Optimal customer class segmentation for the rooms in a hotel, a case study in the Colombian hotel sector

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Abstract

Hotels face many decisions considering the customer's bookings on a daily basis. Commonly, hotels offer their services for different types of clients that have different purposes for staying in the hotel, and so the fares charged by the hotel vary according to the type of customers. Furthermore, the types of customers also have different behaviors regarding their demand. One of the mentioned important decisions is to know the maximum number of rooms to allocate to their different customers in order to maximize revenue. We discuss two types of models for solving this problem and at the end we recommend the use of a proposed Optimization Model. We test this model in a case study in the city of Bogotá.

Keywords: Revenue Management, Hotel sector, Customers class segmentation, Room allocation

1. Introduction

The hotel sector in Colombia, and generally in the world, has experienced major changes during the last two decades. Due to the development of technology and communications, it is nowadays easier to travel and to make business around the world. This phenomenon has facilitated the steady increase of visitors in countries like Colombia. During the last 11 years the number of visitors in Colombia has increased in a yearly average of 10%, for a total of 1.7 million visitors in 2012 in Colombia, from which 900,000 visited Bogotá (The City Paper Bogotá, 2013).

Besides the increase of demand, the Colombian government has incentivized many local and foreign businesses to promote tourism in the country. A 2002 law offers up to 30% of tax exemptions for 30 years for hotel chains that, before 2018, open operations in the country and for current hotels that renew their facilities. The combination of the increase of demand and the government's incentive and promotion of the country has led to a massive arrival of hotel chains to the country, and especially to its capital, Bogotá. It is expected that in the next 3 years 2,500 rooms open in Bogotá and 8,000 in the rest of the country (Cotelco, 2013).

As consequence of the latter situation, at the present time there is a strong competition from the hotels to capture demand which is also expected to increase fiercely in the following years. This necessity of capturing demand is part of the necessity of having steady and healthy financial results and therefore, being resilient in the market. Revenue Management (RM) has been found provides solutions for these types of problems.

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RM may be described as the art of selling the right products to the right consumers, at the right prices, at the right moment (Yeoman and McMahon-Beattie, 2011). RM is the application of disciplined mathematical analytics that has helped different industries to maximize their revenue growth (Quante et al., 2008). It arose as a solution for distinctive airlines to compete against low budget airlines in the 1980's (Tallury and Van Ryzin, 2004), and since then it has been successfully applied to other sectors, such as the hotel sector (Aziz et al., 2011).

We work with a case study, a hotel based in Bogotá. This hotel's intention is to become a strong competitor in city's hotel sector due to the current and future hotels' situation in the city. One of the issues to be solved for our case study is to know the maximum number of rooms that should be allocated for each type of customer the hotel serves. Obtaining and applying these room policies will maximize the hotel's revenue: if the expected revenue of booking a room for an uncertain arrival of a customer that pays a higher price is better than allocating a certain customer that has arrived, then the hotel must not sell the available room to the certain customer. This type of problem is called a Single Resource Capacity Control Problem (SRCCP) (Talluri and Van Ryzin, 2004).

For solving our SRCCP we propose two different alternatives, heuristic models and an optimization model. We discuss the results from both of the models and we focus on a further analysis of one of them and finally recommend our final results to our case study.

The rest of the paper is organized as follows. In Section 2 we present the solution strategy for our problem, we emphasize on the notation and jargon used, explain what is the relevant information that will be used in the proposed models we then describe. In Section 3 we show the analysis for our case study. In Section 4 we present the results for our case study from the different models and focus on one of them for a sensitivity analysis. Finally in Section 5 we conclude and state future steps for this research.

2. Methodology

Our strategy finds a solution to the SRCCP finding policies for the maximum number of rooms to be booked for each type of customer, on every moment of the year, with the purpose of maximizing the hotel's revenues. This strategy encompasses three phases: data analysis, obtaining results upon the proposed models, and sensitivity analysis based on different scenarios. The data analysis phase gives us a complete understanding of the current situation of the hotel and the relation the hotel has with its customers. For obtaining the results we use two types of models and we then compare them based on their expected revenue. Finally, we analyze the impact of varying the variables of the models on the solutions for our SRCCP.

