

Designing and Pricing Services Based on Customer-Perceived Value: An Airline Company Feasibility Study

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We propose a new integrated model for pricing airline tickets that takes into account the perceived value of multiple services associated with a given flight. For instance, clients perceive benefits on different attributes such as refund options, baggage allowances, time slots, days of operations, Web check-in services, as well as airline brand. These elements of perceived values are not, to our knowledge, modeled in existing yield management systems. Our integrated model includes a classical aggregate planner for services as well as a share of choice. In this paper, we have worked closely with an airline company and provided it with relevant managerial recommendations.

Key words: airline pricing; conjoint analysis; mathematical programming; share of choice; perceived value risk

History: Received April 8, 2012; Received in revised form July 2, 2012; Accepted July 5, 2012. Published online in *Articles in Advance*.

1. Introduction

In the last few decades, the airline industry has been open to competition. To survive in this tough market, an airline company's dominant strategy was to offer the cheapest flight. As a consequence, low-cost companies flourished; meanwhile, the quality of service faded. To remain in the market, companies had to efficiently manage their pricing strategy. From the pioneering works of Littlewood in 1972, many models were developed to help companies optimize their revenue (see, for instance, McGill and van Ryzin 1999 for an exhaustive literature review). The popularity and wide use of such optimization techniques can be attributed, among other things, to the creation of the expected marginal seat revenue (EMSR) heuristics (Belobaba 1987, 1989). These heuristics permitted the production of a good solution for real pricing problems encountered by airline companies. The power of these inventory control algorithms and heuristics was recognized throughout the industry, and in the late 1980s, companies such as Sabre Airline Solutions and PROS were created. These companies created specialization solutions that empowered airlines to manage their fares efficiently and scientifically.

Nowadays, the airline industry is gently entering into a new era where services are requested, and not only by a small minority. This is probably because prices are now so low, many clients are now willing to pay a little extra to obtain some services. Therefore, airline companies face a new problem. Before, the strategic decision was to fix the price. Now and going forward, the strategic decision is to design a service and to fix the price. This is a new challenge, and no integrated models have yet been developed to help in making this strategic decision.

To solve this challenge, two tasks have to be done simultaneously. The first task consists of quantifying the clients' perception of the services and choosing the optimal service design in a competitive market. This task can be tackled using standard methods. For example, by conducting a survey and then applying the theory of conjoint analysis, a utility function can be computed. Finally, this utility function is incorporated in a share-of-choice model whose solution provides the optimal service design (for exhaustive reviews, see Green and Srinivasan 1990, Louviere 1994). The second task consists of fixing the price, taking into account planning constraints and costs. This second task can also be tackled using standard methods. Indeed, there exist many methods ranging from yield management to operations management. Because each task has an incidence on the other one, these two tasks must be solved simultaneously. To our knowledge, there exists only one method that

integrates both tasks simultaneously; this method was proposed in two papers (Debély et al. 2008, Fragnière et al. 2008). Roughly speaking, it relies on an integrated model that combines a share-of-choice model with an aggregate planning model. The resulting integrated model is a mixed integer program and can be solved using standard methods of operations research (see, for instance, Schrijver 1998).

The contribution of this paper lies in the fact that it is the first time, to our knowledge, that a real-life problem is tackled with a method that takes into account service design as well as pricing management. The work presented in this paper was done in collaboration with an airline company. For confidentiality reasons, we will not disclose the name of this company and will refer to it as the “partner company.” For this study, it was decided to focus on only one route managed by the partner company—namely, the Malta to London Gatwick route. This method enabled us to provide a recommendation for the service design as well as the pricing strategies that should be implemented on this route.

The rest of this paper is organized as follows. In §2, we propose a brief literature review, adopting a historical perspective, about airline revenue management and consumer preference. In §3, the services relevant to our case are described, and the survey conducted to quantify customers’ perceived value is presented. In §4, the integrated model is presented and explained. In §5, some results are presented. For confidentiality reasons, strategic outcomes are partially disclosed. Finally, §6 concludes this paper.

