day’ graph. The other two have the same format and capabilities. These three graphs are dynamic charts, i.e., the user can control the information displayed on them with the help of one menu and one cell. Immediately above the graph we find a pull-down menu next to the label “Starting date”. By selecting another value from the menu, the graph will be shifted accordingly. We can also type any number in the cell next to the label “Number of days to graph” and the graph will automatically show the corresponding number of days.

Figure 8: Worksheet used to enter the prices of the products
The fourth graph, shown in Figure 10, plots yield versus visits. The axes cross at the average yield and the average visits over the whole season, and each point represents one day. Using the same mechanism described above (pull-down menu and one cell, not shown here), it is possible to specify which days to plot.

The CBT is also equipped with a tool for comparing the visit mix across up to five days. Using the menu shown in Figure 11, the user can select up to five days of the season and...
the data for those days will be displayed on a new worksheet. In addition to the three basic columns displayed for each day, a fourth column for each day will show the visit mix in percentage terms. The advantage of this feature is that the product mix of the days can be compared side-by-side, for example, we can have the information for December 12th next to the information for February 23rd. Otherwise we would have to switch from one worksheet to the next one and back.

![Select Days](image)

Figure 11: Menu used to select the days for which the visit mix will be analyzed

The last important feature of the model is the “what-if” analysis. The original budget can be compared to a new scenario. The possibilities include increasing and/or decreasing prices and/or visits on selected days of the season. This increments and decrements can be in terms of amounts (adding $5, for example) or in terms of percentage (a decrease of 10%, for example). The user can select a date range in which the changes will be applied as well as the days of the week. The last possibility within the “what-if” analysis is the option of blocking products. This will bring the visits down to zero to whichever products were selected on the specified days.

It is important to say that, until some knowledge about price elasticities and consumer behavior is acquired, these changes have to be done under the appropriate assumptions.
For example, we could choose to increase the prices of certain products by $10, under the assumption that the demand for those products will not change. In spite of the fact that at this stage we rely solely on assumptions, this “what-if” tool is very useful. We can safely assume, for example, that a $1 increase in price in some products will not affect their demand in any way.

2.3.2 Benefits and results from using the tool
The tool that we developed was to be tested by one of the resorts during the 03/04 ski season, therefore at this point of time we do not have the final results. However, we came up with some preliminary results.

One of the ski resorts provided us with their lift ticket budget for the 03/04 season. This budget consisted of revenue and visitation figures on a daily and categorical level, i.e., we knew how many customers were budgeted to visit the resort every day of the season for every one of the main product categories, and how much revenue would those visitors generate. In addition to that we were provided with historical visitation data on a product and day level for the 02/03 ski season, i.e., we knew the specific product that was used by every customer every day of the season. Finally, we were also provided with all the prices for all the products for the 03/04 season.

With all this data in our hands and given that the company’s budgeting is traditionally done on a high level (by main product category, as previously mentioned), our objective now was to compare the original revenue budget with a revenue budget created using CBT. This new budget would follow a bottom-up approach. It would take into consideration the price and visitation budget for every single product for every day of the season. In order to do this, we ignored the revenue budget provided by the resort and we then used the historical data to break up the resort’s visitation budget by product type for each day of the season. For example, let us say that one of the main product categories is the window one-day category and that this category is comprised of only three different products, corresponding to the age break, Adult, Youth and Senior. If on Tuesday, January 14th, 2003 we had that 60% of the visitors in the window one-day category were
Adults, 25% Youths and 15% Seniors, we would use those percentages to break up the resort’s visitation budget of the window one-day category for the corresponding day of the 03/04 season, Tuesday, January 13th, 2004.

We then had a visitation budget on a product level. We did this for every day of the season and for every category and we entered the resulting broken-up visitation budget into CBT. We also fed the 03/04 prices into the tool. After doing this, we were able to calculate the revenue resulting from this bottom-up budgeting process and compare it with the resort-provided revenue budget. Figure 12 shows a graph comparing both revenue budgets for one of the main product categories.

![Weekly Revenue, Offsite tickets](image)

**Figure 12:** Comparison of revenue budgets for one main product category

The products in this category (Offsite) are available to local residents only and they are sold through convenience stores. There are only three products in this category, one for adults, one for youths and one for seniors. These products are valid for one day only. Each product has two price points, one is valid from the day the resort opens until March 21st (we will call this period “winter”), and the other price level, a lower price, is valid from March 22nd until the resort closes (we will call this period “late”). A ticket bought at the higher price level can also be used after March 21st. For example, if we buy five one-day adult tickets in February but we only get to use three of them by March 21st, we...
would still be able to use the other two tickets after that date, although from a price point of view, we would be paying more than it was necessary to ski after said date. By analyzing the graph we can see that the revenue budget created by CBT is consistently higher than the resort’s budget until March 21st, then it is lower for the next four points, and finally, although not clearly appreciated in the graph, it is again higher for the last three points. Figure 13 could help to appreciate the effect. This figure is a graph that compares the weekly yields for the same product category. The yields were calculated dividing the corresponding revenue budget by the total number of visitors of the category.

Figure 13: Comparison of weekly yields for one main product category

A possible explanation of this difference would be that the revenue budget provided by the resort assumes a higher percentage of low yielding products (Youth and Senior tickets) from the start of the season until March 21st than what the historical data indicated us. After that date, the resort’s budget is higher for the next four weeks. Since “winter” products can be used during the “late” period, the resort could have assumed that the percentage of “winter” ticket holders using those products after the “late” tickets went on sale was larger than what historical data suggested. According to the data that we analyzed, immediately after the “late” tickets were available, a large percentage of the customers in that category were using the “late” tickets instead of the “winter” products, thus lowering the revenue and yield. However, towards the end of the season we could see an increase in the revenue and yield. Again, historical data suggested us that it was at
this time when the percentage of users of “winter” tickets was again larger than the percentage of users of “late” tickets. Perhaps it was then when “winter” ticket holders suddenly realized that they should use their tickets before the season ended.

Although our revenue budget was based on breaking up the resort’s visitation budget by using the same percentages of each product’s utilization as the season before, we believe that, if the visitation budget holds, historical visitation data may provide a better estimate of the future revenue than the approximation provided by the resort, which we think was mainly based on uniform price increments.

In addition to this, there are some benefits that stand out right away by looking at the features of the tool. The first benefit is the fact that all the important information about the lift ticket business is found in one single spreadsheet. Visitation, yield and revenue summaries are provided. These are available by day, by week, by month, by category and by subcategory. The flexibility of displaying partial information or everything at once is also important. This is done using the buttons labeled ‘1’, ‘2’ and ‘3’ found at the top-left corner of each monthly worksheet. Sometimes we do not need to know how many Senior-window-one-day tickets were sold, but only the total number of Window-one-day tickets.

Representing the information graphically usually makes it easier to understand rather than looking at the data itself. The four graphs included in the tool provide good summaries of the whole season in terms of visitation, yield and revenue. But it could happen that we are not interested in seeing the first and last days of the season in the graph, or displaying the whole season could make the graph considerably small so that is unintelligible. The dynamic charts allow us to select the exact days to graph, so we can focus on what we are really interested in. Using these dynamic graphs, we could analyze the whole season in blocks of one or two months, for example.