2.1. Definitions and notation

To determine the number of rooms that should be booked for each type of customer on every moment of the year, we first introduce some definitions and notation that will be constantly used in this paper.

The customers will be differentiated in distinguishable *classes.* Each class will represent a specific group of people that booked rooms in a hotel. When the classes are discerned, they will be arranged in a hierarchical order based on the average price they pay for a room for one day. The *first class (class 1)* is the class paying the highest fares, and subsequent classes (classes *2*, *3*, …, *n*) will be the *lower* classes where class *n* is the cheapest class, hence denoting the price for class j as p_j, then $p_1 > p_2 > \cdots > p_n$.

The *protection level* is defined as the number of rooms that the hotel should protect for that class and its upper classes. They will be denoted as y_j, where j represents the number of the class in the hierarchal organization explained before. The objective of this paper is to accurately estimate the protection levels for the classes studied. We show an example for the explanation of the protection levels in *Figure 1*.

Protection level example with three classes	
Class	**Protection level**
Class 1	$\boldsymbol{y_1 = 12}$
Class 2	$\boldsymbol{y_2 = 21}$
Class 3	$\boldsymbol{y_3 = 30}$
Hotel's rooms capacity	**30 rooms**

Figure 1. Protection level example

In *Figure 1* we have an example for a three-class problem. The classes' prices are shown beneath each of the classes. The protection levels for each class are shown in the lower table where, for example, $y_2 = 21$, means that a total of 21 rooms should be allocated for Classes 1 and 2. We also observe that $y_3 = 30$, so in this example the total number of rooms is 30. With these results it can easily be interpreted that the maximum number of rooms that should be allocated for Classes 1, 2 and 3 are 30, 18 and 9, respectively.

The *seasonality* of the hotel refers to the non-stationary behavior that the customers have in relation with the hotel. The demand of rooms varies in the different moments of the year. Hence, the variation of prices is a consequence of the change in demand. The seasonality analyzed in this paper refers to different classifications of days and not just to periods of two or three months. For example, as it is going to be explained later, two classifications used in this paper for the seasonality of the hotel were the Weekdays and Weekends.

2.2. Data analysis

The information retrieved in this phase will be the input information for the proposed models. This phase has two main objectives: identify and differentiate the customers' classes that will be used in the models, and characterize each customer class in matters of its arrival rates, fares and lengths of stay.

The main objective for this project is to maximize the hotel's revenue by practicing policies on the allocation of its customers. As we discussed before, the customers must be set in distinguishable classes. An appropriate and recommended way to differentiate the customers is by the fares they pay for the rooms (Aziz et al., 2011). Customers may be differentiated by their nationalities (e.g., Europeans), purpose of stay (e.g., tourists), or age (e.g., youth), and statistical tests must be done to segment them.

With the determination of the classes, we proceed to understand their behavior. We began the process deciding the seasonality used for the models. As the customers do not have a steady demand throughout the year, the arrival rates must be obtained from the database for each class of customers and any given moment of the year.

Similarly, the fares and the length of stay for each class must be determined for each moment of the year. The fares are the prices normally paid by each class for one room on a one night stay in the moment of the year in discussion. Moreover, the customers' lengths of stay indicate the probability that a customer arriving in the different periods of the year, stays a fixed number of days in the hotel.

2.3. Proposed models

This phase consists of running two types of models with the information obtained through the data analysis discussed in the previous section. We proceeded to use this as input for the two types of models explained in this section.

2.3.1. *Expected Marginal Seat Revenue*

This first model is a set of two heuristics based on Littlewood's Two Class Model (Tallury and Van Ryzin, 2011). The latter model is the earliest single resource model for Revenue Management found to be optimal in a two class problem. This model calculates the protection level for Class 1 (y_1) according to the following expressions:

$$y_1^* = F_1^{-1}\left(1 - \frac{p_2}{p_1}\right), \text{ and } y_1 = \lceil y_1^* \rceil,$$

where p_j is the price for class j and $p_1 > p_2$, and the distribution of the demand for class j is denoted by $F_j(.)$.