2. Literature Review

Pricing for intangible goods has been a source of controversy since the 1970s, when revenue management practices were first introduced. These revolutionary concepts were adopted in various service industries. The biggest impact, without a doubt, was felt in the airline industry. Several operations research techniques were developed to satisfy the ever-increasing need for carriers to survive in their aggressive competitive arena.

Revenue management, also referred to as yield management, is all about selling at the right price to the right customer at the right time. It has been heavily used in the airline industry since the 1980s (see Meissner and Strauss 2010 for more details), where perishable goods are sold, seat capacity is fixed, and demand is volatile. Pricing based on traditional revenue management concepts aim to segment customers according to their price sensitivity by imposing conditions and restrictions on the low fares offered (Botimer and Belobaba 1999, Meissner and Strauss 2010).

Littlewood (1972) suggested treating the price management for flights as a control policy (Fiig et al. 2010, Meissner and Strauss 2010). He proposed a rule (referred to as Littlewood’s rule) that involves considering each flight leg separately and accepting a low fare booking only if the revenue contribution received is greater than the cost of displacement (expected revenue loss) of later arrivals. The popularity and wide use of such optimization techniques can be attributed to the creation of the EMSR heuristics by Belobaba (1987, 1989); this method tests the effects of passengers buying up (Botimer and Belobaba 1999, Fiig et al. 2010, Meissner and Strauss 2010). Two variations of this heuristic, referred to as EMSRa and EMSRb, were developed by Belobaba in 1992 and have been applied in industry; both make use of Littlewood’s rule. These heuristics converted the computationally intensive multiclass optimization problem of finding booking limits for thousands of flights to a much more manageable problem that produces good solutions (although not necessary optimal) in a reasonable amount of time (see Phillips 2005). The power of these inventory control algorithms and heuristics was recognized throughout the industry, so much so that in the late 1980s, companies such as Sabre Airline Solutions and PROS, which created specialization solutions that empowered airlines to manage their fares efficiently and scientifically, were founded. Airlines that embraced such systems had a very significant competitive edge. Airlines that did not recognize the importance of revenue management early enough were soon driven out of the market, as Donald Burr, chief executive officer and founder of PEOPLExpress Airlines, found, through harsh experience: “What you don’t know about revenue management could kill you!” (Beer and Loveman 1991, as cited by Vasigh et al. 2008, p. 280).

Traditional models assume that the demand for each fare class is independent and do not take into account passengers buying up or down; they assume that the airline can perfectly segment its customers in these classes (Fiig et al. 2010). Botimer and Belobaba (1999) suggested the use of a “generalized cost” model to estimate the cost incurred by consumers who purchase lower fare products with strict fare restrictions. The emergence of the low-cost carriers caused legacy carriers to reduce—and in certain cases, eradicate completely—all their price restrictions and conditions in an attempt to be more competitive regarding this new market trend. Researchers in the field have also recognized the power of choice modeling to achieve better demand forecasting (for example, see Fiig et al. 2010, Vulcano et al. 2012). Meissner and Strauss (2010) focused on finding ways to optimize the application of their model for mixed fare environments. Incorrect inventory control recommendations are often

caused by overestimated demand forecasts due to what is referred to as “double counting.” This occurs when a passenger cannot get his first flight option, and hence the demand is counted as *spilled* on the first flight; however, the passenger is *recaptured* with the same airline on a second flight (i.e., there is demand for the second flight). Ratliff et al. (2008) presented a multiflight heuristic that efficiently estimates spill and recapture effects in the presence of competition by analyzing customer choices using shopping data. This brief and nonexhaustive literature review about airline revenue management presented the kind of operations research issues that are typically investigated in the field.