Knowing how many days of the season have visits and yield below average is also interesting. Those days could be the ones worth focusing on in order to improve the
overall season result. The days with high yield but low visits are also important. We could then try to increase the number of visitors, by means of marketing campaigns or some kind of promotions, while keeping the same yield. We can find where every day of the season stands relative to the average visits and yield by analyzing the “Location of daily yield and visits” graph.

It is also helpful to do comparisons across days in order to find out why some of them have such a high yield, while in others the yield is well below average. We can do this using the same graph and the “Side-by-side visit mix” tool. We locate the days that we want to compare by means of the “Location of daily yield and visits” graph and we then enter those dates in the menu shown in Figure 10. The visits, revenue, yield and product mix will then be displayed. Again, marketing campaigns or promotions could then be used to try to change the visit mix on the day with the low yield.

Finally, when building the budget, we may want to know what the increase in season revenue would be if we modify certain prices, under the proper assumptions. Or we may want to consider a worst-case scenario in case the weather is not favorable and visitation is not as high as we thought it would be. Or we may notice when we are in the middle of the season that the revenue is below the original budget. We may want to try to hit the original revenue by modifying certain prices and/or projections of visits on certain days. All this scenarios and many more can be created using the “what-if” feature of the tool. The new scenarios can then be compared to the original one so we can decide which the best way to go is.

2.3.3 Shortcomings of the tool
The main limitation of the tool is the “lack of knowledge” about customer buying behavior in response to price changes, or price elasticities of demand For example, if we were to increase the price of the adult-window-one-day-ticket, would the demand for that product stay the same? Would it go down? Could the demand for other similar products, such as adult-online-one-day tickets, be affected in any way? This is a limitation for the “what-if” feature of the tool if we want to apply certain changes that are beyond what we
can safely assume. In the absence of this information, the current tool is incapable of functioning as a basic revenue management system. In the fifth chapter we discuss ways in which this limitation can be overcome.
CHAPTER III LITERATURE REVIEW

3.1 Revenue management

Many academic papers have focused on the subject of revenue management. Geraghty and Johnson (1997) describe how a comprehensive revenue management program was able to save National Car Rental from liquidation. In fact, the initial implementation of revenue management in July 1993 dramatically increased National’s revenue and returned it to profitability. In July 1994, a state-of-the-art revenue management system was implemented by National, improving the revenues by $56 million in the first year.

Cross (1997) describes the case of American Airlines. Facing the threat of competition from low-cost airlines, American had to find a way to compete against them. The low-cost airlines charged fares that were considerably lower than theirs, and, at first sight, high-cost American could not produce seats as cheaply as the low-cost airlines did. But after a late brainstorming session, the strategy staff figured out that American was already producing seats cheaper than the charter operators. All the empty seats on any flight were being produced at a cost of close to zero. They just needed to find a way to sell those empty seats at the prices the charter operators did. That is when they started developing their revenue management system. By means of forecasting and optimization techniques, American was able to accurately estimate demand at different fares, save seats for late-booking high-fare passengers, and allocate the leftover seats to numerous fares. Around 1985 American and Delta, the airlines that were the most advanced in their implementation of revenue management tactics, collectively saw a traffic gain of 15% and a revenue increase of 9%, while the revenues for United and TWA, airlines that had made little progress with revenue management, increased only 2%, despite a traffic gain of 18%.

3.2 Ski Industry Studies

It appears that no studies have been conducted on revenue management applied to the ski lift ticket industry or in other congestible industries. However, a few related studies exist.
Lazarus (2000) describes the case of Grouse Mountain, a resort located in North Vancouver, B.C. The paper describes how Grouse, in an attempt to offer customers more flexibility, developed the Club Grouse Card, the first discount card of its kind. Shortly after, a competing resort introduced a similar concept, and did it better. Grouse, not being able to compete, dropped the idea. In order to differentiate itself from the competition, Grouse decided to drop its complicated pricing structure and go to the market with just one rate each on weekdays and one weekends. The final result was good, but this change in pricing cannot be considered as an application of a revenue management system.

Perdue (2002) discusses yield management in the ski resort industry. He mentions the case of the Vail Resort, Inc. properties at Keystone Resort and the Great Divide Lodge, where switching to a yield management system resulted in more than $1 million in incremental revenue. However, yield management was not applied to the ski lift ticket business, but to the lodging business. He then describes how three resort corporations in Colorado initiated a deeply discounted season pass program, offering 75% discounts from the previous year’s prices. Basically, one resort started offering a family pass for $800 (a family being two adults and two children, residents of Colorado), while the price of an individual season pass during the previous year was $800. The two other resorts immediately matched the program, and then they extended it to four (friends or buddies) residents of Colorado. In the end, the resorts kept reducing the eligibility fences by including nonresidents of Colorado, extending the purchase deadline and recruiting “buddy groups” composed of people unknown to each other. Although this was a form of revenue management, it lacked two important functions fundamental of a revenue management system (Cross 1997): forecasting and optimization. Additionally, the program that was implemented affected only one small part of the whole lift ticket industry, the season passes. Nothing is said about the window tickets, group lift tickets or any other similar products.

Barro and Romer (1987) examine the optimal price of a ski lift ticket. They do a comparison between ride tickets and lift tickets, i.e., charging on a per ride basis vs. charging on a lift ticket basis, equivalent to an entry fee. “Instead of charging for each
ride, a comparable equilibrium can be attained by charging a single price for access to the ski lift and using a quantity constraint to limit an individual's number of rides” (Cowen and Glazer 1991). However, the goods Barro and Romer dealt with were conventional private goods, not club goods. They dealt solely with the rides up a chair lift, not with the ski area as a whole.

Finally, Scotchmer (1985) presents a model in which shared or congestible facilities may charge a membership fee additional to the regular visit fee. This occurs for example in golf courses or other private athletic facilities, which have strong local monopolies. “While these clubs are numerous in the economy as a whole, there are very few that service any viable local clientele. However, in the case of ski slopes there is almost never a membership fee.” They tend to charge on a per visit basis.\(^3\) While in the economy as a whole there are less ski resorts than golf clubs or athletic facilities, they are usually concentrated in very few mountainous areas.

In the next chapter we describe the main characteristics of a revenue management system, the expected results from applying such a system, and some potential conflicts that could arise when implementing it.

3 We do not consider season passes as being a membership fee, since having a season pass is not a requirement for visiting the ski area. Lift tickets can be bought by anyone who can afford it.
4.1 Why should we apply Revenue Management?

First of all, we need to justify the application of revenue management techniques in the ski lift ticket industry and similar congestible industries. As described in the previous chapter, many industries have successfully applied revenue management in their own fields, generating substantial revenue gains. But all those industries dealt with conventional private goods. What we are proposing in this thesis is the application of revenue management in congestible facilities, those that deal with club goods.

Wirtz et al (2003) give a list of the characteristics of organizations suited to revenue management. They consider that revenue management is particularly suited to industries with:

1. finite capacity (once a hotel has assigned all of its rooms for any night, further demand cannot be met),
2. perishable inventory (revenue from empty seats on any flight is lost forever),
3. micro-segmented markets (airlines are able to discriminate between time-sensitive business travelers and price-sensitive leisure travelers),
4. cyclical or fluctuating demand (movie theaters have lower demand during weekdays and demand peaks on weekends),
5. services that can be sold in advance (rental car companies have reservation systems that lets them sell their capacity in advance), and
6. low variable to fixed costs ratios (the cost of transporting one additional passenger on an airplane is negligible when compared to the fixed costs for operating that flight).

