Group Coursework Submission Form

Specialist Masters Programme

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MSc in: Business Analytics

Module Code: SMM641

Module Title: Revenue Management and Pricing

Lecturer: Dr Oben Ceryan	**Submission Date: 22/02/2021**

Declaration:
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Group Coursework 1

REVENUE MANAGEMENT AND PRICING SMM641

FEBRUARY 22, 2021

CASS BUSINESS SCHOOL
GROUP 7

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Question 1

The problem is an example of the single resource, two fare class setting using Poisson distribution. In this case, the single resource is the product at hand and the two fare classes are the sandwiches and croissants. Price for the lower fare is that of the croissant, which in this case is £1.00 and for higher fare is that of the sandwich, which is £1.50. 1. Additionally, it is known that the demand in the morning for individual croissants is Poisson with mean 50 and the demand for croissant sandwiches during lunch is Poisson with mean 20. It is assumed that all the unsold commodities at the end of the period are of no value and must be discarded.

1.a

Café's daily revenue:

Assumption: The café reserves no croissants for lunch time and serves ALL customers based on a first-come first-serve basis, setting the protection level to 0.

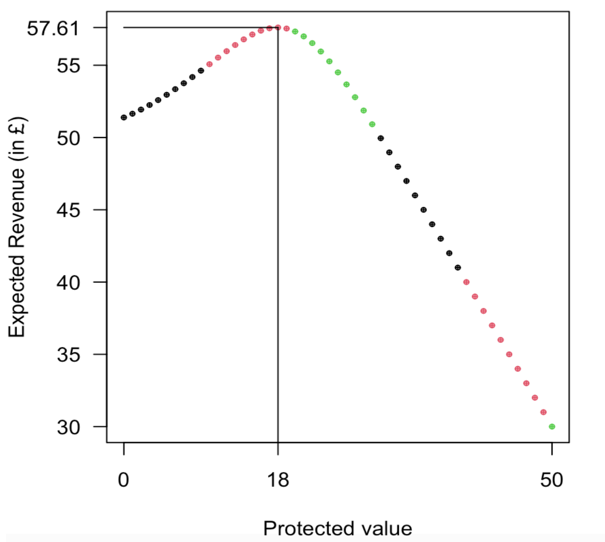
Result: The café's expected revenue lies at a lower limit of 51.4. And with "perfect foresight" assuming that we are applying the best allocation, lies at 60.

1.b

Maximise expected daily revenue:

In order to calculate the optimal limit so as to increase the revenue to the highest possible extent, analysis was carried out on the basis of Littlewood's rule. It was found that the optimal protection level for high-fare demand is 18. This also means that the optimal protection level for low-fare demand is 32.

Graph 1: Protected value, expected revenue – mean demand for low-fare and high-fare being 50 & 20 respectively, price for low-fare and high-fare being £1 and £1.50 respectively.



1.c

Percentage Improvement:

Upon further analysis, it was also found that the difference in percentage among the approach 1 and approach 2 is roughly 12%. Suppose the bakery were to sell its products on an FCFS basis, they would make 12% lesser profit than they would, if they prioritised selling in order to maximise revenue.

1.d

Allocation decision changes with changes in expected demand was analysed. 7 instances were covered. It can be noticed that with the increase in mean demand for fares, there is a rise in the expected revenue. Albeit, doubling of the protection value from instance 2 to instance 3, the expected revenue only increases marginally. This is also the cases noticed in the next set of instances. Therefore, it may not be advisable to increase the protection levels. In case of the occurrence of some unexpected events which could affect the expected demand for the lunch time (e.g., weather conditions). In this case, the protected commodities will be redeemed useless.

Mean demand for high fare	10	10	20	25	30	40	40
Mean demand for low fare	10	40	30	25	20	10	40
Protection Value	9	9	18	23	28	37	37
Expected Revenue	**25**	**51.41**	**56.13**	**58.53**	**60.94**	**65.82**	**66.6**

Question 2

2.a

General Assumption:

- At the end of the terminal period, all unsold tickets are worthless
- There are a total of 301 periods, including the terminal period. As a result, the periods analyzed starts from 300 which corresponds to 0 in R programming computation.

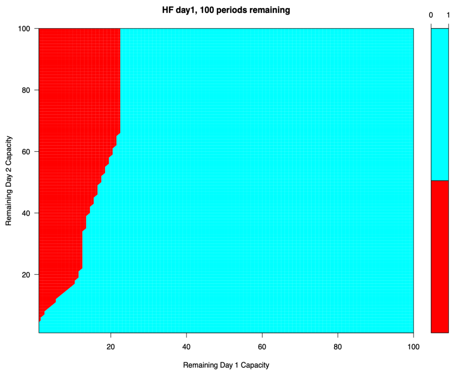
Results:

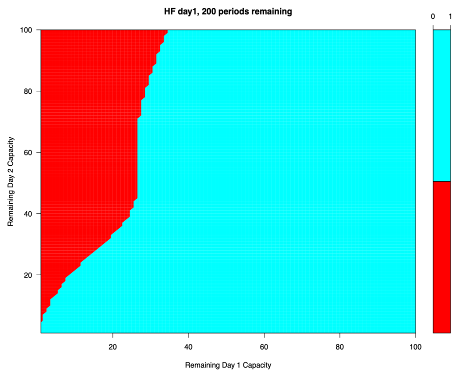
- Generated Revenue: **22679.83**
- Algorithm run time: ~ 13.402 seconds

Insights:

Structure of the Optimal Acceptance Decision

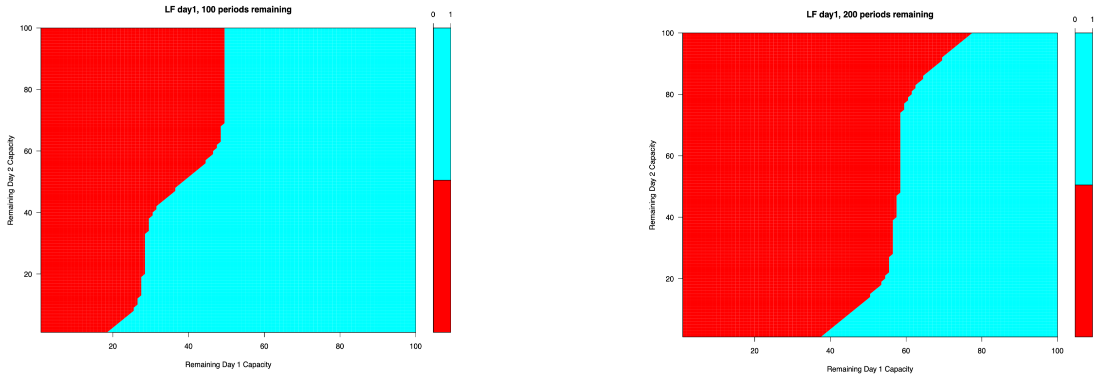
Graph 2: High Fare Class Day 1





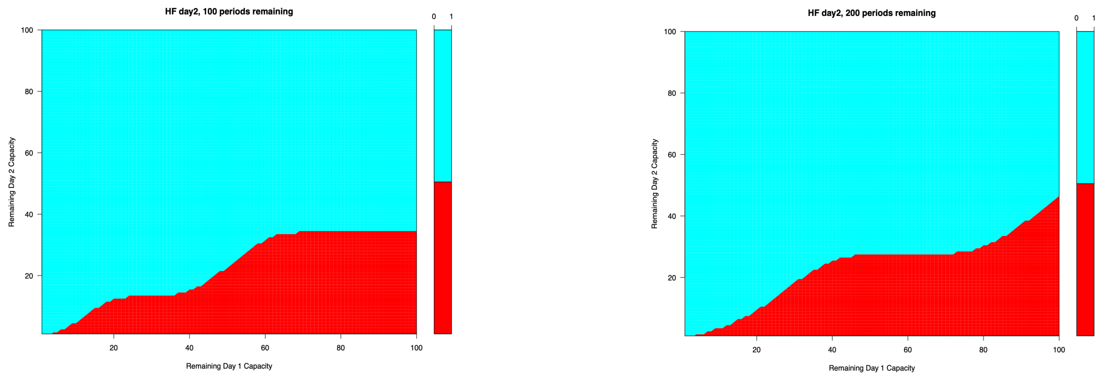
Analyzing the graphs above, it is possible to conclude that High Fare class Day 1 requests are more likely to be accepted given that there is a greater availability of Day 1 tickets. However, it is evident that there is a quite large quantity of tickets remaining for Day 2, consequently the High Fare Class Day 1 requests are more likely to be rejected in order to preserve the combination of Day 1 and Day 2 tickets. Lastly, with fewer periods remaining, the High Fare Class for Day 1 requests are less likely to be rejected. This is a logical conclusion as one would be less confident whether, with the remaining periods, the combination of both tickets can still be sold.

Graph 3: Low Fare Class Day 1



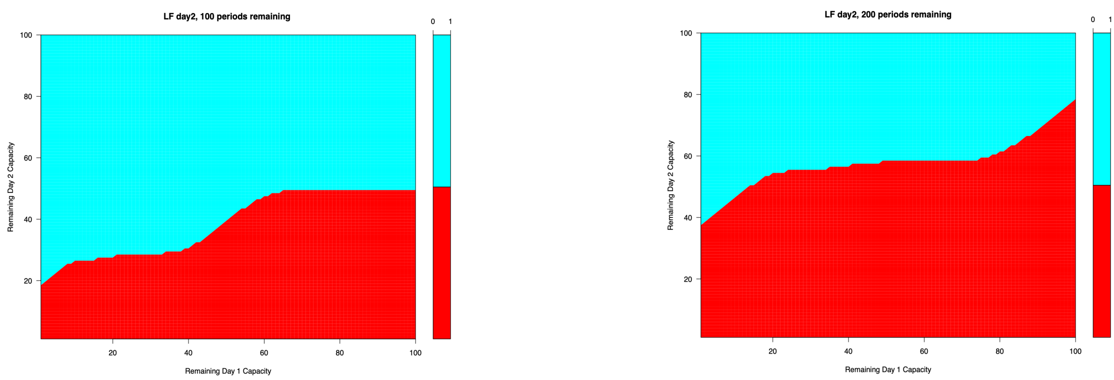
The interpretation for the graphs above is very similar to the High Fare Class for Day 1 case. Overall, Low Fare Class for Day 1 is more likely to be rejected given the same availability of Day 1 tickets. Indeed, this is a logical decision as we are more confident that we can sell a High Fare Class Day 1 ticket, which contributes to a higher revenue amount for a limited availability. Also, it is evident that one should be more decisional sensitive about accepting or rejecting the Low Fare class – as in practice, one would innately want to accept only the High Fare class, due to the fact that the ticket price is higher by 33% than the Low Fare's ticket price, regardless of the number of periods remaining.

Graph 4: High Fare Class Day 2



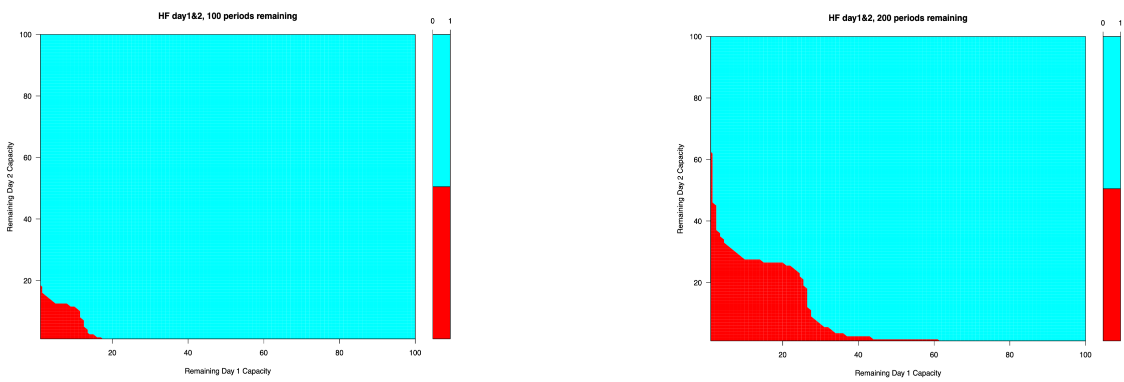
Analyzing the graphs above, it is evident that when there is higher level of availability of Day 2 tickets, High Fare Class requests for Day 2 are more likely to be accepted. However, it important to notice that when there is greater level of availability of Day 1 tickets, the High Fare Class requests for Day 2 are likely to be rejected. The reason behind the previous decisions relies on the fact that instead of selling individually the High Fare Class for both day tickets, it would be optimal to bundle the two-day tickets and sell the tickets bundled. Hence, the tickets have been reserved for such cases. Furthermore, it is important to notice that as availability for Day 1 tickets decreases, the requests for this product are less likely to be rejected because one would be less confident whether the combination of both tickets can be sold given the remaining periods. Lastly, given more time periods to go, the requests for the product are more likely to be rejected because given Day 1 availability one would be more confident that the bundled tickets can be sold.