In parallel to these developments in the airline industry, another important operations research area arose that was related to consumer preference. The significance of models that focus on consumer preference may be clearly seen by the extensive literature containing research that aspires to gain better insight into consumer behavior. According to Green and Srinivasan (1990), interest in this area took off in the 1970s. Researchers started to recognize the power of forecasting customers’ choices and borrowed techniques that were developed by mathematical psychologists and statisticians in the 1960s (Green and Rao 1971, Green and Wind 1975, Orme 2005). Srinivasan and Shocker (1973) were the first to formalize the consumer preference problem as an optimization share-of-choice programming problem. They made use of linear programming techniques on a multidimensional joint space to find a product location that maximized the number of consumers that have the new product location closest to their individual “ideal points.” The distance measures they considered were the weighted and unweighted Euclidean distances, which are popular metrics used in cluster analysis techniques. Albers and Brockhoff (1977) showed how the problem can be formulated as a mixed integer nonlinear programming problem. Other more recent studies include Camm et al. (2006), who made use of an exact branch-and-bound algorithm and showed that this approach is very appropriate for large-scale problems as well as cases with partworths containing estimation errors, and Gruca and Klemz (2003), who presented an innovative method that utilizes genetic algorithms to come up with an optimal positioning strategy. Draganska and Jain (2006) showed that yogurt’s consumers value line attributes more than flavor attributes through a discrete-choice model formed by both a demand-side and a supply-side model. Other studies contain sophisticated operations research models that take into consideration consumer preferences as well as several tests to check the reliability of results obtained from different models (for example, see Netzer et al. 2008; Camm et al. 2006; Green et al. 1991, 1993).

Despite all the studies that focus on the share-of-choice model, very scarce literature can be found on models that combine all the following factors: resource planning, pricing, product of service design, and customer preferences. Fragnière et al. (2006) suggested the use of dollar-based methods to create fair pricing schemes that take into consideration a customer’s perceived value for intangible goods. A more concise application of this approach may be found in Fragnière et al. (2008). In this paper, the formulation of the problem that makes use of surrogate market techniques, in particular the shadow price approach, is created for the case of a travel agency’s service design optimization. In practice, a share-of-choice model coupled with a production model was applied to come up with the optimal product design for the services offered by the travel agency, and shadow values for the expertise were then produced.

In view of the lack of applications of this innovative approach, it was decided to investigate the applicability of the concept to another area in the travel industry—namely, the area of airline ticket pricing.

3. The Survey

After conducting interviews with the chief officer commercial and revenue management analysts of the partner company, we concluded that for the Malta–Gatwick route, seven attributes were relevant. The attributes and their respective levels can be found in Table 1.

Table 1. Attribute and Level Selection

Variable	Attribute name	Attribute levels
1	Brand	Air Malta, British Airways, easyJet
2	Price	€99, €140, €200, €300
3	Timing	KM_Slot, BA_Slot, U2_Slot
4	Baggage	20 kilos, 30 kilos
5	Web check-in	No, yes
6	Schedule	Daily; excluding Sunday, Tuesday, and Thursday; excluding Monday, Thursday, and Saturday
7	Refund	No, yes

Table 2. Slot Times

	KM_Slot	BA_Slot	U2_Slot
Outbound flight			
Departure	0840	2035	1120
Arrival	1055	2250	1335
Inbound flight			
Departure	1155	1530	0625
Arrival	1600	1945	1040

At the time of the selection of attributes, Air Malta and easyJet were both offering a daily service on the route, whereas British Airways service did not include Sunday, Tuesday, and Thursday. The inventory analyst responsible for the revenue management of this route suggested that one of the schedule levels should be a configuration of the days that excludes the Monday, Thursday, and Saturday services because these were shown to be weak demand days. The slot times are given in Table 2.

Using these attribute levels, there are 864 possible ways of designing the service. The collection of respondents' preferences may be done through a variety of tasks. These tasks can be communicated through person-to-person or telephone interviews, mail questionnaires, or even through interactive online surveys. There are four main techniques that should be considered at this stage: the full-profile, two-factor, self-explicated, and hybrid approaches (Green et al. 1993). Each of these methods has its advantages and limitations. In this paper, we decided to use the full-profile approach. The next stage of the analysis required the choice of profiles to be shown to the survey subjects. If the complete factorial design was used, this would mean that, with the current seven attributes, a total of 864 cards would be required. This is far too many to conduct a survey, so we reduced the number of cards to a reasonable level. It was therefore decided to use the generate orthogonal design in SPSS. This software offers a method to compute a minimal orthogonal set of full-profile cards. The 16 card profiles obtained with this method and used for the survey are listed in Table 3. According to our experience, the number of cards should not exceed 16; otherwise, the respondent could be confused.