It is easy to see how (2), (3), (4), (5) and (6) are also characteristics of congestible industries. Ski resorts, museums, zoos, and amusement parks can easily adopt reservation systems so that customers can call in advance in order to book a ticket. This is already a common practice for many ski resorts. They have call centers where customers can call to reserve lift & lodging packages, ski lessons, or simply lift tickets. Also, the cost of
serving one additional customer on the ski runs is simply insignificant. However, in regard to (1), a more detailed explanation is needed.

In spite of congestible industries not having the first characteristic of the list previously presented, we still believe that revenue management is an appropriate system to apply in these industries. As congestion increases, the quality of the benefits enjoyed by the customers diminishes. This increased congestion can have detrimental effects in the future, be it short or long-term. It could happen that people start to notice that during the holidays it becomes significantly unpleasant to ski at a particular resort, due to the excessive amount of people on it. Thus, in future years, demand for that particular resort could start to decrease. The other possibility is that, because of the excessive congestion on the mountain, visitors tend to consume less of the secondary products available at the mountain, like food, beverages, clothing and accessories sold at the facilities on the mountain. We will give two examples showing why we think this might happen. First, if somebody wants to buy something at one of the clothing or accessories stores but that person sees that the facility is very crowded, s/he might then choose not to buy anything or to buy it at another place. Second, the same thing can happen with the restaurants, customers just turn around if they see that there are no tables available. We can even find customers that, since they already know how congested the facilities can be, carry some snacks in their backpacks in order to avoid having lunch at a restaurant. Therefore we consider appropriate to set a “flexible” capacity limit so that the facility does not face excessive congestion. Revenue management will then prove to be an appropriate system to apply. Section 4.4.1 will deal in greater detail with this issue of a “flexible” capacity limit.

In addition to the list of characteristics already presented, Marmorstein et al (2003) list some factors that identify when a firm can greatly benefit from implementing a revenue management system. We have found that some of these factors apply to congestible industries. Two of them are explained in the following paragraph.
The extent of excess capacity can determine how suited a particular industry is for adopting revenue management tactics. We already said in the second chapter that many of the ski resorts that we analyzed seem to be underutilized during most of the season (see Table 1). We can safely assume that this is the case of many other ski resorts and some other congestible industries. Revenue management could help to increase usage on periods of low demand. Additionally, as we said some lines above, revenue from secondary products (food, clothing, souvenirs, etc.) could benefit from the new consumers visiting the area on these low-demand periods.

The authors also mention some factors that are particularly enhanced by the Internet. Some industries realize very suddenly the amount of excess capacity that they will face during the next few days. For example, a ski resort could be seriously affected by changes in the weather or even by weather forecasts. If the local market sees that the weather during the day will not be favorable for skiing, a lot of customers could change their mind about visiting the resort. In the pre-Internet era, it was very difficult to convince those customers to visit the resort, in spite of the bad weather. However, with the help of Internet and fast e-mail communications, selected customers could be quickly advised when special offers become available.

Another factor that has become particularly enhanced by the Internet is the ability to customize information for the consumers. One important feature of revenue management is the need to customize products or services for specific individuals or market segments. This often proves to be very difficult, so marketers typically had a propensity to discount deeply those products or services. Instead of discounting the goods so heavily, the original prices could be less affected if special offers were to be sent via e-mail together with information related to the product or service being offered. In the case of a ski resort, a weather forecast (favorable to skiing, obviously) could accompany the special offer being promoted.

For the reasons previously presented, we consider it advisable to adopt a revenue management system in the ski lift ticket industry and in similar congestible industries.
4.2 The building blocks of a revenue management system

As we already said at the beginning of this thesis, the primary goal of revenue management is to increase overall revenue by predicting consumer demand at the micro-market level and finding the optimal price for each product or service offered. There are several fundamental features of a revenue management system. The two elements that we consider to be the most important ones are: forecasting and optimization. As Cross (1997) said, “forecasting and optimization are the functions of a revenue management system that set it apart from any other corporate computer applications. The real value of the data is in using it to predict customer behavior and deciding what actions to take to maximize revenue.”

In the case of the ski lift ticket industry and other similar congestible industries, we would try to achieve those revenue gains on, simply put, two different scenarios. One is when we face a lot of congestion and the other one is when demand is weak. There is a difference in what we should do in order to increase overall revenue on each of these opposite scenarios. On the typically congested days we should try to increase the yield (revenue/customer). On days with low demand we should try to increase the number of visitors. In general, we need to charge more in periods of high demand and lower the prices when demand is weak, assuming inelastic demand on the congested days and elastic demand on the weak periods. Optimization and forecasting come into play at this point, when we need to determine how much to charge in each period in order to maximize revenues, by either increasing yields or by attracting more customers.

The primary goal of forecasting in revenue management is to predict consumer demand in response to changes in the market place. By analyzing past transactions, we may be able to understand what are the key elements that affect customer behavior. According to Cross (1997) ideally we should establish a forecasting model that uses 100% of the past transactions for at least the last twelve months. Additionally, seasonality and historical trends should be incorporated into the forecast to account for cyclical patterns. Finally, the forecasts should be adjusted to account for any actions done by the company that
could have affected the historical booking patterns. For example, if a special ‘2x1’ offer was being advertised this could have affected the number of bookings.

Optimization is the tool that tells us what to do in response to customers actions in order to maximize our overall revenue. Facing a given scenario, we could react in several different ways. This optimization can be done by means of mathematical equations that, by changing the values of the decision variables (variables whose value we can control), minimize or maximize specific functions, given some constraints.

In the following three sections we describe how forecasting and optimization could be used in three different pricing strategies.

4.3 Traditional pricing
Based on our observations, this is the pricing strategy used by most ski resorts for setting the prices of the different lift tickets offered.

4.3.1 Optimization model
Let us consider the following mathematical model:

\[
\text{max } Z = \sum_{i \in I} \sum_{t \in T} d_{i,t} p_{i,t} + \sum_{x \in X} \sum_{j \in J} b_{x,j} r_{x,j} - \sum_{t \in T} C_t \left( \sum_{i \in I} d_{i,t} + \sum_{j \in J} u_{j,t} \right)
\]  

(Eq.1)

subject to

\[
LB_{i,t} \leq p_{i,t} \leq UB_{i,t}
\]

\[
LB_{x,j} \leq r_{x,j} \leq UB_{x,j}
\]

\[
d_{i,t} \geq 0 \quad \forall i, t
\]

\[
b_{x,j} \geq 0 \quad \forall x, j
\]

\[
C_t \geq 0 \quad \forall t
\]

\[
u_{j,t} \geq 0 \quad \forall j, t
\]
where,

decision variables:

\[ p_{i,t} = \text{price of product } i \text{ for use in period } t \]
\[ r_{x,j} = \text{price of product } j \text{ when sold in period } x \]

parameters (which are functions of the decision variables):

\[ d_{i,t} = \text{forecasted demand for product } i \text{ for use in period } t \]
\[ b_{x,j} = \text{forecasted demand for product } j \text{ sold in period } x \]
\[ C_t = \text{congestion costs for period } t \]
\[ u_{j,t} = \text{forecasted usage of product } j \text{ in period } t \]

Regarding the constraints presented above, the first two indicate that the prices of every product should be bounded by a corresponding minimum (LB) and maximum price (UB). These values are specific to every product and depend perhaps on its price for the previous season and some economic indicators, like inflation. In order to maintain the company’s image, a ski resort would probably not want to either increase or decrease excessively its prices.