Graph 5: Low Fare Class Day 2



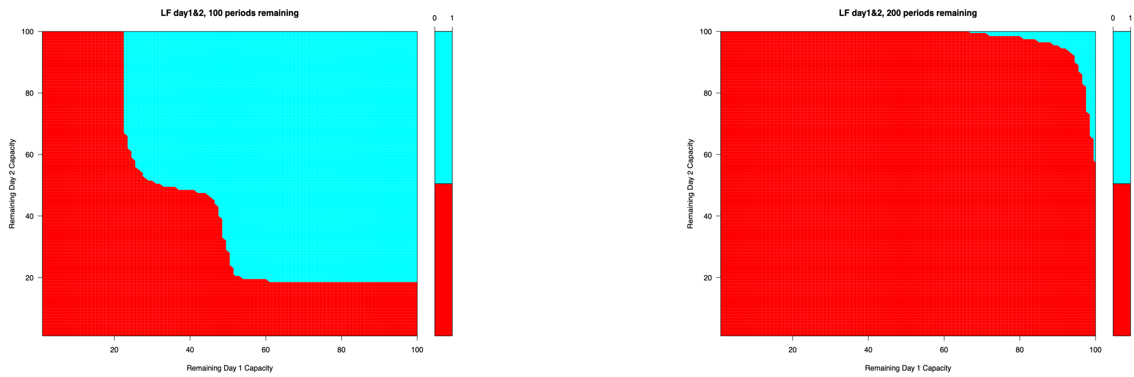
The interpretation of the above graphs is similar to that of High Fare Class for Day 2 tickets, except that most of the requests for this product are rejected compared to High Fare Class for Day 2. The logic behind the decision relies on the fact that High Fare Class for Day 2 tickets contribute to a higher level of revenues. It important to notice the sharper difference at t = 100 and t = 200, compared to the High Fare Class for Day 2. One possible explanation could be that the ticket price generated by accepting Low Fare Class is considerably lower than High Fare Class (50% less), and hence one could be more decisional sensitive about accepting or rejecting the Low Fare class.

Graph 6: High Fare Class Day 1 and Day 2



The above graphs follow the same reasoning as described in the previous set of graphs. Particularly, these two graphs illustrate that, on most occasions, we should accept the High Fare Class Day1 and Day 2 requests except for situations where the availability of remaining tickets of both Day 1 and Day 2 is low. The reason relies on the fact that selling the tickets individually, instead of the combined tickets, can yield more revenues (i.e., HF day1 + HF day2 > HF day1&day2). Hence, one is confident that when tickets' supply is limited, one can sell the tickets singularly. Indeed, when there are more periods to go, the requests are more likely to be rejected given the remaining tickets, because there are still more periods available to sell the tickets individually.

Graph 7: Low Fare Class Day 1 and Day 2



Lastly, the interpretation of these two graphs is very similar to the previous analyzed scenarios– except that in this case, the Low Fare Class requests for Day1&Day2 are more likely to be rejected than High Fare Class requests for Day1&Day2 for a given supply availability. In fact, as a consequence of the fact that there more remaining periods, one is more likely to reject this class and to favor other requests. Mainly, 200 remaining periods illustrate that one almost always rejects the requests from this product. This analysis conforms with the shadow-price analysis, which shows that the product's price is lower than the calculated bid price and hence any incoming requests of this product should be denied unconditionally. However, when there are 100 remaining periods, the request of this product is more likely to be accepted if there is great availability of tickets remaining, but still reject when the tickets' supply is limited for either Day 1 or Day 2.

To summarise, for this algorithm, the client can inspect the aforementioned structure of the optimal acceptance decision graphs and make a decision in order to help maximizing the revenue accordingly. Further, the advantage of this approach is the fact that it can achieve the optimal solution and make error free decisions due to the nature of dynamic programming. Disadvantage of the algorithm is that it's run time can be larger than other heuristic approaches. It can additionally be generalised to other cases that will be illustrated in the following analysis below.

2.b

Results:

- Generated revenue: **19719.77**
- Algorithm run time: ~ 4.7 seconds

Insights:

The FCFS approach has a faster run-time but generated less revenue (~ 13% less) than the first one.

2.c

Results:

- Generated revenue: **21915.6**
- Algorithm run time: ~ 4.518 seconds

Insights:

Incorporating bid-price result reduces the number of products from six to five, as the Low Fare Day1&Day2 price (150) is less than the calculated bid price (100 + 80 = 180). Hence, we reject the Low Fare Day1&Day2 requests for all cases. This result is very close to the optimal revenue (particularly it is 3.4% lower than the optimal revenue value), and the algorithm is computationally inexpensive as the algorithm run time is very low. However, caution must be applied in this scenario as, when calculating the bid prices the absolute numbers of demand for each product are assumed to be known unlike just probabilities in the previous algorithms.

2.d

Results:

- Generated revenue: **22664.31**
- Algorithm run time: ~ 7.4 seconds

Insights:

As a result of the information gathered from the bid-price solution, we reject the LF day1&day2 requests for all cases. Additionally, the structure of the optimal acceptance decision figures, illustrated and analyzed previously, have shown that High Fare products are more likely to be accepted compared to Low Fare products of the same class, given approximately the same tickets' availability. Given the aim to reduce computational time, the FCFS approach has been applied to all High Fare classes, but still compares the expected revenue generated from accepting the Low Fare class with the one obtained from rejecting them and hence, choosing the one which generates more revenue as the aim is to obtain as much revenue as possible with faster algorithm run-time compared to 2.a solution. The obtained revenue is roughly similar (0.06 % less) to the revenue obtained in 2.a. But, on average, the algorithm runs much faster (81 % faster). This is a predictable phenomenon as the products in consideration have been reduced from six to five and particularly three of the products have been clearly simplified which allow for an increase in computational speed. Furthermore, it still keeps the algorithmic decisions based on value functions for the other LP products and hence achieves a closer solution to the optimal revenue.

