CHAIRS: A CHOICE-BASED AIR TRANSPORT SIMULATOR APPLIED TO AIRLINE COMPETITION AND REVENUE MANAGEMENT

Mitsuyoshi Fukushi (mafukushi@uc.cl)
Felipe Delgado (fdb@ing.puc.cl)
Sebastian Raveau (sraveau@ing.puc.cl)
Department of Transport Engineering and Logistics, Pontificia Universidad Católica de Chile
Bruno Santos (b.f.santos@tudelft.nl)
Air Transport and Operations, Faculty of Aerospace Engineering, Delft University of Technology.

ABSTRACT

Analyzing the performance of Revenue Management (RM) systems is a costly and complex task. In this document, we discuss and test the implementation of a simulation model, designed to analyze Revenue Management performance. The simulator replicates the behavior of various passengers that have the possibility of acquiring seats offered in multiple flights by a group of airlines. To test and showcase the simulator, we use it to study the entrance of a new airline in a competitive context. We implement and evaluate different RM strategies in response to the introduction of new competition, and discuss the results highlighting the interpretability and accuracy of the framework.

Keywords: Revenue Management, Simulations, Discrete Choice Models

1. INTRODUCTION

The objective of Revenue Management (RM) is to offer the right product to the appropriate customer (Smith et al., 1992). To achieve this goal, RM systems use different techniques in a two-stage process, first forecasting the demand behavior and then recommending optimal interventions in the control variables of the offered products. Increases in revenue by applying RM have led to the widespread adoption of these techniques in multiple industries, such as transportation, hospitality, broadcasting, and advertising (Strauss et al., 2018). In air transport, in particular, a correctly applied RM system can generate an increase in revenue of around 5% of the expected income (Cetiner, 2013).

Due to its importance, there is extensive research of RM techniques and multiple applications are described in the literature. The methodologies proposed are increasingly sophisticated and are constantly being updated due to the continued innovations required in the industry. Recent literature accounts for the relevance and interest in applying new RM systems. To see a review of the development of RM techniques, we recommend (Strauss et al., 2018; Klein et al., 2020).

Selecting an appropriate RM strategy is usually a time-consuming and complex task. Because the successful implementation of a RM method depends on the specific context of the airline, there are no solutions that are always superior, so the process involves implementing and testing different RM systems. This process is complex due to several limitations when evaluating the performance of a RM system, particularly when using historical data. The main problem is that the behavioral model that determines the demand cannot be fully characterized due to missing information. This problem limits the ability of disentangling and explaining the interactions of the numerous factors that can influence the performance of the RM systems used. Furthermore, the interaction between the forecasting and optimization stages of the RM process makes it even harder to assess the performance using historical information (Perera & Tan, 2019; Lurkin et al., 2017, Guo et al., 2012).

As a result, specialized literature recommends using simulations to assess RM systems' performance (Frank et al., 2008). The main challenge in the application of these techniques is the definition of a valid behavioral model to define the decision process of the demand. In our simulator, we use Discrete Choice Models (DCM) to overcome this problem. These models have been widely tested and validated in the academic literature and present ample applications in the industry, granting researchers and practitioners the ability to replicate any behavior grounded on the well-known random utility maximization framework (Williams, 1977).

The associated benefits that a well-applied RM system reports to airlines justify the need for a simulation tool capable of replicating scenarios in controlled environments in efficient and affordable ways. Counting with the appropriate tools to propose and test new policies or adjust RM systems already in use by airlines can help RM practitioners learn (Cleophas, 2012) and improve their understanding (Doreswamy et al., 2015) of the problems faced in competitive environments. Such a tool could be essential in the industry's current state, with macroeconomic events rapidly shifting competitive contexts. Additionally, the use of

simulation by well-known operators in the air transport industry validates the relevance of these techniques.

In this document, we implement and test CHAIRS (Choice-based Air Simulator) a dynamic air transport market simulation framework. The simulator aims to study the predictive performance and the economic benefit of applying different RM systems under predefined assumptions in an artificial and controlled environment. To do so, we use DCM to simulate the behavior of different groups of passengers. Our simulator's distinctive features allow it to i) replicate almost any passenger behavior model using a mixed logit formulation, ii) handle different demand taste heterogeneity assumptions and substitution patterns, and iii) replicate complex behavior (e.g., competition, the temporal evolution of preference).