Another constraint that we consider appropriate to incorporate is what we call the “commitment hierarchy” constraint. This deals with the relationship between the prices of different products offered. These relationships should establish that, for example, the price of a multi day lift ticket on a per day basis should be equal to or lower than the price of single day tickets for use on the same dates. Or prices for the tickets sold to groups should also be lower than prices for tickets sold to individuals, if sold for use on the same date. Basically it is a way of offering a better deal to those customers who commit more. Each company would need to determine what this “commitment hierarchy” should look like.

What we are trying to maximize is the total revenue for the season due to lift ticket sales. This is given by the sales of every product for each day of the season multiplied by the
corresponding prices. The demand of every product is a function of the corresponding prices, given by the price elasticities. From this we need to subtract the congestion costs. As more people are using the facility at the same time, the quality of the benefits enjoyed by the customers decreases. This reduction in benefits could cause a deterioration of the image of that particular company, effect that could reduce the future revenues of the ski area. Or, as explained in section 4.1, the excessive congestion reduces the total revenue resulting from sales of secondary products. Therefore we believe that the ski resort is the one bearing the congestion costs, thus the need of subtracting the congestion costs in equation 1. It is important to say that the congestion costs are a function of the visitation at the area. We would expect to see that, as the number of visitors increases, the congestion costs also increase and are convex in the number of visitors.

We define a product as any kind of ticket that gives the customer the right to access the slopes and the facilities on the mountain. It is important to differentiate between products of type $i$ and products of type $j$. Products of type $i$ are all those “limited-use” products, i.e., products valid for a specific number of days. Examples of these products are day tickets, lift & lodging tickets, lesson package tickets, etc. Products of type $j$ are all those “unlimited-use” products, i.e., products for which the customer pays a determined fee and then s/he can visit the ski resort as often as desired. The most common example of this type of product is the season pass. The importance of this differentiation is because for products $i$ we can directly create a link between the visits to the ski area using these products and the number of tickets sold (and therefore the revenue generated), while for products $j$ there is no such link. One season pass holder could have visited the area 20 times during the season while another one could have skied only 4 times, however both of them paid the same fee, generating the same revenue but contributing differently to the congestion of the area.

We can also find products that combine features of both categories. One example of such a product is a “frequency card”. A customer pays a fixed amount for the product, which gives him the right to visit the area on any ‘n’ number of days in the season. After the $n^{th}$ visit, any subsequent visits can be purchased at a discount. It combines the flexibility of
the \( j \) products because the customer decides when to use the product (subscript \( t \) in variable \( u_{i,t} \) of equation 1) up to the \( n^{th} \) visit. After that, it behaves like a product \( i \). For the sake of simplicity we will only consider the two basic types of products.

From equation 1, the only variables that we can directly manipulate are the prices of each product \((p_{i,t} \text{ and } r_{x,j})\). By modifying these prices we should be able to affect the demand for every product. However, in real life, this ability to manipulate prices is not very well exploited. The optimization procedure is typically done only once before the season starts. With the information available at that time, prices are set for each time period that maximize revenue, further these prices are fixed throughout the season. This prevents the resorts from being able to react to changes or conditions in the market. For example, historically congested days will still face the same congestion levels, while limiting the capacity of generating additional revenue. Or periods of historically low demand will still be underutilized, even when skiing conditions are suddenly favorable.

In the one-time optimization previously described, the subscripts \( t \) and \( x \) for the prices of products \( i \) and \( j \) typically adopt only a very limited range of values. For example, in the case of a ski resort:

\[
t \in \{ \text{Early Season, Peak Season, Regular Season, Late Season} \}
\]

\[
x \in \{ \text{Early Bird, Regular Rate} \}
\]

If we consider that a typical ski season has about 150 days, for our previous example we would only have up to four different prices for each product \( i \) (limited-use) and two price points for products \( j \) (unlimited-use). This is very limiting in terms of potential revenue gains. There is no way we can increase the revenue by raising prices if we see that conditions are favorable. We are also wasting a lot of usable capacity on traditionally low-demanded periods. Finally, our ability to control the degree of congestion the area faces on a particular date is limited by the prices that we set at the beginning of the season.
There exist some strategies to get around this problem. For example, some inexpensive products are “blacked out” for historically congested days. But these strategies are not very effective as revenue management tools. We believe that dynamic pricing, an outcome of applying a revenue management program, can deal with these issues satisfactorily. We introduce this strategy in section 4.4.

### 4.3.2 Forecasting

We believe that demand is typically forecasted by means of simple rules. For example, when forecasting the demand for the next season \((d_{i,t} \text{ and } b_{x,j})\), an ‘x’ percent increase in demand from the previous season could be used as a simple prediction. This is done without considering the effects of price and cross-price elasticities. It could happen that, due to irregular price changes, the real effects on demand are not consistent with the expected prediction based on a uniform percent increase.

As for the usage of the unlimited-use \(j\) products \((u_{j,i})\), this is probably forecasted on a high level based on historical data, i.e., a prediction of the average visits per product is made, and therefore the total usage for the season is also estimated. But we do not have an estimate on a day basis, which is important in terms of the congestion.

Similar to the optimization procedure, forecasting is typically done only once, before the season starts. Whatever information is acquired throughout the season is not taken into account. Effects like unusually favorable weather or “9-11” are not properly dealt with. Some of these effects may have a significant impact on future demand, thus creating the need to reassess past decisions, like the setting of prices.

In section 4.4.2 we describe what we believe should be the best way to deal with demand forecasting.

### 4.4 Dynamic pricing

In order to properly address the problems mentioned at the end of section 4.3.1, we need to be able to react in a timely manner to changes in the conditions of the market place.
We need to forecast daily demand and continuously update the prices that we offer so that we can achieve the maximum revenue attainable. These changes in prices need to be as frequent as needed. We can achieve this by adopting a dynamic pricing strategy. This type of pricing strategy can also be described as a dynamic programming model. Dynamic programming is a mathematical method for determining the optimal combination of sequential decisions. According to Puterman (1994), “the key ingredients of a sequential decision model are:

- a set of decision epochs,
- a set of system states,
- a set of available actions,
- a set of state and action dependent immediate rewards or costs, and
- a set of state and action dependent transition probabilities”.

In the following two sections we describe how optimization and forecasting can be used in this type of pricing strategy and how does the optimization model fit into the dynamic programming framework.