Each respondent has to rank the 16 cards according to its preference. It was decided to construct an online survey for three main reasons. First, it is the best way to collect responses in the shortest time possible. Second, an online survey mimics the purchase of airline tickets through popular online travel agencies. And finally, it eliminates the possibility of bias, which can often result from face-to-face interviews. Although several free online survey software tools exist, none was adequate to carry out the 16-card full-profile ranking exercise.

We therefore decided to construct the survey from scratch. So a Web application was developed, which was deployed on a PHP server posted at <http://airlinesurvey.webhop.net>. The two main pages of the online survey can be found in Figures 1 and 2.

Table 3. List of Profiles

Card ID	Brand	Price (€)	Baggage (k)	Refund	Schedule	Time	Web check-in
1	KM	200	30	No	Excluding Monday, Thursday, and Saturday	KM_Slot	Yes
2	KM	200	30	Yes	Daily	KM_Slot	No
3	BA	140	20	No	Daily	KM_Slot	No
4	BA	200	20	Yes	Excluding Sunday, Tuesday, and Thursday	U2_Slot	Yes
5	BA	99	30	Yes	Excluding Monday, Thursday, and Saturday	BA_Slot	No
6	U2	140	20	Yes	Excluding Monday, Thursday, and Saturday	KM_Slot	Yes
7	U2	200	20	No	Excluding Sunday, Tuesday, and Thursday	BA_Slot	No
8	KM	140	30	Yes	Excluding Sunday, Tuesday, and Thursday	U2_Slot	No
9	KM	99	20	Yes	Excluding Sunday, Tuesday, and Thursday	KM_Slot	Yes
10	KM	99	20	No	Excluding Sunday, Tuesday, and Thursday	KM_Slot	No
11	BA	300	30	No	Excluding Sunday, Tuesday, and Thursday	KM_Slot	Yes
12	KM	300	20	Yes	Daily	BA_Slot	Yes
13	U2	300	30	Yes	Excluding Sunday, Tuesday, and Thursday	KM_Slot	No
14	KM	300	20	No	Excluding Monday, Thursday, and Saturday	U2_Slot	No
15	U2	99	30	No	Daily	U2_Slot	Yes
16	KM	140	30	No	Excluding Sunday, Tuesday, and Thursday	BA_Slot	Yes

Figure 1. Instruction Page for the Online Survey

Ranking Instructions

✘

Thank you for telling us a little bit about yourself! We are now ready to go to the ranking question.

You will now be presented with 16 fictitious airline tickets, each box representing a RETURN ticket from Malta to London (Gatwick) and back. Go through all products before you start ranking items!

Press the **red X** or [click here](#) to close the instructions window and proceed to the survey.

Sample Ticket:

Airline's Logo

Outbound Flight
Departing FROM Malta
Destination TO London

Inbound Flight
Departing FROM London
Destination TO Malta

Baggage Check In Allowance
E.g. 20 kilos

C **Airline Logo**

Sun Mon Tue Wed Thu Fri Sat

MLA-LON: 08:40 - 10:55

LON-MLA: 11:55 - 16:00

20

Refundable: YES

Price: 140 Euros

Schedule
Flights available only on days marked in **GREEN**

E.g. Flights only available on Sunday, Tuesday, Wednesday & Friday.

Departure Time
e.g. 08:40

Arrival Time
e.g. 10:55

Web Check In with Seat Selection

Available
 NOT Available

Ticket Cancellation Refund
If ticket is cancelled prior departure, ticket fare is refunded.

Price for return ticket, inclusive of all taxes and fuel surcharge.

Figure 2. Ranking Exercise for the Online Survey

The screenshot shows a web browser window titled "Airline Survey - Mozilla Firefox" with the URL "http://airlinesurvey.webhop.net/". The main content area is titled "Ticket Ranking - Step 2 of 2" and contains a grid of 16 airline ticket options (A through P). Each ticket card displays the airline logo, flight schedule (outbound and inbound), baggage allowance, refundability, and price. A "Finish" button is located at the top right of the grid. On the left, there are "Instructions" and a "Helpful Tip". On the right, there is a "Legend" section explaining the symbols used in the ticket cards, such as the Schedule Bar, Baggage Allowance, Web Check In with Seat Selection, and Refund status.