To showcase the flexibility of the simulator, we study the introduction of a low-cost carrier (LCC) to a competitive market where two incumbent airlines are already present, one LCC and one full-service carrier (FSC). The experiments show the simulator's ability to account for heterogeneity in the passenger's behavior, the temporal evolution of passenger's preference, and the application of forecast and optimization techniques used by RM systems proposed in academia and used in RM practice.

The document is structured as follows: in section 2, we present an applied example of the simulator, replicating the entrance of a new competitor in an established competitive air transport market. In section 3 we assess and discuss the obtained results. Finally, in section 4 we present the conclusions and propose some future work.

2. CASE STUDY: SIMULATION OF THE INTRODUCTION OF A NEW COMPETITOR

In this section, we present a case study designed to showcase some of the main features of CHAIRS. We first describe the objective of the study and the simulation set-up, then the details of the passenger choice model and finally the main characteristics of every airline in each competitive scenario.

2.1. Overview of the simulation set-up

Using three experiments, we replicate the entrance of a new competitor to an established air transport market. We simulate: 1) a base competitive market, 2) the introduction of a new airline and 3) the response of the incumbent airlines to the introduction of new competition. By studying these competitive scenarios, we analyze the main characteristics of both passenger and airline behavioral models proposed in CHAIRS.

For the passenger behavioral model, we intend to show the flexibility of the latent class mixed logit model approach to replicate taste heterogeneity and temporal evolution of the preference.

To account for taste heterogeneity, we define different passenger groups that vary in their continuous approximation of departure time valuation and in their fare valuation. Each group also differs in the choice model used to compare the available alternatives. The probability of a passenger belonging to a group is defined by a class membership model. To replicate the temporal evolution of the preferences, we modify the class membership probability along the time-axis. We assess the appropriateness of the passenger choice model by analyzing the observed emergent behavior

In addition, the three proposed experiments highlight the ability of the CHAIRS to account for critical factors in a competitive scenario, such as RM controls (Gorin and Belobaba, 2008) and the effect of the temporal evolution of the fares (Varella et al., 2017). In the base case, experiment 1), we start with a competition between an FSC (Airline A) and an LCC (Airline B). Experiment 2) introduces a new LCC (Airline C) to the market. The new airline presents lower prices while entering the market and focuses on low-fare passengers. Finally, in experiment 3) we simulate a response to the entrance of the new competitors by the incumbent airlines, proposing different RM techniques. As a result, each airline can control the pricing of its products and implement dynamic pricing procedures. We also highlight the ability of each RM system to replicate the effect of the loss of information observed in practice.

The case study aims to show, using simulations, the importance of the inclusion of a RM system and a dependent demand passenger behavioral model to correctly assess the impact of the entrance of a new carrier when considering competitive scenarios.

2.2. Passenger choice behavior

In this section we define the demand characteristics that will be used in the simulation. We describe the parameters, the proposed utility function, and the choice model for each passenger group.

The arrival model samples a Poisson distribution with a mean of 900 passengers per period. The total number of passengers is then disaggregated in different segments. Each segment represents a different buying behavior. We define two main categories, business and leisure (Dresner, 2006), which are further subdivided into more specific groups. The groups mainly differ in their utility function parameters and the choice model, but the functional form of the utility is the same for all groups. The utility function of passenger i is shown in equation 1:

$$V_i = \beta_{fare} * fare_i + b_1 * sin(\tfrac{2\pi * DT_i * 60}{1440}) + b_2 * sin(\tfrac{4\pi * DT_i * 60}{1440}) + b_3 * sin(\tfrac{6\pi * DT_i * 60}{1440}) +$$
$$+ j_1 * cos(\tfrac{2\pi * DT_i * 60}{1440}) + j_2 * cos(\tfrac{4\pi * DT_i * 60}{1440}) + j_3 * cos(\tfrac{6\pi * DT_i * 60}{1440}) + \beta_q * Q_i \qquad (1)$$