4.4.1 Optimization model

In this case we want to continually reassess the conditions of the marketplace. Again, we can only manipulate the prices of every product, but this time we want to update and re-optimize these prices as new information becomes available, such as weather reports and advance product sales. We also want to be able to differentiate between a product sold many days before its planned use and a product sold on the same day it is being used. Let us consider a ski season consisting of periods (potentially days) 1 through \( N \). In the last period \( N \), we have the following mathematical model:

\[
\max_{y_i} Z_N = \sum_{y_i} d_{N,i,N} p_{N,i,N} + \sum_{y_j} b_{N,j} r_{N,j} - C_N \left( \sum_{y_{o}} \sum_{y_i} d_{o,i,N} + \sum_{y_j} u_{j,N} \right) \\
\text{subject to}
\]

(Eq.2)
\[ LB_{o,i,t} \leq p_{o,i,t} \leq UB_{o,i,t} \]
\[ LB_{x,j} \leq r_{x,j} \leq UB_{x,j} \]
\[ d_{o,i,t} \geq 0 \quad \forall o,i,t \]
\[ b_{x,j} \geq 0 \quad \forall x,j \]
\[ C_t \geq 0 \quad \forall t \]
\[ u_{j,t} \geq 0 \quad \forall j,t \]

where,

decision variables:
\[ p_{o,i,t} = \text{price of product } i \text{ when sold in period } o \text{ for use in period } t \]
\[ r_{x,j} = \text{price of product } j \text{ when sold in period } x \]

parameters (which are functions of the decision variables):
\[ d_{o,i,t} = \text{forecasted demand for product } i \text{ sold in period } o \text{ for use in period } t \]
\[ b_{x,j} = \text{forecasted demand for product } j \text{ sold in period } x \]
\[ u_{j,t} = \text{forecasted usage of product } j \text{ in period } t \]
\[ C_t = \text{congestion costs for period } t \]

This time we incorporate a new subscript \( o \) for the demand and the prices of products \( i \) (limited-use). This subscript takes into account the period in which the product was actually sold, thus creating a difference between a product \( i \) sold one month before its planned use and the same product \( i \) sold on the same day it will be used. This gives us more flexibility in controlling issues such as congestion and underutilization. We will expand on this later on in this same section.

Now we consider the objective function for period \( N-1 \):
\[
\max Z_{N-1} = \sum_{N-1} d_{N-1,i,N-1} P_{N-1,i,N-1} + \sum_{N-1} d_{N-1,i,N} P_{N-1,i,N}
\]
or equivalently:
\[
\max Z_{N-1} = \sum_{vi \leq N-1} \sum_{t \leq N-1} d_{N-1,i,t} p_{N-1,i,t} + \sum_{vi} b_{N-1,j} r_{N-1,j} - C_{N-1}\left( \sum_{vi} \sum_{t \leq N-1} d_{a,i,N-1} + \sum_{vi} u_{j,N-1} \right) + Z_N
\]
\[\text{(Eq. 4)}\]

Extending this to period 1 we get:
\[
\max Z_1 = \sum_{vi \leq n} \sum_{t \leq n} d_{i,i,t} p_{i,i,t} + \sum_{vi} b_{i,j} r_{i,j} - C_i\left( \sum_{vi} \sum_{t \leq n} d_{a,i,t} + \sum_{vi} u_{j,i} \right) + Z_1 + Z_2 + \ldots + Z_N
\]
\[\text{(Eq. 5)}\]

And a generalized form of the objective function is:
\[
\max Z_n = \sum_{vi \leq n} \sum_{t \leq n} d_{n,i,t} p_{n,i,t} + \sum_{vi} b_{n,j} r_{n,j} - C_n\left( \sum_{vi} \sum_{t \leq n} d_{a,n,t} + \sum_{vi} u_{j,n} \right) + \sum_{k=n+1}^{N} Z_k
\]
\[\text{(Eq. 6)}\]

Comparing this model to a dynamic programming model, the decision epochs in our model are clearly each one of the periods or days of the season. The state of the system is given by the congestion level on the period of interest, which depends on external factors, such as weather and holidays, and on ticket sales, both past sales and expected future sales. The set of available actions includes any possible combination of price changes for the products being offered (\(r_{xj}\) and \(p_{o, it}\), \(t \geq 0\)): This could mean anything from not changing any price at all to updating every price for every product for every future period. The state-and-action-dependent immediate rewards are defined by the revenue resulting from ticket sales minus the congestion costs due to previous sales. Finally, the state-and-action-dependent transition probabilities can be defined as the probability of our demand forecasts actually becoming realized demand.
As opposed to the traditional pricing model, the values of \( t \) and \( x \) in \( p_{o,ij} \) and \( r_{xj} \) are intended to take a wide range of values, such that:

\[
\begin{align*}
  t & \in \{1,2,3, \ldots, N-1, N\} \\
  x & \in \{1,2,3, \ldots, N-1, N\}
\end{align*}
\]

Similarly the subscript \( o \) could take any value ranging from 1 to \( N \). As previously mentioned, this flexibility allows us to better control and affect the expected demand and therefore the congestion on every period of the season. For example, if in period \( o<t \) we see that demand for products to be used in period \( t \) suddenly starts increasing and we are approaching a pre-determined level of congestion, we might want to increase the prices \( p_{o,ij} \) so as to slow down demand and avoid reaching an excessive congestion level. At the same time, this price increase could bring more revenue. Or if in period \( t-1 \) we see that demand for period \( t \) is very low, we might want to make the necessary adjustments in order to try to bring more people to the area.

This is what we meant by “flexible” capacity limit in section 4.1. We are not trying to allocate a fixed number of goods. We could sell lift tickets non-stop and the ski area will always have space left for more visitors. But, as we already said, as the area gets more and more congested, the quality of the benefits enjoyed by each visitor tends to decrease. Thus, by means of price changes, we should try to slow down the demand whenever we see that the expected congestion in the area is approaching a certain level. Note that this is not equivalent to ceasing to sell tickets at all.

Similar to the traditional pricing model, in the dynamic pricing model we are also considering the maximum and minimum price constraints. In general, prices should be increased in periods of high demand and decreased when demand is low. But, as we said at the beginning of section 4.3.1, we should avoid increasing or decreasing the prices excessively in order to maintain the image of the company. The commitment hierarchy constraints should also be applied in this model.
Overall, the main goal of the model presented in equation 6 is to find the maximum possible revenue for the season. We do not know the exact shape of the nonlinear function resulting from adding up the first two terms (revenue generated by sales of all tickets), neither do we know if the congestion costs are convex in prices.

In general, at the beginning of each period we would try to set up the prices of whatever products we are going to sell in the current period for use in the same period and in any future periods. But these prices have to be set up so as to maximize the total expected seasonal revenue, as opposed to the daily revenue. This means that we also need to consider inter-temporal effects, i.e., how a price offered today for a determined product could affect the sales of either the same or a different product to be sold sometime in the future. As we move from period $n$ to period $n+1$, we acquire some new information. Based on this information and on the outcome of our previous actions, we need to re-optimize and update the prices.

Each decision we make will have a different effect on the overall revenue but it could also cause different results in the long run. We cannot focus solely on the short-term revenue. Some decisions can affect the company’s future success. Therefore it is important to consider the results of the optimization process together with the potential problems that could arise. We will deal with these potential conflicts in section 4.7.