Table 4. Attributes' Averaged Importance Values

Value	Importance score
Price	46.8
Brand	12.5
Timing	11.6
Refund	8.7
Schedule	8.5
Web check-in	6.3
Baggage	5.5

A total of 150 valid responses were collected in one week. Using a nonmetric algorithm of conjoint analysis available in SPSS, we then calculated an additive utility function for each respondent. These utility functions are the core of the share-of-choice model embedded in our aggregated model, presented in next section. At this point, we can already mention an interesting result revealed by this survey: the price factor is, as expected, the most important factor, followed by brand and timing. The average attribute's importance scores can be found in Table 4. We observe that the "Brand" value is high because of loyalty issues regarding this given route.

4. An Integrated Model

The integrated model presented in this section borrows findings from operations management, marketing, and service science. Roughly speaking, the integrated model combines a share-of-choice model with an aggregate planning model. The resulting integrated model is a mixed integer program. The model has been implemented and solved using Xpress-MP software. It is important to note that we developed a specific simulation model to generate the competitors' pricing strategies. This simulation model uses past data to compute the probability distributions of pricing strategies. Then, the pricing strategies are generated using a Monte Carlo simulation method. These price strategies are finally incorporated in the integrated model.

We are now ready to give the mathematical formulation of the integrated model. First, we have to define the sets as follows.

n = respondent, where $n = 1, \dots, N$.

t = days before departure (time), where $t = 1, \dots, T$.

i = changeable attributes, where $i = 1, \dots, I$.

j = level of changeable attribute, where $j = 1, \dots, J_i$.

p = price level (class), where $p = 1, \dots, P$.

Then, parameters are defined as follows.

$d_t(t)$ = forecasted demand for market, Malta (MLA) to London Gatwick (LGW), per time period (t).

$u(n, i, j)$ = utility for respondent n for attribute i and attribute level j .

$u_{\text{Brand}}(n)$ = utility for the partner company brand for respondent n .

$u_{\text{Price}}(n, p)$ = utility for respondent n for price p .

$c(i, j)$ = cost of implementing the attribute level j for the attribute i .

$V(p)$ = value (revenue) obtained from gross price p , excluding all taxes and airport charges.

s = capacity (number of seats the partner company allocated to the Malta–Gatwick route in November 2009).

δ = minimum increase in utility to turn respondent n into a consumer.

ξ = expected percentage of customers that will request a refund.

ω = cost of extra fuel burn-off (in euros) for 10 kilos of luggage.

ψ = approximate revenue per period collected from excess baggage fees.

μ = company's market share target applicable for each period t .

We have two kinds of decision variables.

$X(i, j)$ = service configuration (1 if attribute i is set to level j and 0 otherwise).

$Y(p, t)$ = partner company's pricing strategy (1 if price p is set available at time t and 0 otherwise).

The following dependent variables are used in calculations.

- $U_{\text{PAR}}(n, t)$ = total utility for partner company's service for customer n at time t .
- $U_{\text{COMP}}(n, t)$ = maximum total utility for the best competitor service for customer n at time t .
- $S(n, t)$ = preference (selection) for respondent n (1 if the respondent becomes a passenger of the partner company and 0 otherwise).
- $P_{\text{PAR}}(t)$ = expected number of passengers of the partner company at time t .
- $R(t)$ = revenue from expected passenger ticket sales at time t .
- C_{Refund} = cost from offering refunds for ticket cancellation.
- C_{Timing} = cost of changing slot times.
- C_{Baggage} = cost of changing baggage allowance policy.
- C_{Web} = cost associated with Web check-in service.