We define a fare valuation parameter (β_{fare}), a quality (Q) valuation parameter (β_q), and 6 parameters ($b_1, b_2, b_3, j_1, j_2, j_3$) for the valuation of departure time (DT). The fare and quality

valuation parameters are scalar magnitudes and can be different across passengers. The valuation of quality parameter is of variable magnitude for each group and mainly depends on the behavior we aim to reproduce. There is plenty of evidence in the literature to support its presence and define their values for each group (Wu & So, 2018). The fare valuation parameters are obtained from itinerary choice DCM found in the literature (Coldren & Koppleman, 2005). The valuation of the departure time uses 6 parameters (Ben-Akiva & Abou-Zeid, 2013) to calibrate a continuous function. The use of this kind of function appears as a continuous alternative to the use of categorical time valuation attributes and has been successfully tested (Carrier, 2008). The representation uses trigonometric functions to generate a utility function that modifies its value during the day, but that is equal across days. With this approximation it is possible to account for complex continuous departure time preferences, with multiple peaks and valleys. Similar patterns of preferences have been observed in the valuation of the departure times of air transport itineraries (Garrow et al., 2007).

The temporal evolution of the preference across the sale horizon has been widely documented in the literature (Morlotti et al., 2017). To simulate a similar effect, we modify the passenger mix across different periods. At the beginning of the simulation (DCP1) the passenger arriving will be 70% leisure and 30% percent business (Gorin and Belobaba, 2008). As the departure date comes near, the proportion of leisure passengers will decrease, and the proportion of business passengers will increase in a linear way. In the last period (DCP6) leisure passengers will be 30% and business 70%.

The main difference between leisure and business passengers is their fare valuation parameter (Jung & Yoo, 2014). Leisure passengers will be more sensible to spend an additional unit of money on their preferred product, presenting increased price elasticity (Morlotti et al., 2017). To represent leisure and business behavior, we set their fare valuation coefficient to -0.068 and -0.051, respectively. The magnitude of the parameters is obtained from equivalent nested logit models applied by Lurkin et al., 2018 to represent itinerary choice. The researchers found the parameters were consistent across time and space.
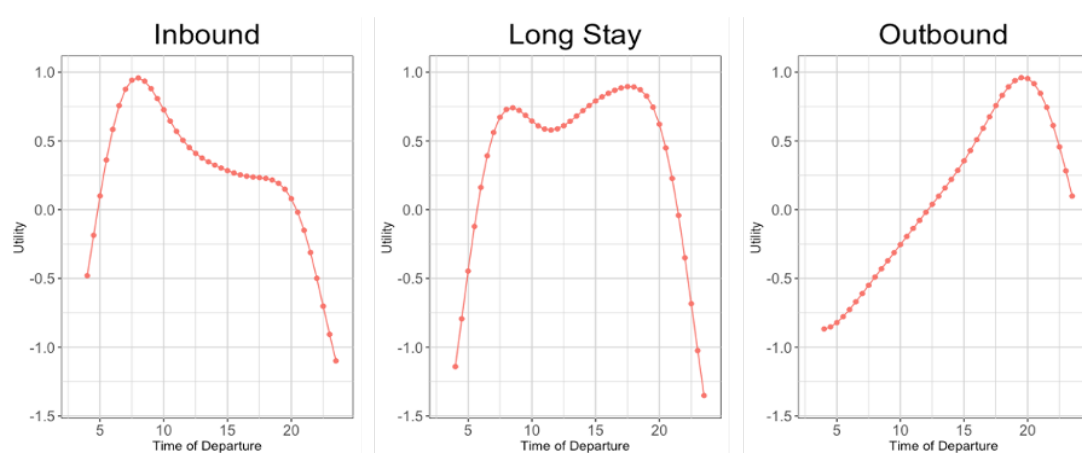

Figure 1 - Departure time valuation presented as the utility of each group of passengers according to different time of departures.

Inside of each passenger group, we define different subclasses according to their departure time preference. As recommended in the literature, we differentiate inbound and outbound traffic (Wu and So, 2018). Thus, we divide business passengers between those who prefer to fly in the morning, coined "Inbound" and those who prefer to fly in the afternoon, coined "Outbound". Inbound passengers may prefer to fly in the morning to work during the day in a different location, while Outbound passengers could be returning from their work on the same day. Finally, we define a third group coined "long stay" that does not show any special preference for morning or noon flights. These three departure date valuation profiles are similar to the ones obtained by Garrow et al. (2007). Leisure passengers are also sensible to departure time, but follow the "long stay" profile, not showing a particular preference between morning or noon flights. Figure 1 presents these three profiles; the x-axis represents the departure time, and the y-axis is the utility associated with each time.