Littlewood's Two Class Model is regularly quoted as basis for other *n*-Class Models trying to get to a solution for a SRCCP with more than two classes. The Expected Marginal Seat Revenue version *a* and version *b* (EMSR-*a* and EMSR-*b*) heuristics were introduced by Belobaba and are the two most popular heuristics for solving SRCCPs due to their rapid solving time and the near-to-optimal results. Although EMSR-*a* is the most widely known heuristic of the both, EMSR-*b* generally provides better revenue performance (Tallury and Van Ryzin, 2011).

Version *a* of the EMSR heuristics calculates the protection level for the different classes individually by adding the protections levels resulted from applying Littlewood's Two-Class Model in the comparison of each class with all of its higher classes. For example, the calculation of y_j through EMSR-*a* is the result of adding each protection level resulted by Littlewood's of comparing prices p_{j+1} with prices p_k where $k = 1 \dots j - 1$.

On the other hand, version *b* calculates the protection level for the different classes applying Littlewood's only once. For calculating y_j it compares through Littlewood the price of class $j + 1$ and the price of a pseudo class j^*, which is the result of merging classes j and higher $(j, j - 1, \dots 1)$. The merging process consists of obtaining the aggregated demand for the merged classes that will behave as the function $F_{j^*}(.)$, and obtaining the weighted average for their prices (weighted by the expected demand of each class), p_{j^*}.

These models are known to work well solving SRCCPs, but their original intention was to solve these types of problems in the airlines sector or other similar industries where applicable (Yeoman and McHahon-Beattie, 2011). However, applying these heuristics to the hotel sector may not be that practical due to the fact that they do not incorporate the lengths of stay of the customers in a hotel. This is not an issue the airline sector, because the problem is how to allocate the seats on a single flight in which a single customer may only demand one seat. On the contrary, in the hotel sector, a single customer may demand one room for an undetermined number of days.

To solve this issue, we propose an expression to adjust the demand of the customers of the different classes. The demand function that EMSR heuristics use is based on the previously described airlines sector's demand: one demand for a seat in a flight. Therefore, the demand for the customers in the hotel sector, based on their arrival rates, must be adjusted according to each customer's length of stay in the hotel by the following expression:

$$\lambda_m = \lambda_o + \lambda_o * \sum_{l=2}^{\infty} (l - 1) * d_l,$$

where λ_m is the modified arrival rate, λ_o is the original arrival rate, and d_l is the probability that a customer stays for l days. With this modified arrival rate, a new demand function for each of the customers in each of the analyzed moments of the year is found, and the EMSR models can be applied to the hotel sector, and therefore to our project.

2.3.2. Optimization Model

The proposed Optimization Model is an adjusted version of the model proposed by Aziz et al. (2011). It will receive the information obtained as from the data analysis phase.

The model formulation includes a set of classes subscribed in J and indexed by j, and a set of days subscribed in L and indexed by l. The model parameters $p_{j,l}$ describe the price for a room in a one night stay on day l for a customer of class j. And we denote $d_{l,l',j}$ as the number of rooms booked by a customer of class j that arrives on night l and will check-out on day l'.

The model decides the number of bookings effectively allocated. Aggregating these decisions, the number of customers of class j allocated for day l that finish their stay on day l' is denoted by the variable $X_{l,l',j}$. The variable I_l is used in the model as an auxiliary variable that controls the number of available rooms before day l takes place. In addition and for convenience in the results interpretation, the variable $Q_{l,j}$ explains the total number of rooms assigned for customers of class j on day l. The proposed model is as follows:

(1) $$Max \sum_{l \in L} \sum_{l' \in L} \sum_{j \in J} p_{j,l} * X_{l,l',j} * (l' - l + 1)$$

subject to,

(2) $$I_1 = Hotel's\ Maximum\ Capacity$$

(3) $$I_l = I_{l-1} - \sum_{l' \in L} \sum_{j \in J} X_{l-1,l',j} + \sum_{\substack{l'' \in L \\ l'' < l}} \sum_{j \in J} X_{l'',l-1,j} \qquad \forall\, l \in L | l > 1$$