2.e

Table 1: Comparisons among all models

Algorithms	Run-time (seconds)*	Revenue Generated (pounds)	% Different of run-time from the baseline	% Different of revenue generated from the baseline
2.a	13.402	22679.83	NA	NA
2.b	4.7	19719.77	-185.14894	-15.010621
2.c	4.518	21915.6	-196.63568	-3.4871507
2.d	7.4	22664.31	-81.108108	-0.0684777

* The result has been performed 10 times, and obtained as average values on a similar setting on MacBook Pro 2020 (Processor: 2.3 GHz Quad-Core Intel Core i7; Memory: 16 GB 3733 MHz LPDDR4X; Graphic: Intel Iris Plus Graphics 1536 MB)

Suggestion:

It can be argued that in a world of inundated data and intense competition, a difference in algorithmic milliseconds can have a tremendous impact on a business bottom line (Osipovich, 2020). For this reason, we advocate the algorithm 2.c, which achieves slightly less (3.4%) than the optimal revenue but is computationally faster (196.6%) to run.

Question 3 – 2021 Monaco Grand Prix Case Study

Introduction

The Monaco Grand Prix is a well-renowned and traditional Formula One motor race, first held in 1929. Out of the other circuit locations, which include Bahrain, Italy, United States and United Kingdom, Monaco is very unique comprising a 3.18km circuit and a 300m tunnel included in the track (Scaglione, 2003). Being located at the heart of a tourist location, it certainly attracts a massive international crowd of motor racing lovers, contributing to Monaco's hospitality sector and, consequently, its economy.

The Monegasque Institute of Statistics and Economic Studies (IMSEE) concluded that the economic benefit of Monaco Grand Prix in 2017 summed up to 90 million euros over a period of 4 days (Monaco, 2018). What is even more apparent is the contribution of general sporting events – not only in Formula One racing. Statista's Digital Market Outlook publication in 2019 showed that the global sports events segment amounted to 25 billion US dollars and is still expected to grow (Maglovska, 2020). The main sources of the growth are the prominent roles of these events in creating employment opportunities and bringing more tourists into the nation. In particular, the Monaco Grand Prix is also quite influential in shaping the principality's image, with such a popular sporting event drawing and raising public attraction and awareness. Of course, if the event is managed well and professionally, it certainly heightens its prestige and people's perceptions of the principality, or any other countries holding such an event. Furthermore, the event itself is much beneficial to the principality than it is for its stakeholders: the Formula One teams/drivers are able to entertain, compete and have the honours of being crowned awards with the ability of gaining several sponsorships, while the spectators are able to enjoy the thrills of the high speed race and any hospitality services. All in all, it is evident that the Monaco Grand Prix is one of the most, if not the most, important event for the principality and the most impactful for all of Monaco's businesses, particularly the hospitality sector.

In Monaco, leisure tourism represented 79% of total hotel activity, with an average of 600,000 overnight stays per year – while visiting day tourists in Monaco are estimated at over 5 million each year (lsc.hbs.edu, 2011). However, the effects of Covid-19 have to also be considered. At the moment, the Monaco government have set strict rules with regards to social distancing, travel and gatherings – currently, gatherings of more than 5 people are prohibited (Monaco, 2021) – hence, it is expected that attendance of the event will drastically decrease if the green light is given to hold the event in the coming months.

Considering all these factors, the aim of the Question 3 analysis is to observe the effects the Monaco Grand Prix has on the principality's hospitality sector, particularly through focusing on some collected data and some simulated, dynamic programming methodologies and analyses on how the Fairmont Monte Carlo Hotel – a luxury and popular hotel overlooking the Grand Prix racetrack – can potentially improve their revenues during the event this year in May.

Demand

As mentioned in the introduction, the Monaco Grand Prix is a globally known event with a rich tradition and, of course, its reputation undoubtedly attracts tourists and spectators from a local and international audience. Consequently, the demand for hotel rooms is likely to rise sharply both before and during the event. However, again, due to Covid-19, the number should be much lower than in a Covid-19-free scenario, though there should be an increase given its current demand. Furthermore, there are typically 3 types of people involved with the event: the drivers – who are the active participant of the event; the spectators – whom many of them are tourists; and media reporters, journalists and commentators – who observe any occurrences during the event. These stakeholders generally correspond to the types of people received at hotels, with the inclusion of other leisure tourists, businesspersons and motor racing engineers/personnel. Although, it is likely that there will be less leisure tourists and spectators, given the restrictions and potential deterrence due to the seriousness of the virus, though drivers, businesspersons and motor racing engineers are highly likely to stay at hotels during this period.

There are quite a few limitations to our demand set-up. First and foremost, we are unable to predict whether Covid-19 cases will increase in the lead up to the 2021 Monaco Grand Prix, which can either cause it to be cancelled (as announced for the 2020 Monaco Grand Prix) or be held behind closed doors. It is also important to recognise that a majority of attendees are international visitors/tourists, and depending on the restrictions in those countries, e.g., with the UK restricting international travel, attendance could fall further. All these factors directly correlate to the demand for hotels – if there is no event, it is likely that hotels, including the Fairmont Monte Carlo Hotel, will not experience any increases in revenue than it currently is. However, if the event is held behind closed doors, we expect there to be a small to medium increase given the drivers, engineers and other Formula One personnel need a place to stay. All in all, in our demand set-up, we consider an almost best-case scenario, given the current pandemic, whereby a limited public audience will be allowed to attend the event, as well as stay over in hotels during the event period.

Supply

The following analysis focuses on evaluating an optimal pricing strategy to maximise revenues for the Fairmont Monte Carlo Hotel during the Monaco Grand Prix. The hotel's choice to analyse has been careful evaluated based on different factors. Firstly, the Fairmont hotel has always been linked to the Monaco GP because of its worldwide known prestigious location surrounded by the circuit. Secondly, it represents a mainly touristic attraction for true aficionados, fans and corporate guests during the Gran Prix period. In fact, individuals and corporate groups account for 70% of the bookings with a minimum stay of 3 nights (Sylt, 2016).

The Monte Carlo total hotel capacity is 2623 guestrooms, but the Fairmont accounts for the 23% by supplying 602 guestrooms (Andreadi et al, 2011). The F1 Grand Prix period cause a high peak demand, particularly Monte Carlo supply-and-demand dynamics in the luxury tourism is characterized by the demand being much higher than the supply (Scaglione, 2003).
The tourism's nature is such that competition is to a large extent global, but within Monaco standards and quality control based on the start rating system is transparent among the assessment of each hotel's capabilities, as a consequence local competition amongst Monaco's hotel is not very intense because it is controlled by the Tourism Authority, which requires a collaborative strategy. However, it is important to consider competitors in order to strategically set the prices and identify the target demand to accept. The Fairmont hotel's main competitor is the Monte Carlo SBM, which the market leader supplying a total of 1000 rooms across its four hotels (Andreadi et al, 2011).