4.4.2 Forecasting
As we mentioned at the beginning of section 4.4.1, the only variables that we can directly manipulate are the prices of every product for every period of the season. By modifying these prices we should be able to get the maximum revenue. But we do not really know the value of the demand $d_{0,t}$, since total revenue is a function of the demand, we need to forecast these demands. We also cannot ignore price and cross-price elasticities. We deal with this in Chapter V. We also talk about the inter-temporal effects that we mentioned in the past section.
We are aware of the difficulty of forecasting on a product-day level. Therefore, an alternate approach is to forecast at the market segment level and from there we could apply assignment rules in order to allocate the demand for every different product. It is up to every company to find the best way to segment the market. In the case of the ski lift ticket industry, a very basic market segmentation could be comprised of the following groups: destination guests, local day-sensitive visitors (can only ski during weekends), local day-insensitive visitors (can ski potentially any day of the week), and ski school participants. Of course, this segmentation could be subdivided in order to better separate the customers. The final goal is to arrive at a segmentation that lets us predict what each market segment is willing to pay for a particular product at a particular point of time.

It is important to consider that customer behavior and the market place itself are very dynamic. While it is possible that, under certain circumstances, a customer is willing to pay a price ‘x’ for a specific product on a determined date, the same customer could no longer be willing to pay that price if either the individual’s circumstances change or something happens in the market place, like the launching of a special offer from a competitor. Therefore, this forecasting should also be dynamic. The conditions in the market place should be constantly reassessed, and customer demand should be frequently reforecasted.

Something worth noticing from equation 6 follows. Let us consider one part of the equation’s third term:

\[ C_i \left( \sum_{o \leq t} \sum_{V_i} d_{o,i,t} \right) \]  

(Eq.7)

We can say that the congestion costs due to products of type \( i \) (limited-use) are part stochastic and part deterministic. When \( o \) is many periods ahead of \( t \), we would anticipate the actual demand for the specific period \( t \) to be equal to zero (deterministic) and the predicted demand for the same period to be equal to our forecast (stochastic). Under normal conditions, as period \( o \) approaches period \( t \), the deterministic part becomes larger.
while the stochastic portion becomes smaller. This is due to customers buying or booking products for the specific period as we approach it. Thus, as we get closer to period $t$, the randomness in the equation will decrease. But at the same time, as we get closer to period $t$, either we will not be able to act appropriately or our actions will not have the desired effect. Therefore it is important to find a threshold that indicates how many days in advance we need to start producing the forecasts. As we already said, these forecasts have to be revised continuously and adjusted according to the most recent information available.

4.5 Dynamic pricing with options
One of the limitations of the dynamic pricing scheme previously presented has to do with the fact that we can only partially control the congestion due to products of type $j$ (unlimited-use) and the revenue generated by them. As we have already said, these are products like the season passes, which are typically sold at the beginning of the season for a predetermined rate and then throughout the season the pass holder can visit the ski area as often as desired. The congestion caused by these products is partially controlled via the setting up of blackout dates (like weekends or Christmas and New Year), in which season pass holders cannot access the area using the passes. The revenue generated by those products is partially controlled by letting the subscript $x$ take a wide range of values. However, other than the blackout dates and the varying prices until the moment the product is sold, once the customer buys the product we stop being able to affect the congestion and revenue generated by that product.

In the next section we describe a way in which we can transfer more control from the customer to the company, via a modification in the definition of products of type $j$.

4.5.1 Optimization model
If we go back to our definition of products of type $i$ and products of type $j$ in section 4.3.1, we would notice that these two types of products were very different from each other. We will now make products $j$ a subset of products $i$. 
Instead of some customers paying a high price for a season pass that gives them unlimited access, the product could be redefined as an option. As defined by Levi (1996), currency options are financial instruments that give the buyer the opportunity, but not the obligation, to buy at the price stated in the contract sometime in the future. Coming back to our field, we could take some characteristics of currency options and apply them to certain products in a congestible industry. Customers could pay an upfront fee (option price) and that would give them the right to, for example, a 50% discount from the window rate on any day of the season. The difference here is that there is no stated price. The product merely gives them the right to purchase at a discount in the future. The customer decides when to exercise his right to go skiing, but the ski company is the one that decides how much they need to pay. This would cause that products \( j \) behave as a regular product \( i \), with the addition of the required option price or upfront fee.

Of course, different option-like products could be offered, depending on the upfront fee and on the percent discount. One option could consist of, for example, a $100 upfront fee and a 20% discount, or another option could cost $300 with a 40% discount. The goal is to maintain some control over the price paid by the customer and, via this price, regulate the congestion on the area and the revenue generated by the product.

The optimization model would look as follows:

\[
\max Z_n = \sum_{\forall i} \sum_{t=1}^T d_{n,i,t} p_{n,i,t} + \sum_{\forall j} h_{n,j} f_{n,j} - C_n \left( \sum_{\forall o} \sum_{\forall t} d_{o,j,n} \right) + \sum_{k=n+1}^N Z_k
\]  

(Eq.8)

subject to

\[LB_{o,i,t} \leq P_{o,i,t} \leq UB_{o,i,t}\]

\[LB_{x,j} \leq f_{x,j} \leq UB_{x,j}\]

\[d_{o,i,t} \geq 0 \quad \forall o, i, t\]

\[h_{x,j} \geq 0 \quad \forall x, j\]

\[C_i \geq 0 \quad \forall t\]

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where,

**decision variables:**

\[ p_{o,i,t} = \text{price of product } i \text{ when sold in period } o \text{ for use in period } t \]

\[ f_{x,j} = \text{upfront fee of product } j \text{ when sold in period } x \]

**parameters (which are functions of the decision variables):**

\[ d_{o,i,t} = \text{forecasted demand for product } i \text{ sold in period } o \text{ for use in period } t \]

\[ h_{x,j} = \text{forecasted demand for product } j \text{ sold in period } x \]

\[ C_t = \text{congestion costs for period } t \]

and

\[ j \subseteq i \text{ such that } j \text{ is an option-like product} \]

In addition to the maximum and minimum price constraints and the commitment hierarchy constraints, a new constraint would also need to be considered. This would force the price of the exercised option-like product \( j \) to be equal to a determined percentage of the price of a regular window ticket (or whichever ticket the option’s price is linked to) if bought on the same day for use on the same period. As for the upfront fees paid by the customers, or the option price, we could choose to either fix them \((f_{x,j} = k, \forall x)\) or let them vary according to the demand.

As in the simple dynamic pricing case, we are trying to maximize the total expected seasonal revenue by selecting the prices that would give us the best overall result, i.e., not the maximum revenue on a day-by-day basis, but considering the effects of one price today on future revenue. As we move from period to period, we need to reassess the conditions of the market and we have to update the prices.

### 4.5.2 Forecasting

The main difference between equation 6 and equation 8 is that we have removed the second term from the parenthesis of the congestion cost. By doing this we believe that we
also made it simpler to forecast the congestion on any given period. With the regular season passes, customers using those products could show up at the ski area on almost any day of the season without any notice, so if we wanted to calculate the congestion costs due to season pass holders we needed to forecast their expected usage of the product. Customers using other products often tend to buy the tickets a few days in advance of their expected usage, so at least we have a partial figure of the congestion that we will face in the future. With the redefinition of the season passes as options, now it is more probable that every customer will tend to buy or book the tickets in advance. This will give us more valuable information earlier on during the forecasting process. Again, we need to continually reassess the state of the system and reforecast as soon as new information becomes available.