(4) $$\sum_{l' \in L} \sum_{j \in J} X_{l,l',j} \leq I_l \qquad \forall\, l \in L$$

(5) $$X_{l,l',j} \leq d_{l,l',j} \qquad \forall\, l \in L\,, \forall\, l' \in L, \forall\, j \in J$$

(6) $$Q_{1,j} = \sum_{l' \in L} X_{1,l',j} \qquad \forall\, j \in J$$

(7) $$Q_{l,j} = Q_{l-1,j} + \sum_{l' \in L} X_{l,l',j} - \sum_{\substack{l'' \in L \\ l'' < l}} X_{l'',l-1,j} \qquad \forall\, l \in L \mid l > 1, \forall\, j \in J$$

(8) $$X_{l,l',j} \in \mathbb{Z}_+ \qquad \forall\, l \in L\,, \forall\, l' \in L, \forall\, j \in J$$

(9) $$I_l \in \mathbb{Z}_+ \qquad \forall\, l \in L$$

(10) $$Q_{l,l',j} \in \mathbb{Z}_+ \qquad \forall\, l \in L\,, \forall\, l' \in L, \forall\, j \in J$$

The objective function (1) maximizes the hotel's revenue, which is estimated as the product of the number of allocated bookings, the fare for a room per day and the total number of days of stay for each booking. Constraints (2) and (3) define the total rooms available before a day takes place. Constraint (4) guarantees that the total number of bookings allocated on a specific day is not more than the total number of rooms available. Constraint (5) states that the number of allocated bookings must not be higher than the demanded bookings. The set of constraints (6) and (7) defines variable $Q_{l,j}$ that will help to interpret results. Finally, (8), (9) and (10) define the non-negative integer nature of the decision variables.

2.4. Sensitivity analysis

The last phase of the proposed methodology is to do a sensitivity analysis on the results varying variables of the model. We used the elasticity of the demand of the customers to understand how the change of the prices affects the results from the previous section. Initially we tested the impact of changing the prices of all classes at the same rate, and then we proceed to change the prices of only one class at a time.

3. Case Study

Bogotá is Colombia's capital and its highest populated city (~8,500,000 people); it also ranks 6th among cities in Latin America in population (Alcaldía de Bogotá, 2013). Over the last 10 years Bogotá has achieved huge development in its economics, security and infrastructure issues, overcoming many capitals in Latin America and becoming a popular place to visit and to do business in. The city has become an obliged stop for tourists due to its rich culture, gastronomy and landscapes. Likewise, the arrivals from corporate people to do business in the city has increased in the last years due to Bogotá's economic expansion that has permitted the city to become a national and international hub for businesses.

Our case study is a hotel located in Bogotá's downtown, nearby the historical part of the city and one of the areas with high density of offices. This hotel is part of a national hotel chain with over 20 years of experience in the national market. The hotel is known for its flexible policies regarding corporate stays; they commonly establish contracts with large companies so their executives may stay in the hotel for extended periods of time. For the allocation of its guests, it has a total of 37 rooms available.

3.1. Data analysis

The hotel provided us their historical check-in database. We used the data from August 2011 to January 2013 which included information for a total of 4,618 customer bookings. To complete the data analysis phase we also gathered from each booking the following information: number of rooms booked, fares for the rooms booked, number of days booked, customers' nationality and the hotel's classification for the type of customer. The latter is an internal classification in which the hotel classifies a customer either as corporate or non-corporate.

3.1.1. Classes

We also evaluated the possibility of class segmentation within the non-corporate customers. The classification of classes was based on the fares paid by the different types of customers for their rooms. After some interviews with the hotel officials, they recommended us to differentiate the customers by their nationality since there were some variations of the fares depending on where the customer came from.

ANOVA and paired t-tests were done to statistically determine which groups of customers were significantly different from one another, regarding the average fares they are charged in the hotel.

Comparison	t-Statistic	P(T<=t)	Conclusion
Colombia vs. US	5.86	0.00	Statistically different
US vs. Others	-6.01	0.00	Statistically different
Colombia vs. Others	-0.90	0.37	Statistically equivalent

Table 1. Classes' classification results from statistical tests

Table 1 shows some of the final comparisons reduced to three paired t-tests. In this table, the category *Others* refers to the customers from every part of the world but Colombia and United States. As the table shows, from the paired t-tests we concluded that the fares paid by the Colombian and the Others categories of customers were statically equivalent and that they both are statistically different from the fares paid by the US customers.