The customers of the Fairmont hotel are mainly individuals passionate about motor racing, the invitees of large companies, and the F1 personnel, which includes journalists. These demand categories usually pay for the accommodation one year in advance and present a 10% rate of cancellation. The revenue mainly depends on the economic conditions and the sport event timing but the Grand Prix generates stable revenues yearly, as the demand vastly exceeds the supply of rooms (Scaglione, 2003).

Data and analytics specialists demonstrated that the Monaco's average rate at hotels increases by 250% the night before the Grand Prix compared to the monthly average. The average daily rate at hotels rose by 246%, particularly from $610 average for the month of May to the weekly peak of $2113 on the night before the Grand Prix in 2015. The rate remains stable on the F1 night and its pricing impact is still evident on further weeks. Also, the Grand Prix event benefits Monaco's hotels for the whole F1 week as the hotel's average rate dramatically increases from Wednesday night to Thursday night. Compared to Thursday, Saturday's price increases by 5.4% and Sunday's price reaches a 6.6% increase. The tremendous weekend price increases are due to the occupancy peak, which reaches 86.1% average rate compared to the average rate of 69.2% for the month of May. In fact, 100,000 people are estimated to be in Monaco for the Sunday event. The total week contributes to an estimated turnover for the city around $100 million (Sylt, 2016).

Data Collection

Through a very carefully conducted data collection, prices and arrival probabilities have been defined for Product 1 and Product 2 for the Fairmont Hotel in the period between May 20th and May 24th, as shown in Table 2.

Table 2: Final Data for Estimated Revenue Maximization (2 Products Analysed)

	Booking Type	Fare (Per Night)	Total Cost	Arrival's Probability	Mean Demand
Product 1	3 Nights (May 21st-24th)	£230,00	£690 for Low Fare	65%	70
Product 2	4 Nights (May 20th-24th)	£200,00	£800 for High Fare	25%	30
Capacity = 60 guestrooms			Probability of No Arrival: 10%		

Product 1 has been defined as the guests willing to stay three consecutive days from May 21st to May 24th and who are willing to pay £230 pounds per night. Product 2 has been defined as the guests willing to stay three consecutive days from May 20th to May 24th and who are willing to pay £200 pounds per night. Furthermore, the prices have been collected from Skyscanner, which is a metasearch engine and online travel agency. The original price for Product 1 was £2,315 per night, while the original price for Product 2 was £1,997.5 per night. For computational purposes, the original prices have been reduced by 90%, so the final price for Product 1 is £230 per night and the final price for Product 2 is £200 per night. Lastly, the final total combined prices used are: £690 for Product 1 which corresponds to the Low Fare class, and £800 for Product 2 which corresponds to the High Fare Class. As a result, the total cost values (Table 2) have been used as the price for Product 1 (Low Fare Class) and the price for Product 2 (High Fare Class) in the computational procedures.

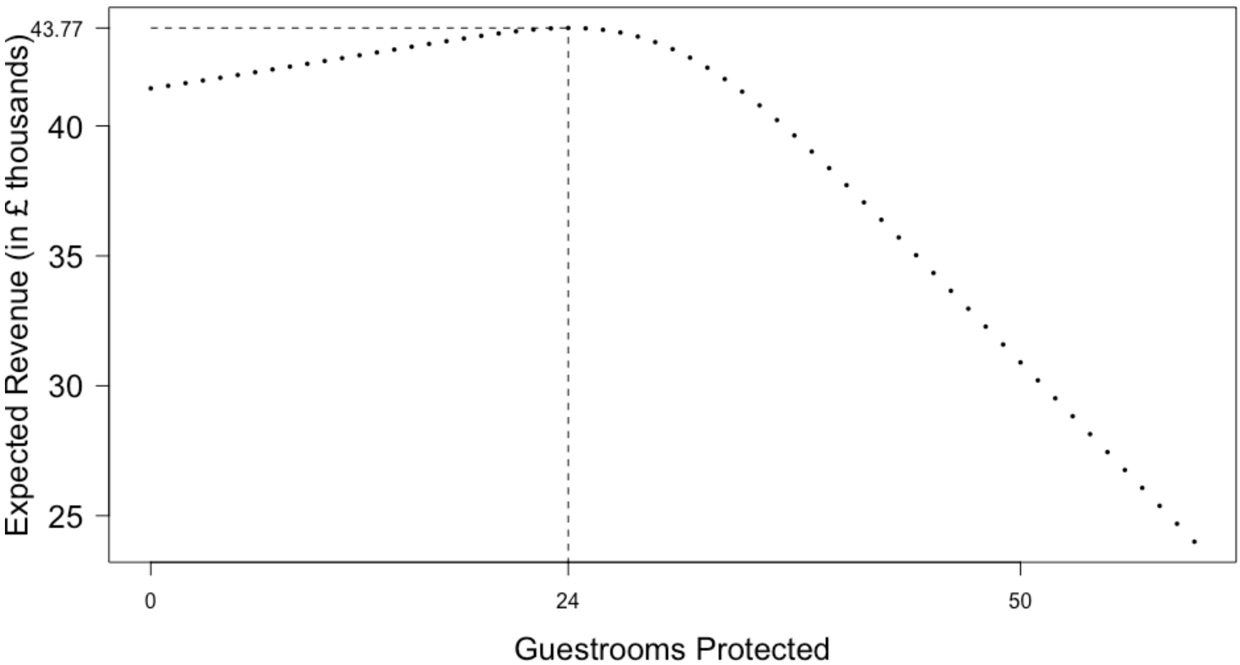
The Fairmont Monte Carlo hotel has an original capacity of 602 guestrooms, but the analysis does not cover the management allocation for suites, which account for 6 rooms. As a result, the following analysis will consider a total capacity of 592 guestrooms. Similarly, the Fairmont Hotel capacity under analysis has been scaled by 0.1 which corresponds to a total of 60 guestrooms to strategically allocate to maximize the hotel's expected revenue during the Grand Prix period.

The demand for Product 1 has been assumed to follow a Poisson distribution with mean set to 70. Instead, the demand for Product 2 has been assumed to follow a Poisson distribution with mean set to 30. Lastly, the arrival probability related to Product 1 has been estimated to be 65% and the arrival probability for Product 2 has been estimated to be 25%. Particularly, the probabilities have been estimated based on what has been discussed in the Supply Section. In fact, given that occupancy reaches an 86.1% occupancy peak for the Grand Prix weekend and that 100,000 people are expected to participate to the Grand Prix Sunday's race, the biggest weight on the arrival's probability has been assigned to Product 1. Also, a probability of no arrival has been set to 10%, meaning that it has been assumed that the client (Fairmont Hotel) will not receive any requests for any period with a probability of 10% due to external factors, such the Covid-19 travel restrictions.