The integrated model can now be presented as follows. For each respondent and for each time period t , the utility for the partner company's service is calculated as follows:

$$U_{\text{PAR}}(n, t) = u_{\text{Brand}}(n) + \sum_{i=1}^I \sum_{j=1}^{J_i} u(n, i, j)X(i, j) + \sum_{p=1}^P u_{\text{Price}}(n, p)Y(p, t).$$

In other words, this equation links our integrated model with the survey. It is worth mentioning that the parameters of this utility function are obtained from the survey (conjoint analysis). The partworths for each respondent were calculated using a nonmetric conjoint procedure in SPSS. The calculations of the utility for each respondent for the competitors' service is a function of the partworth for the attribute levels that correspond to the service they currently offer to customers and a generated price per period. $U_{\text{COMP}}(n, t)$ is the utility of the best competitor.

For each respondent $n = 1, \dots, N$, the following two inequalities must hold:

$$U_{\text{COMP}}(n, t) + \delta \leq U_{\text{PAR}}(n, t) - (S(n, t) - 1)M,$$

$$U_{\text{COMP}}(n, t) + S(n, t)M + \varepsilon \geq U_{\text{PAR}}(n, t).$$

These two inequalities mean that the prospect becomes an airline partner client if the utility of the service is greater than the utility offered by either of the existing competitors' service plus a minimum increase in utility δ . In our study, δ has been assumed to be the same for each respondent. We also assumed in this study that δ is strictly greater than 0 to be sure that the prospect becomes a client solely if there is a surplus in utility. Then M is a big number and ε is a small number (relative to other parameters, in order to have logical constraints). These two inequalities force $S(n, t)$ to take a value of 1 if the utility for the partner company service is greater than the utility offered by either of the existing competitors' service plus a minimum increase in utility δ to turn respondent n into a passenger of the partner company. These first three equations are the core of the share-of-choice model embedded in our integrated model.

Expected market share of the partner company for time period (t) is hence found as follows:

$$S_{\text{PAR}}(t) = \sum_{n=1}^N \frac{S(n, t)}{N}.$$

One of the carrier's performance targets is a minimum market share percentage μ . A strategy that allows expected market share to be lower than μ at any time period is considered to be too risky for the company; hence one of the model constraints was set as follows:

$$S_{\text{PAR}}(t) \geq \mu.$$

The absolute expected number of passengers for the partner company and per period t is computed using the following equation, using market share per-period estimates as well as market demand forecasts per period:

$$P_{\text{PAR}}(t) = S_{\text{PAR}}(t)d_f(t).$$

Clearly, the partner company has a tangible seat capacity limit for November 2009 flights; this is described by the following capacity feasibility constraint:

$$\sum_{t=1}^T P_{\text{PAR}}(t) \leq s.$$

The expected passenger revenue per time period t , for a given price class, is calculated as follows:

$$R(t) = P_{\text{PAR}}(t) \sum_{p=1}^P V(p)Y(p, t).$$

The expected cost from offering refunds for ticket cancellation is a function of the expected number of customers that will request a refund and the base fare values of the tickets they purchased:

$$C_{\text{Refund}} = \sum_{t=1}^T \xi R(t).$$

The cost of changing the flight timing attribute ($i = 1$) was calculated using the equation below:

$$C_{\text{Timing}} = \sum_{j=1}^{J_1} X(1, j)c(1, j).$$

The expected cost of increasing the current baggage ($i = 2$) allowance limit to 30 kilos ($j = 2$) is a function of the cost of extra fuel burn-off for the extra weight ω and the loss of current revenue obtained from overweight luggage fees ψ :

$$C_{\text{Baggage}} = \sum_{t=1}^T (P_{\text{PAR}}(t)\omega + \psi X(2, 2)).$$

The costs/savings associated with offering Web check-in service were estimated as follows:

$$C_{\text{Web}} = \sum_{j=1}^{J_3} X(3, j)c(3, j).$$

For each changeable attribute $i = 1, \dots, I$, we must have the normalization

$$\sum_{j=1}^{J_i} X(i, j) = 1.$$

For each time period t , we normalize the price set as follows:

$$\sum_{p=1}^P Y(p, t) = 1.$$

Finally, the objective is to maximize the partner company's profits:

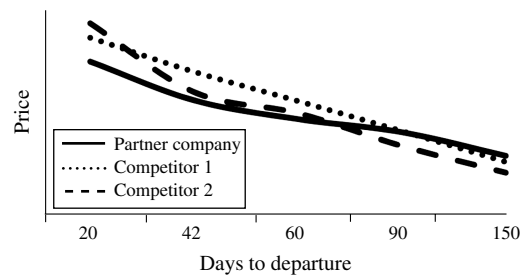
$$\Pi = \sum_{t=1}^T R(t) - C_{\text{Refund}} - C_{\text{Timing}} - C_{\text{Baggage}} - C_{\text{Web}}.$$

5. Results

This study was carried out in the first quarter of 2009, and it was then decided to focus on the Malta–Gatwick route for November 2009. Three companies propose flights on the Malta–Gatwick route: Air Malta, British Airways, and easyJet. Several scenarios were explored, but we present here only the results for one scenario. For confidentiality reasons, the detailed results are, however, not disclosed, and some results are given partially.

The optimal service design for the partner company was obtained by solving the integrated model with Xpress-MP software. The following service design was recommended: Refund and Web check-in should be proposed to the client. Baggage should be limited to 20 kg. The proposed flight should be on Tuesday, Wednesday, Friday, or Sunday. For the slot time, the departure from Malta is at 0840 and the departure from Gatwick is at 1155. For the price, the model recommends that the partner company must position itself lower than the competing carriers. The pricing recommendation can be seen clearly in Figure 3, where the only markup the partner company is suggested to make is far from departure and could be considered to be almost negligible. It is interesting to mention that for scenarios with only one competitor, the optimal strategy is to put a markup on fares offered by the competition. This is explained in this study by a strong loyalty to the brand, as we observe in Table 4.

Figure 3. Recommended Price Positioning



Note. For confidentiality, the price scale is removed.

The model also provides other results such as profits, average passenger revenue, and market share per period. However, for confidentiality reasons, we cannot disclose them here.

6. Conclusions

In this study we implemented an innovative method that permits us to obtain optimal service design and optimal pricing strategy for our partner company on the Malta–Gatwick route. Although this method can be used to take long-term strategic decisions in terms of service design and pricing, we believe that it should only be used as a complementary tool for fixing the prices on a short-term basis (that is, as a complement of yield management schemes). Despite this limitation, we are convinced that this method is very powerful and will help airlines to optimize their pricing management and their service design. We have obtained through interviews of experts in the field that this kind of results offers sound insights to better design pricing systems in the long haul.

We conclude this paper with a comment provided by the pricing analyst of the partner company toward the end of this project. With regard to practical use of the model, he suggested that it would provide valuable customer insight and be implemented as a decision support tool for revenue management analysts and higher management alike. The model could be used to measure the return on investment for intangible service components that are directed toward improving and increasing the service value offering. Often, heavy investments are carried out with the aim of improving services, and relatively no analysis is done to measure how this would be perceived by customers. In terms of revenue management, he expressed reservations towards seeing this model sending automatic recommendations into the reservation system; instead, he views the tool as being a much-needed decision support tool that will help analysts manage pricing more effectively and analytically after having collected feedback from a model representing customer preference and market changes.

An interesting research approach would be to test whether revenue cannibalization occurs by passengers moving from one airport or timing to another, motivated only by a cheaper available price. Our model could easily take into account this dimension. Additionally, a technique could be developed to efficiently deal with large amounts of group bookings on the route, because seat capacity available for non-group traffic is directly affected by such bookings.

In this paper, the utilities required for the aggregate model were estimated by means of an online card-based questionnaire. There is a trend to employ data-mining techniques directly on shopping data. We could thus derive the utility function parameters from shopping data rather than from surveys. However, great obstacles are faced by researchers when trying to obtain this type of data; alternative data sources, such as Marketing Information Data Tapes (MIDT) booking data, Ticket Control Number (TCN) for fares, and Availability Status (AVS) for availability, have been suggested by Ratliff et al. (2008). A viable solution still needs to be determined.

Finally, we would like to reinforce that this research merely corresponds to a feasibility study, as indicated in the title. However, we hope that this original modeling concept, which was tested successfully by the airline partner, will ultimately enable us to develop a comprehensive case study. The goal would then be to provide convincing performance figures as was done by Smith et al. (1992) in *Interfaces* regarding the well-known application at American Airlines.

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