Hence, we merged the Colombian category with the Others. Thus, the final class segmentation that was used for the solution of the problem was: Corporate Customers, US customers, and Others customers.

Segmentation within the Corporate customers was not done due to the contracts their companies have with the hotel. The corporate contracts are made regardless of the customers' nationality or the location of their corporation's headquarters.

3.1.2. Arrivals, fares and lengths of stay

Before calculating the other inputs for the models, we defined the seasonality periods that were going to be used for the project. After some interviews with the hotel's officials and internal discussions we identified five different moments of the year when the seasonality affects the customer's arrivals and therefore the fares charge. The mentioned moments are described in *Table 2.*

Day classification	Description
Weekday	Arrivals during a day before any business day (Sundays through Thursdays)*
Weekend	Fridays and Saturdays*
Holy Week	Arrivals during any day of the annual Holy Week (from Sunday to Saturday)
Holidays	Arrivals the day before of any holiday celebrated in Colombia†
Christmas	Arrivals during the Christmas season (December 23rd - January 1st)

Table 2. Day classification and corresponding description

The arrival rates for the different classes were calculated for each of the five time ranges specified before. These results are shown in *Table 3* in units of number of arrivals per day. For instance, 6.062 customers of the class Others are expected to arrive during a Weekday. It is notable that there are not any arrivals of Corporate customers during Holy Week nor Christmas season. As described previously, these are common times for family vacations in Colombia thus Corporates customers will not be arriving for business purposes to the hotel. For the purposes of the project, the arrivals were assumed to follow a Poisson process.

	Arrival rates		
	Corporate	**US**	**Others**
Weekday	0.432	1.653	4.955
Weekend	0.474	1.625	6.062
Holy Week	-	0.250	4.375
Holiday	0.115	1.923	4.071
Christmas	-	0.667	1.852

Table 3. Arrival rates for the different classes in the different moments of the year

Similarly, the fares for a room for a one day stay were calculated for each of the combinations of classes and ranges of days. The fares are expressed in United States Dollars (US$). The calculated fares are shown in *Table 4.* Alike with the arrival rates, the fares of Corporates during Holy Week nor Christmas season, cannot be calculated.

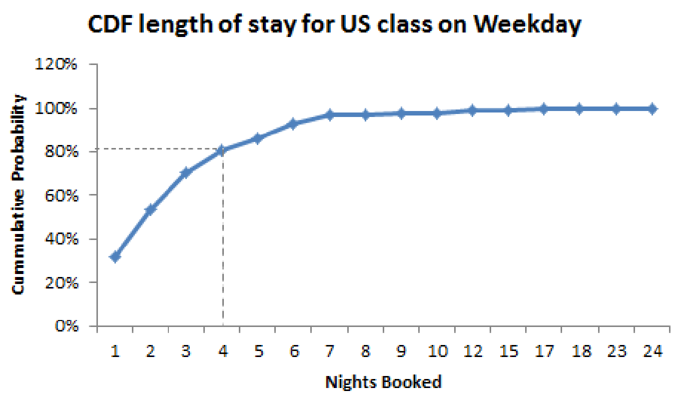
* Do not include week or weekend days that belong to any of the other classifications.

† Besides from the Holy Week and Christmas' holidays, Colombia celebrates 15 other holidays.

	Fares		
(US$)	Corporate	US	Others
Weekday	$ 98.16	$ 103.77	$ 108.45
Weekend	$ 95.14	$ 102.41	$ 113.12
Holy Week	-	$ 139.87	$ 111.39
Holiday	$ 114.69	$ 94.81	$ 99.49
Christmas	-	$ 157.42	$ 120.62

Table 4. Fares for the different classes in the different moments of the year

To conclude with the data analysis phase in our case study, we calculated discrete probability functions of the lengths of stay for each of the classes that arrive during each of the five periods of time analyzed. By doing this we estimate the probability that a customer of class j that arrives on day l stays a fixed number of days in the hotel. An example of one of the probability functions obtained is shown on *Figure 2.*



The probability that a US customer books a room for more than 4 days if she arrives on a weekday is ~19%.