Analysis 1

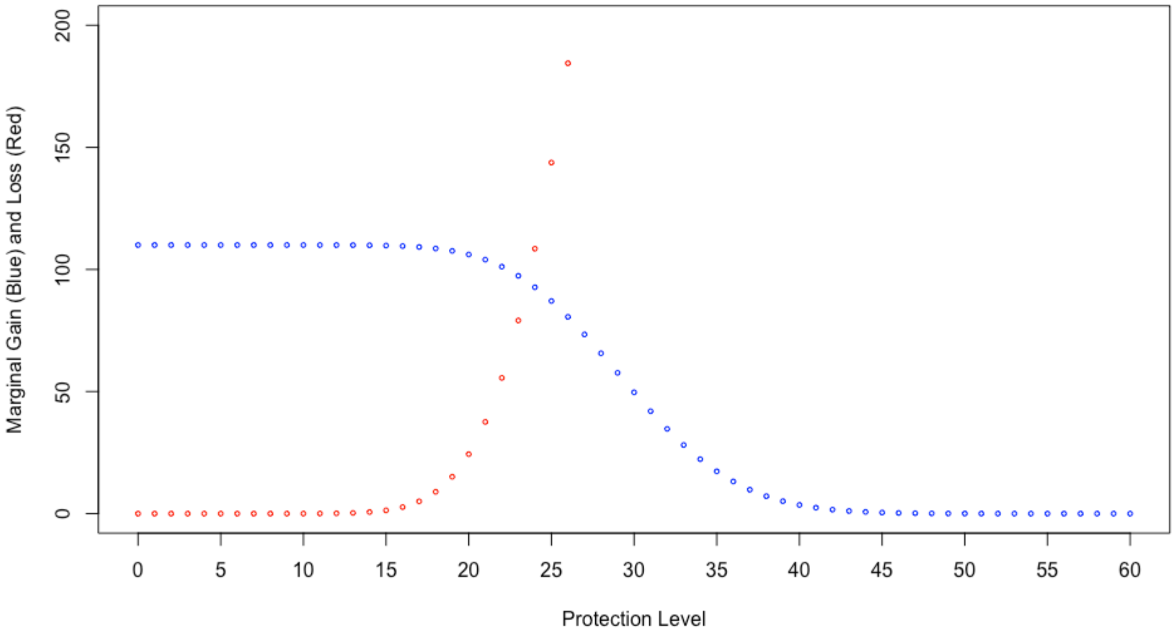
The following analysis aims to find the optimal protection level for the High Fare class demand, which corresponds to Product 2. Using an algorithm which iteratively goes through all protection possibilities (Method 1), we find that the optimal protection level equates to 24 – which, in other words, means that to optimise revenue, 24 rooms need to be protected for Product 2. Subtracting this value from the total capacity (60) gives us the optimal protection level for Product 1, which produces 36 rooms. Graph 8, offers a visual representation of the effect of marginal increases in rooms with expected revenue, and we observe that there are diminishing marginal returns after the 24th room. Thus, the total expected revenue will be £43772.45.

Graph 8: Expected Revenue vs. Protection Level



Graph 8 shows the number of guestrooms to protect on the X-axis, and the Expected Revenue (£ thousands) on the Y axis. Particularly, the dashed perpendicular line denotes the optimal value of the protection level for the High Fare Class, which is 24 guestrooms. On one hand, it is possible to notice from Graph 8 that if any room is protected for the High Fare class, the total expected revenue amounts for slightly more than £40,000. On the other hand, when the total capacity amounting for 60 guestrooms is fully protected for the High Fare class requesting Product 2, the total expected revenue dramatically decreases reaching values below £25,000. Initially, protecting additional seats contributes to additional units of expected revenue. In fact, Graph 8 shows that the expected revenue reaches the maximum amount of £43,772.45 at the interception point with protection level set at 24 guestrooms. After the protection level of 24, any other additional protected seat becomes detrimental for the expected revenue, which shows a decreasing trend.