4.6 Expected results

Cross (1997) reports that “revenue gains of 3% - 7% are often realized with relatively little incremental cost”. One essential step before adopting a revenue management system is to estimate the expected increase in revenue. We need to know how much incremental revenue we can generate, where can we get that revenue from, and how would we obtain it. We will then be able to compare the final result with our initial revenue targets and we will have a way to evaluate if the implementation was successful or not. The estimation of the expected increase in revenue can be done via, for example, simulation modeling. Based on appropriate assumptions and on the knowledge that we get from the data, different “what-if” scenarios could be created so that the potential increase in revenue can be estimated.

In a very general way, we would expect to increase the yield on congested days by raising the prices. As more people book tickets for those days, we should tend to increase the prices. This price increase will probably cause that some customers change their minds about visiting the area on those days. We would consider that whatever revenue is lost due to the fall in total number of customers can be more than offset by the additional revenue generated through higher prices. Moreover, due to the expected decrease in congestion, we could also anticipate an overall increase in sales of secondary goods, like
food, beverages, clothing, and accessories offered at the different facilities located on the mountain.

We would also expect to increase revenue on days with historically low demand. Some of the customers that were turned down because of the increase in prices on highly congested days could now go on periods of low demand. Most probably some prices would need to be lowered in order to attract more customers on these days. But the final result should be an increase in total revenue. This decrease in prices should come together with a well planned advertising campaign. By making specific market segments aware of the discounts, this campaign would minimize the discount offered. Targeted e-mails could be sent to price-sensitive customers who typically do not ski until the prices have gone down. Or in some cases the new prices could also be advertised in the company’s website, so that everybody knows that, for example, if they go skiing on a particular day they will pay 30% less than the regular weekend rate. All these special offers and promotions have to be well planned so that only those customers who otherwise would not go skiing are either targeted or able to buy those discounted tickets. For example, destination guests most probably do not mind paying the same rate on weekends and on weekdays, since they are on vacation. Local visitors are the ones who could be attracted by the discounted tickets. Showing proof of residence could be a way to limit the sell of those tickets to local guests only.

4.7 Potential conflicts
As we mentioned in section 4.4.1, potential conflicts can arise when adopting a revenue management system. Marmorstein et al (2003) describe some of these conflicts and some ways in which these problems can be solved. Perhaps the biggest conflict that could arise is the perceived fairness. In its most basic form, this means that customers normally would expect to pay the same price as another customer for the same goods. Revenue management surely violates this rule by modifying the prices based on the expected demand. Some techniques that can be applied to minimize, or disguise, the effects of this price difference are bundling, limited time offers, and targeted advertising.
By offering bundles of products, like lift & lodging or lift & lesson, it becomes difficult to compare prices on a per-product basis. Limited time offers can attract only those very price-sensitive customers who would react fast to such an offer in order to get the product that they want at the price they want. Targeted advertising can also help in reducing this perceived unfairness by selectively e-mailing coupons to specific customers.

Wirtz et al (2003) also mention some of the potential conflicts and propose various strategies that can be employed to reduce such conflicts. Again, the idea of perceived unfairness is an important potential problem. The authors affirm that rate fences can help differentiate the prices offered to different market segments. For example, a 10-day advance purchase could be required for discounted lift tickets, or a higher-priced product could include a coupon valid for 10% off of a future visit.

Another problem that we consider could arise when adopting a revenue management system is related to customer service as perceived by season pass holders. One of the advantages of having a season pass is that there is no need for the customer to stand in line at the ticket window. They buy the season pass before the season starts and then, every time they want to go skiing they would go directly to the lifts. The option-like products, as we defined them, require the customers to pay an upfront fee and then paying a discounted rate every time they visit the area. Normally this would mean that the option holders have to go to the ticket window in order to pay that discounted rate. But this nuisance to the customer could be avoided with the use of technology. An option could be linked to the customer’s credit card, so that every day the option holder goes skiing, the employees scanning the tickets at the lift line would also scan the option, charging automatically the customer’s credit card.

The next chapter specifies the requirements, in terms of data collection, for adopting a revenue management system.
CHAPTER V REQUIREMENTS OF A REVENUE MANAGEMENT SYSTEM

5.1 Data requirements for forecasting

Adopting a revenue management system is no simple task. In any case, the first thing to be done when implementing such a system is “to gather as much data as possible about consumer behavior” (Cross 1997). In the case of the ski lift ticket industry, the basic data that would need to be collected is the following:

- daily visits for every product,
- the price at which those products were sold, and
- date of purchase/bookings for every product.

We need to know which days of the season face the most congestion, therefore we require daily visits for every product. We also need to know whether specific prices can be increased or decreased, thus we need the price at which the products are sold. Finally, it is very valuable to have an idea of how congested will future days be and how far in advance can we expect those days to start congesting, for that reason we consider important to collect the date of purchase or booking for every product.

Ideally, this data would have to be collected at least for the previous twelve months, so that minimum one whole year worth of data can be analyzed. It is worthwhile mentioning that all this data should be collected as accurate and complete as possible. The more accurate and more complete the data is, the better the decisions that will be made. It is a common practice for firms to perform end-of-month reconciliations of accounting statements. If discrepancies are found, these should not be treated lightly. “Dumping” a large amount of, for example, visits into one or two days could seriously affect the performance of the revenue management system. Ideally, firms should try as hard as possible to allocate in its proper “place” whatever data is missing.

Some other “external” information could also be collected. This includes, but is not limited to, weather and economic indicators. At the beginning it might be hard to codify
and incorporate these two things into the models developed, but once that a certain level of expertise is achieved, that data could prove to be very useful.

In addition to what we just listed as data to be collected, there is something else that we need to have in order to better understand the market and to make decisions that would bring the most benefit. This is the price elasticity of demand and the cross-price elasticity of demand. The first one can be defined as the change in quantity demanded of one good divided by its change in price. The latter can be defined as the percentage change in demand of one good divided by the percentage change in price of another good. With this in hand we can learn how the demand of certain products would react to changes in price and which products are complements, substitutes or independent.

But obtaining this information is rather complicated. This data is not directly available. Usually, this information can be obtained either by running experiments or by analyzing historical data. The most important thing to consider when calculating these elasticities is to make sure that the changes in demand are due only to changes in prices of the product(s) of interest, i.e., not due to external factors. In its most general form, a formula that can be used to estimate price and cross-price elasticity is:

\[
\ln(d_{o,i,t}) = \alpha + \beta \ln(p_{o,i,t}) + \gamma \ln(p_{o,i',t}) + \delta \ln(p_{o,i,t'}) + \varepsilon_{o,i,t}
\]  

(Eq.9)

where,

\(d_{o,i,t} = \) forecasted demand for product \(i\) sold in period \(o\) for use in period \(t\)

\(p_{o,i,t} = \) price of product \(i\) when sold in period \(o\) for use in period \(t\)

\(p_{o,i',t} = \) price of product \(i'\) when sold in period \(o\) for use in period \(t\), \(i \neq i'\)

\(p_{o,i,t'} = \) price of product \(i\) when sold in period \(o\) for use in period \(t'\), \(t \neq t'\)

\(\beta = \) price elasticity of demand

\(\gamma = \) cross-price elasticity of demand

\(\delta = \) inter-temporal elasticity of demand
The fourth term in equation 9 ($\delta \ln(p_{o,i,t'})$) accounts for inter-temporal elasticity, i.e., how a price change on a particular day for a certain product affects the demand for the same product on another day. Index $t'$ should take any possible value that could affect the demand for a given product $i$ sold on a given day $o$. Also, depending on whether we are calculating price or cross-price elasticity, $\gamma$ should be set equal to zero or its value should be estimated.