Figure 2. Example CDF for the length of stay for the different classes on the different moments of the year – US class on Weekdays

3.1.3. Other assumptions

Besides the input calculated for the models in the data analysis phase, some assumptions had to be made to implement the models correctly.

The fares charged for a customer are fixed according to the day when they arrive. If a customer arrives during a weekday and one, or more, of the days of stay belong to any of the other time ranges, the fare for all of its days of stay is as a weekday.

Another assumption made is that the demand behaves steadily throughout the year. Arrival rates do not incorporate growth or decay trends. Then, the same arrival rates for a weekday are the same for February and November. These arrival rates do not take into account external variables such as new positive or negative trends of demand due to political, economic, social or infrastructural issues in Bogotá or in Colombia (i.e. a hypothetical new highway that starts in the airport and passes by the hotel, which will presumably lead to higher demand).

4. Results

In this section we show the results from the two proposed models, compare them and decide on which of them we are confiding the final results of the project. Afterwards, we analyze the impact of changing the class prices to the results.

4.1. Expected Marginal Seat Revenue

After adjusting the arrival rates of the demand for the hotel and the prices for each of the three classes of customers for each time range, we could obtain results of the EMSR models. As we mentioned in the previous section, the output for these models is the protection level for each class. Now, we are presenting their results showing not the protection levels but the maximum number of rooms that should be protected for each class on each of the five periods of the year taken into account. These results are shown in *Table 5*.

	EMSR-*a*		
	Corporate	**US**	**Others**
Weekday	8	15	37
Weekend	12	19	37
Holy Week	35	37	35
Holiday	37	10	35
Christmas	34	37	34

	EMSR-b		
	Corporate	**US**	**Others**
Weekday	10	15	37
Weekend	14	19	37
Holy Week	35	37	35
Holiday	37	12	35
Christmas	34	37	34

Table 5. Maximum number of rooms that should be protected for the different classes in the different periods of time according to EMSR-a and EMSR-b

Results from this table may be interpreted as following: results from EMSR-*a* state that on Holidays, the maximum number of rooms that should be allocated to US customers is 10, 35 for Others and 37, i.e., the hotel's maximum capacity, for Corporates. This indicates that if in a certain Holiday the hotel has 10 rooms already booked for US customers (including checked-in US customers from previous days that have not yet checked out), they must not allocate any more rooms for them. Similarly, the results from the EMSR-*b* model may be analyzed in the same way.

It can be observed that the results are consistent with the order of the prices for each class. For each type of day, the least-maximum number of rooms allocated for each class is always bestowed to the class paying the lowest fares. In contrast, the class paying the highest fare is the one that the hotel should be reserving its full capacity for. This behavior follows the Littlewood equation results (Tallury and Van Ryzin, 2011) where the full capacity of the resources is protected for the first class.

The results from both models are alike, but in general the results for EMSR-*b* are more conservative. For each type of day they are opting to give more rooms for the lower classes. This is a consequence of the conservative and more intuitive way the protection levels are calculated in this model; they are the result from comparing only two classes at a time, not each class with each of the possible higher classes.

The expected revenue from implementing the EMSR-*a* policies is US$676,300 a year, and that of the EMSR-*b* policies is US$677,500 a year. These revenues are consistent with the affirmation made by Talluri and Van Ryzin (2004), that generally EMSR-*b* provides better revenue performance.

4.2. Optimization Model

The proposed Optimization Model was run using as input the results from the data analysis phase. The price parameters were fixed and as shown in *Table 4*. Nonetheless, the demand parameters were generated randomly following the obtained arrival rates the customers and the length of stay for each customer.

The model was run for a total period of 50 years; there were 10 different runs for 5 years each. The days for the 5 years of each run were arranged in order to follow a typical Colombian year: a calendar that has a total of 15 holidays that do not belong either to Holy Week or to the Christmas season; the majority are celebrated on Mondays, but some may fall on any other day of the week.