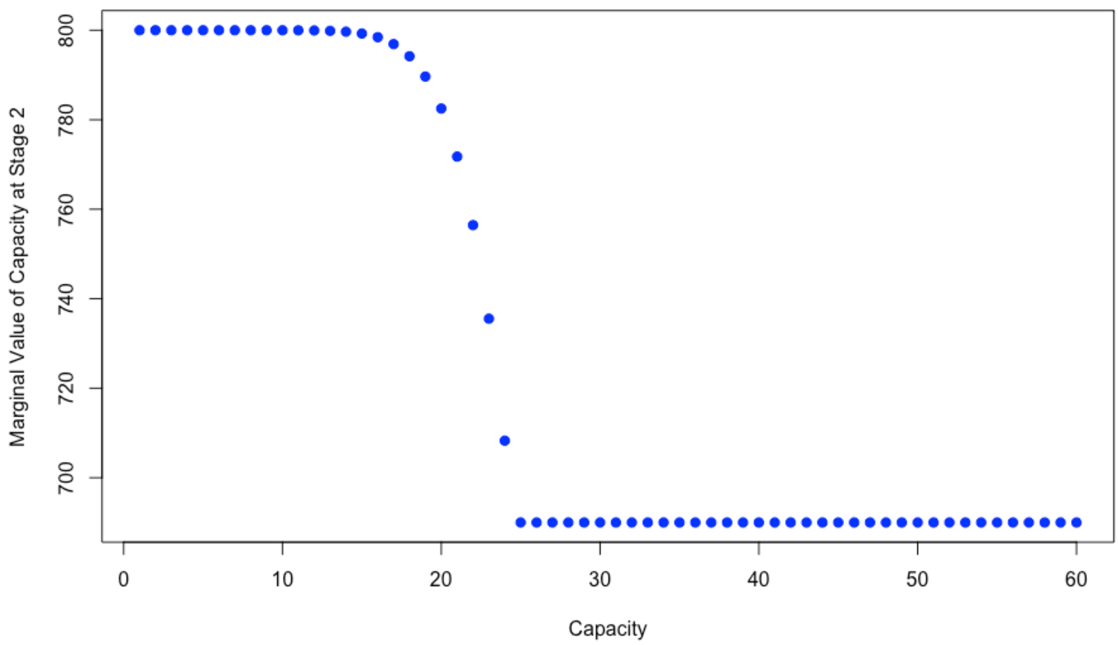
Graph 9: Marginal Gain vs Marginal Loss



Graph 9 shows how changes in protection level actually affect the marginal revenue and the marginal loss. Particularly, the blue dotted line represents the expected gain for any additional protected guestroom. The red dotted line represents the expected loss for any additional protected guestroom. Supposing, no guestrooms have been protected, then the entire capacity supplied by the Fairmont Hotel would be available for the Low Fare class requesting Product 1. However, any additional room, until a maximum of 24 guestrooms, is certain that can be sold to the High Fare class rather than to the Low Fare Class. In fact, for any additional room, it is evident that the marginal gain is above the marginal loss until the interception between the two lines corresponding to 24 guestrooms. However, after the optimal protection level of 24 guestrooms, protecting one additional room is not profitable because, given the High Fare demand distribution, there is less likelihood that the room will be purchased by the High Fare class due to the fact that demand will not be sufficient to purchase the additional protected room. In fact, if the Firemont Hotel protects the whole capacity, so 60 guestrooms, for the High Fare class there are no chances that the rooms will be purchased and as a consequence the marginal loss will dramatically exceed the marginal gain. Mainly, the hotel, by protecting over the optimal protection amount for the High Fare class, will be losing the amount of prices paid by the Low Fare Class for Product 1. Graph 9 confirms that the optimal level to protect is 24 guestrooms, which is the point where the marginal gain and the marginal loss are balanced.

The analysis also opted to explore the optimal admission decisions for the two-fare classes with sequential arrivals to assess any changes (Method 2). Using dynamic programming recursion, it has been essentially obtained the same results as before, protecting 24 rooms and total expected revenue amounting for £43,772.45.

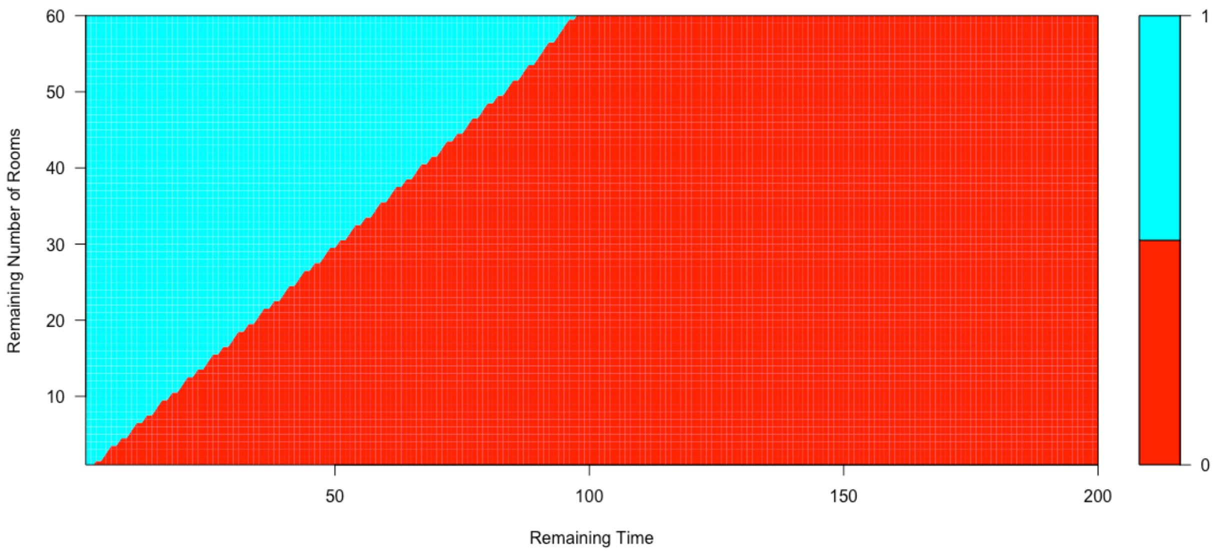
Graph 10: Value of an Additional Unit of Capacity



Graph 10 shows the capacity level on the X-axis and the marginal value of Capacity for each additional room given. The main observation is that the marginal value of capacity decreases as capacity level increases. When the availability of rooms is quite large, it is more likely to sell that room to customers willing to pay a lower price, mainly Product 1. When the rooms' availability is quite limited and small and there are sufficient periods to go, then it is certain that some of the rooms will be sold to the High Fare Class willing to pay a higher price. But when the rooms' availability is large, then it is less likely that some of the rooms are sold to the High Fare class. But after a certain level of capacity available, there are less chances that rooms will be sold to the High Fare Class at £800 for Product 2. For example, if there are still 40 rooms available, it is very likely that there will be High Fare customers willing to pay roughly £780 for some rooms. Particularly, after a given quantity one should settle on a marginal value for rooms of £620. For example, if there are 30 rooms still available, then each additional room sold will contribute by £620 to the total revenue. In fact, given that very likely there will not be High Fare demand for those 30 rooms remaining, it should be optimal to sell that capacity level to the Low Fare Class. As a result, it is possible to notice that the marginal revenue drops massively for additional capacity when the capacity level reaches 24 guestrooms.

The following research also aims on understanding the optimal admission decision for the two-fare classes with mixed arrivals (Method 3). What is meant by this is that a scenario where customers or guests would arrive at different times is considered, given some assumed set probabilities. Particularly, the analysis estimated a probability of arrival set to 25% for the High-Fare class and a probability of arrival set to 65% for the Low-Fare class. Furthermore, it has been assumed a probability of 10% that there will not be any booking requests for any period. In summary, a total expected revenue amounting to £46,845.32 has been obtained.

Graph 11: Optimal Policy Structure



Graph 11 provides an indication of the acceptance policy and whether to accept or reject Product 2 at a particular given capacity and given time. Particularly, the blue region represents the area where one should accept the Product 1 requests, whereas the red region represents where Product 1 requests should be rejected. For example, if the remaining number of rooms equates to 20 but the remaining time is 100, then Product 1 should be rejected as it is very likely that those rooms could be sold for Product 2 requests. It is important to notice that the rejection region is much larger than the acceptance region, suggesting that, most of the time, we want to wait for Product 2 requests rather than accepting Product 1 to gain an optimal revenue. Unless, there is a limited number of periods remaining, coupled with a quite large number of remaining rooms, then it is suggested to accept Product 1 requests. Hence, what is crucial is to observe the monotonicity of the threshold as it is able to determine the best acceptance policy and decisions.