As for the index $t'$, when estimating cross-price elasticities we need to consider all the products that could affect the demand of each product $i$. It is important to say that when estimating these elasticities, either by running experiments or by analyzing historical data, for every observation, the change in price of a given product should be the only one happening at the time, everything else should remain equal.

Finally, the price and cross-price elasticities previously discussed were meant to be “internal” elasticities, i.e., how does the demand of a specific product change due to variations in price of the same product or of competing products of the same ski resort. But this could also be extended to inter-resorts elasticities, since changes in prices of products from a competing resort are likely to affect the demand of our own products.

All this can also be extended to similar congestible industries like museums and amusement parks. Daily visits, prices of every single product, booking data, price and cross-price elasticities, all this data would be required in order to apply revenue management. It might even be easier in these other industries due to the usually smaller amount of products offered.

5.2 POS vs. scanning systems

The last thing to consider in this chapter is the type of system to be used to collect the data. We will refer to the case of the ski industry, because that is where we know the systems typically used. Ski resorts normally have a POS (point of sale) system and/or a
scanning system. The POS system tracks the sales of the different products according to the date of sale. The scanning system tracks the usage of those products previously sold.

Both systems play a crucial role in the application of revenue management tactics. We cannot rely solely on the information provided by one of the two systems. Let us consider the following example. Suppose that a ski resort offers, among many other products, window-multi-day tickets. These are tickets that allow the user to ski on X out of Y days. For example, we could buy a ticket valid for five out of seven days. The POS system would capture the date on which that product was sold. Regularly this would be one or two days before the customer starts skiing. If there were no scanning system, the POS system would allocate those five visits on the day of purchase, which is obviously wrong. We would not be able to determine the actual usage of the product, so we would not have a way to determine, for example, the days with the most congestion.

The need for a scanning system becomes more apparent when we consider products such as season-passes. These are typically sold before the ski season starts, so a POS system would only tell us that a certain number of season passes was sold in October. Without the scanning system, we would not be able to determine when those season passes were used, so we would not know the total number of visitors on each day of the season. Moreover, the scanning system can tell us how many days was each season pass used, so based on that we could decide to increase or decrease the price of the passes in seasons to come.

On the other hand, if we only had a scanning system, we would only know when were the products actually used, but we would not be able to determine when those products were sold. One part of the products is typically sold (or booked) in advance, while the rest are sold on the same day they are used. Since a revenue management system requires forecasting the demand of the different products, knowing the date on which the products are sold is essential. This gives us a “snapshot” of the usage of days to come. Based on these “snapshots” and on the forecasts for the other products, we could make decisions
such as to increase the prices for the remaining of the day or to launch a special offer in order to attract more customers.
6.1 Applicability of revenue management

In this thesis we have discussed the applicability of revenue management in the ski lift ticket industry and in similar congestible industries. While revenue management is a common practice for many industries that sell private goods, we see an important area of opportunity for industries that deal with club goods. Congestion problems are common in some periods of time for companies in this area. Although it might not seem evident, this congestion could be affecting the company’s future revenue, due to decreased quality in service. Furthermore, there is typically a lot of unused capacity during some other periods of time. The cost of admitting one additional customer is negligible when compared to the fixed costs. This spare capacity could be better used, at practically no extra cost, if an appropriate revenue management system is adopted.

We have also shown that congestible industries share many of the characteristics of the companies in which revenue management has already been successfully applied. Moreover, the power of internet now makes it easier to apply such a system. Communicating promotions to customers and customizing products is simplified by the web. One may think that changing the prices dynamically in this kind of industry is a little bit irrational. But let us not forget that when revenue management was first introduced by the airline industry, a lot of people thought that customers would not tolerate those rapid changes in price. Nowadays we take for granted that the price of a plane ticket can change every single day, if not every hour. Something similar could happen with the introduction of revenue management techniques in congestible industries. Changes are always controversial, but if we take care of the details, that change could be smoothed.

6.2 Areas for further investigation

Further to what we presented in this thesis, we consider that there are some interesting areas that could complement the application of a revenue management system. We present two of them.
6.2.1 Auction theory

Auction theory is a type of mechanism that deals with the allocation of goods and the formation of prices for those goods. In an auction, individuals submit bids to express the value they associate with the good. Everyone knows his/her own values only. There are different kinds of auctions. Two of them are the ascending bid auction (English auction) and the descending bid auction (Dutch auction). In the English auction, the seller sets an initial price and the buyers bid incrementally, until there are no more bids. Whoever submitted the last (and highest) bid is the one who gets the good. In a Dutch auction, the seller starts from a high price and starts lowering the price until a buyer is willing to buy at the current price.

Auction theory could be used in the ski lift ticket industry in conjunction with revenue management in order to try to find the correct price of each lift ticket, i.e., the price that the customers are willing to pay for each of the different products. It could also be used in order to try to sell the suddenly-available excess capacity on certain days of the season. By using auction theory it might be possible to increase the revenue potentially attainable by revenue management alone.

It is also important to point out that the internet now makes it easier to apply auction theory in almost any field. There are many websites dedicated to auctioning all sorts of products or services. Two of the most popular auction websites are eBay and priceline.com.

6.2.2 Game theory

Game theory is a mathematical theory that deals with interactive competitive decision problems. In a game, several players or adversaries strive to maximize their expected utility by selecting specific combination of strategies. Each player’s final utility payoffs depend primarily upon the combination of strategies chosen by the adversaries. We can find applications of game theory in very different contexts. Military battles, political campaigns, marketing and advertising campaigns by competing firms, all these are examples involving adversaries in conflict (Hillier and Lieberman, 2001).
The simplest case of game theory is the two-person, zero-sum game. This kind of game involves only two adversaries and whatever one player wins the other one loses, so the sum of their net winnings is zero. We can think of an example of a two-person zero-sum game in the ski lift ticket industry. This could happen if, for example, one ski resort is competing against just another resort. The total demand would be split between the two resorts, so whatever actions are chosen by one resort, they directly affect the other resort. If a customer decides to go skiing and the prices are more favorable for him at resort A, the customer will not go to resort B. The revenue from that customer would be lost by the second resort and it will be collected by the first one.

Of course, there are more complicated types of games. Some of these are the n-person game and the two-person, constant-sum game. The first one is self explanatory, it involves more than two adversaries. In the second one, the sum of the net winnings of the two players is a constant different from zero. It could be negative if, for example, the two players share some cost, or positive if they share some reward.

Game theory may prove to be an interesting area for further investigation. If one company decides to adopt a revenue management system, the company would be better off by also analyzing its competitor’s actions via game theory. Price adjustments would then be made based not only on the company’s forecasts and on the “internal” optimization process, but also based on the expected reactions of the different competitors.
REFERENCES