The model is formulated so that there is an optimal value for the maximum number of rooms to be reserved for each type of customer for each day. In order to obtain a final set of results we organized these daily results as follows: after separating the results from all of the 10 runs according to the type of customer that they belong to, we sorted them into the five different periods of the year analyzed. We then had 15 groups of results: each group with the same number of results as the number of days of that category in 50 years (e.g., there were 750 results in the Holidays group for each class– 15 holidays per year X 50 years-). Finally, to obtain a punctual result, we calculated the averages for each one of the 15 groups. These averages are the final results for the simulation done with the Optimization Model, which are shown in *Table 6*.

Optimization Model			
	Corporate	**US**	**Others**
Weekday	20	25	37
Weekend	22	25	37
Holy Week	21	37	34
Holiday	37	24	34
Christmas	26	37	34

Table 6. Maximum number of rooms that should be protected for the different classes in the different periods of time according to the Optimization Model

The results from the Optimization Model are denoted in the same form as the EMSR models. The number shown for each combination of class and type of day represents the maximum number of rooms that should be allocated on that particular type of day for the specified class. For instance, if a Corporate customer arrives to the hotel on a Weekday and there are already 20 rooms booked for other Corporate customers – whether arriving that same day or on previous days –, she should not be allocated a room for that night.

Although the results from the two EMSR models are very similar, it can easily be appreciated that the results from this model are not very similar to the results from the EMSR models. We choose to continue working with the Optimization Model for two reasons. First, its results are optimal values and the EMSR's results are approximation through heuristics. Furthermore, its results regarding the expected yearly revenue are of US$678,500, being better than the EMSR-*b*'s expected revenue of US$677,500. Henceforth, the results that will be considered as final and that will be analyzed thoroughly in a sensitivity analysis will be the those of the proposed Optimization Model.

4.3. Sensitivity analysis

Having decided to recommend the results from the proposed optimization model for our case study, we proceeded to analyze these results by changing some parameters of the model. Since the main objective for the problem is to maximize revenue for the hotel, we decided to verify the impact of changing the prices have on the final results.

To test the sensitivity of the prices we used the results from Imbett et al. (2013), in which they analyzed the elasticity of the demand for the customers of our case study. Their results are presented in *Table 7*, where d_{jl} denotes the demand from customer j on day l, and p_{jl} represents the price a costumer j pays for a room on day l.

Elasticity results	
Non-Corporate customers	**Corporate customers**
$d_{jl} = 5.72e^{-0.0018133 * p_{jl}}$	$d_{corporate,l} = 20.15e^{-0.0012427 * p_{corporate,l}}$

Table 7. Elasticity results from Imbett et al. (2013)

These equations were used for calculating the demand after varying the prices. The first was used for the demand of customers of the classes US and Others, and the second equation was used for Corporate customers.

Two exercises were done in the sensitivity analysis phase. The first was varying the prices of all of the classes at once for every of the analyzed periods of the year at the same rate. The second exercise was to vary the price of only one class at a time for every moment of the year.

4.3.1. First exercise

For the first exercise, we tested to increase and decrease the prices for all classes at the rates of 1%, 5% and 10%. After analyzing the results for these three scenarios, we observed that the conclusions for the three were the same, therefore we are going to show the results from the scenario where we increased and reduced the price by 10%. These results are shown in *Table 8*, where we also show the baseline results and compare each of the results with the latter.

	Baseline		
	Corporate	**US**	**Others**
Weekday	20	25	37
Weekend	22	25	37
Holy Week	21	37	34
Holiday	37	24	34
Christmas	26	37	34

(a)

	+10% on all classes		
	Corporate	**US**	**Others**
Weekday	21	26	37
Weekend	21	25	37
Holy Week	22	37	35
Holiday	37	23	33
Christmas	27	37	34

(b)

	-10% on all classes		
	Corporate	**US**	**Others**
Weekday	20	25	37
Weekend	20	25	37
Holy Week	22	37	35
Holiday	37	24	33
Christmas	25	37	34

(c)

	+10% on all classes differences		
	Corporate	**US**	**Others**
Weekday	1	1	0
Weekend	-1	0	0
Holy Week	1	0	1
Holiday	0	-1	-1
Christmas	1	0	0