Conclusion

In conclusion, it is important to note from what has been previously analysed that if the Fairmont Hotel expects a larger demand for Product 2 than the one this research has anticipated, then the optimal strategy should be to adopt Method 3. In fact, Method 3 generates the highest optimal revenue of £46,845.32. The logic behind strategically adopting Method 3 is that the computational procedure involves the use of the probability of arrivals and does not include the expected demand. But the drawback could be that if the expected demand for Product 2 will be realised at a mean set to 30, as the analysis anticipated, then probably Method 3 will not work and will not be an optimal strategy. In fact, in the scenario where the Fairmont Hotel is certain that the anticipated expected demands for Product 1 and for Product 2 will turn out to be the actual demands, then Method 1 and Method 2 are operationally inexpensive procedures to achieve the aim of revenue maximisation. In this particular scenario, the overall revenue created by Method 1 or Method 2 could be substantially larger than the one produced by Method 3 because the latter one requires a team of tech experts who constantly check and update the dashboard that has been generated. Lastly, Method 1 and Method 2 are generated using the expected demand and contribute to the same amount of revenue. But even though Method 3 is generated by using the arrivals' probability, Method 3 produce a total expected revenue which is 7% higher than the Method 1 and Method 2 total expected revenue.

Analysis 2

The following analysis is an extension of the previous one. Particularly, this scenario aims to allocate the given available capacity of 60 rooms to different customers willing to stay at the Fairmont Hotel during a longer analysed period of time compared to the previous analysis. In fact, the period under consideration ranges from May 18th to May 24th. Table 3 shows assumed prices and demand for three additional products under consideration.

Table 3: Final Data for Estimated Revenue Maximization (5 Products Analysed)

	Booking Type	Fare (Per Night)	Total Cost	Mean Demand
Product 3	2 Nights (May 18th-19th)	£40	£80 for Low Fare	100
Product 4	2 Nights (May 19th-20th)	£200	£400 for Medium Fare	50
Product 5	3 Nights (May 18st-20th)	£150	£450 for High Fare	35

In addition to Product 1 and Product 2, this analysis evaluates three further products. Product 3 has been defined as the guests willing to stay two consecutive days from May 18th to May 19th and who are willing to pay £40 pounds per night. Product 4 has been defined as the guests willing to stay two consecutive days from May 19th to May 20th and who are willing to pay £200 pounds per night. Product 5 has been defined as the guests willing to stay three consecutive days from May 18th to May 20th and who are willing to pay £150 pounds per night. It is important to notice that the prices related to Product 3, Product 4, and Product 5 are assumed and hypothetical. Lastly, the final total combined prices used are: £80 for Product 3, £400 for Product 4 and £450 for Product 5. As a result, the total cost values (Table 3) have been used as prices related to Product 3, Product 4 and Product 5 in the computational procedures. For what concerns the demand, it has been assumed that Product 3 follows a Poisson distribution with mean set to 100, Product 4 follows a Poisson distribution with mean set to 50, Product 5 follows a Poisson distribution with mean set to 35.

Analysis 2 aims to maximise the following objective function:

690*P1 + 800*P2 + 80*P3 + 400*P4 + 450*P5 = Z

Where Z is the obtained revenue and P1 represents the demand for Product 1, P2 represents demand for Product 2, P3 represents demand for Product 3, P4 represents demand for Product 4, P5 represents demand for Product 5 and P5 represents demand for Product 5.

Furthermore, the following constraints have been included in the analysis:

1. **Demand for all products under analysis cannot be less than 0:**

   P1, P2, P3, P4, P5 ≥ 0

2. **The demand cannot exceed the predicted expected demand:**

   P1 ≤ 70

   P2 ≤ 30

   P3 ≤ 100

   P4 ≤ 50

   P5 ≤ 35

3. **The total booking for each day must be less than the total capacity, which amounts to 60 guestrooms:**

   (May 18th) Tuesday: P3 + P5 ≤ 60

   (May 19th) Wednesday: P3 + P4 + P5 ≤ 60

   (May 20th) Thursday: P2 + P4 + P5 ≤ 60

   (May 21st) Friday: P1 + P2 ≤ 60

   (May 22nd) Saturday: P1 + P2 ≤ 60

   (May 23rd) Sunday: P1 + P2 ≤ 60

The Linear Programming results indicate that the Fairmont Hotel should exclusively reserve rooms for Product 1, Product 4, and Product 5, while rejecting any requests arriving from Product 2 and Product 3. Specifically, it has been obtained that in order to maximize the total expected revenue, the available rooms should be allocated as follows:

- A total number of 60 rooms should be allocated to Product 1, which represents customers (Low Fare Class) who stay in the hotel from May 21st to May 24th and pay a total price of £690;
- A total number of 25 rooms should be allocated to Product 4, which represents customers (Medium Fare Class) who stay in the hotel from May 19th to May 20th and pays a total price of £400;
- A total number of 35 rooms should be allocated to Product 5, which represents customers (High Fare Class) who stay in the hotel from May 18st to May 20th and pays a total price of £450;

This strategic rooms allocation to different identified customers would ensure that the Fairmont Hotel achieves an optimal revenue worth £67,150. However, if the Fairmont Hotel aims to retain the obtained optimal solution, it is important to note that the sensitivity analysis demonstrated that the price for Product 4 is the most sensitive one as it ranges from £190 to £450. Conversely, the other products are characterized by considerably larger ranges compared to Product 4 (see R-script for more details). The previous described ranges are logic consequences as Product 5 and Product 6 are direct competitors, and hence both products share the allocation. In fact, increasing the price of Product 5 to a value above £450 could generate a higher amount of revenue, given the same mean demand. Indeed, the analysis also indicates that a unit increase in the expected mean demand of Product 5 increases the revenue by £50, given that the expected demand is lower or equal than 60 and greater or equal to 10. As a result, it is advisable and very profitable to identify this kind of customer segment and adopt advertisement strategies to entice this group of customers in order to increase the related expected demand.

Conclusion

In conclusion, the previous evaluated Analysis 2 surely generates the highest maximum revenue amount, while representing a very comfortable decision. However, Analysis 2 shows some drawbacks. In fact, the strategy of reserving rooms exclusively for selected products could backfire if some unexpected events happen. For example, in scenarios where the targeted customers segment for Product 1 bookings is characterized by mainly international travelers, a third-wave of Covid-19 and the related travelling restrictions might decimate the reserved rooms, hence forgoing opportunity costs of accepting other requests from Product 2 and Product 3.

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