(d)

	-10% on all classes differences		
	Corporate	**US**	**Others**
Weekday	0	0	0
Weekend	-2	0	0
Holy Week	1	0	1
Holiday	0	0	-1
Christmas	-1	0	0

(e)

Table 8. Results from varying price on all classes by 10%

From the results of the first exercise of the sensitivity analysis, shown in *Table 8*, we see that there are no significant variations from the baseline results (*Table 8.a)*. In any case the biggest variation was to reduce only two rooms the maximum allocation permitted to Corporate customers on Weekends when prices were reduced by 10% *(Table 8.e)*. As we had affirmed previously, we faced the same type of results when varying prices by 1% and 5%; there was no significant impact on changing all the prices at a time. These results are understandable due to the nature of the exercise: by changing all class prices at the same rate the behavior of the customers will still be the same, and hence the hierarchical organization of classes will be unaffected.

4.3.2. Second exercise

From the conclusions of the first exercise, we went on studying the impact of changing the prices of only one class at a time had on the results. This exercise was done for each of the three classes by applying changes of their prices by 10%. Once again, the results from the three scenarios were very alike and they all presented the same conclusions, consequently we only show the results from one of the scenarios: varying the prices of only the Others class. As shown in *Table 9*. Once again, for further comprehension of the results we indicate the baseline results and their comparisons.

Baseline	**Corporate**	**US**	**Others**
Weekday	20	25	37
Weekend	22	25	37
Holy Week	21	37	34
Holiday	37	24	34
Christmas	26	37	34

(a)

+10% on Others Class' fares	**Corporate**	**US**	**Others**
Weekday	21	26	37
Weekend	20	25	37
Holy Week	21	37	34
Holiday	37	22	33
Christmas	27	37	33

(b)

-10% on Others Class' fares	**Corporate**	**US**	**Others**
Weekday	22	37	33
Weekend	20	37	32
Holy Week	22	37	35
Holiday	37	34	26
Christmas	26	37	34

(c)

+10% on Others Class' fares differences	**Corporate**	**US**	**Others**
Weekday	1	1	0
Weekend	-2	0	0
Holy Week	0	0	0
Holiday	0	-2	-1
Christmas	1	0	-1

(d)

-10% on Others Class' fares differences	**Corporate**	**US**	**Others**
Weekday	2	12	-4
Weekend	-2	12	-5
Holy Week	1	0	1
Holiday	0	10	-8
Christmas	0	0	0

(e)

Table 9. Results from varying fares for Others class by 10%

The results from the second exercise are more interesting for the considerable changes they have with the baseline results. As it is shown in *Table 9.e.*, when the prices for Others class is reduced by 10%, there are three moments of the year (Weekdays, Weekends, and Holidays) when the results experience significant variations. For instance, during a Weekday the hotel should increase the maximum allocation for US by 12 rooms, increase the protection of Corporate rooms by 2 and reduce by 4 rooms the maximum allocation for Others customers. These three significant changes take place in the moments of the year when the reduction of the price for Others class implies a change in the hierarchical order of the prices: when the price of Others is reduced by 10% on a Weekday, the Others class passes from being the first class to the second class, permitting the US class to be the first.

5. Conclusions and Future Work

The SRCCP for our case study was solved via the analysis of its data and by using an optimization model. Reliable results of the maximum number of rooms that should be allocated to each type of customer on every moment of the year in order to maximize the revenue were obtained for our case study.

We worked on two types of models, the EMSR heuristics and an optimization model. For this particular problem using the data of our case study we found that the results from the Optimization Model were more reliable than those from the EMSR models for the method they were obtained and for their results on expected revenue.

Significant variations of the final results are observed when the changing of prices of the classes incur into changes in the hierarchical order of the classes. By changing the price of one class in specific intervals, for the order of the classes not to be affected, the results obtained will still be the recommended.

For future work, it is suggested to understand the effects of relaxing the assumption that the arrivals of the customers followed a Poisson process. Likewise, it is also suggested to study the implications of annual negotiations with Corporate customers on the results.

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