Finally, we assign a choice model to each passenger. We propose two different models to represent a compensatory (Wu and So, 2018; Gonzales-Valdes and Raveau, 2018) and a lexicographic (Wang, 2015) behavior. The lexicographic model considers only the subset of alternatives that present the lowest available fare in the market. If there is a draw, it uses the compensatory model to decide. The proposed compensatory model corresponds to a nested logit, and its structure is depicted in Figure 2. There is evidence to support the use of this structure in the literature of DCM applied to itinerary and fare-class choices (Coldren & Koppelman, 2005; Lurkin et al., 2018).
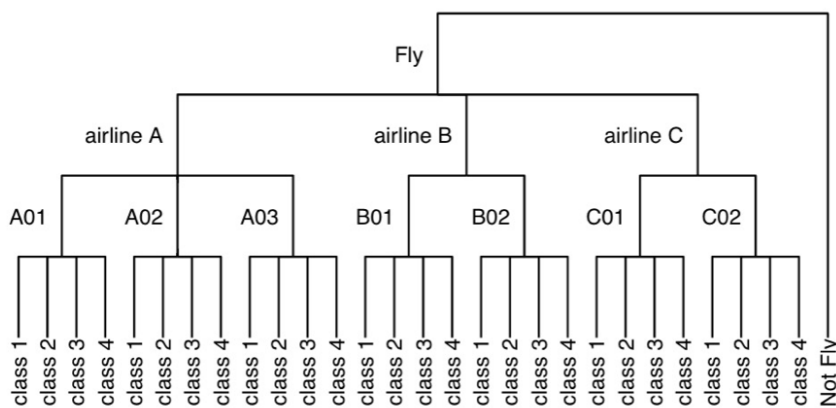

Figure 2 - Nested compensatory fare class choice model used to model passengers' behavior

2.3. Airline behavior

In this section, we describe the characteristics of every airline in each proposed experiment. For each scenario, we define the operational configuration of every airline, commenting on the number of flights, the departure times and the RM systems implemented for pricing and capacity control.

2.3.1. Base experiment

In the base experiment, two carriers compete in a unique OD pair using different strategies. Airline A presents an FSC behavior, while Airline B is an LCC. Airline A considers a greater number of flights (Baker, 2013) and better coverage of departure time across the day than airline B. Airline B (LCC) concentrates its flights around periods that usually have more demand. Both airlines use the same type of aircraft. Figure 3 presents the departure time of each flight operated by each airline. In the base experiment, only airlines A and B are present.
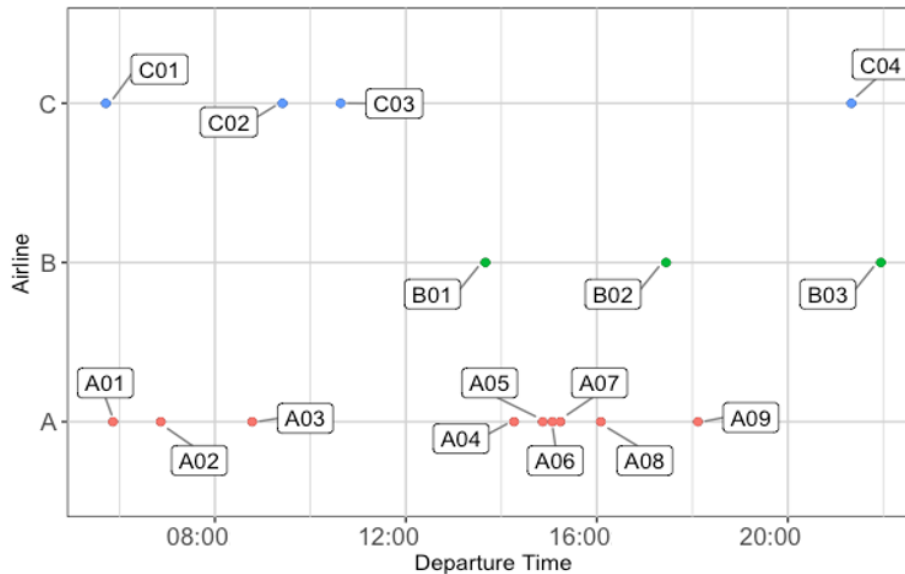

Figure 3 - Flight itinerarioes for each airline according to their departure time.

Both Airlines present four fare classes and modify their availability and fare across periods. The average fare of the classes offered by Airline B is 40% lower than that of Airline A (Lawton, 2002). Airline B (LCC) uses a simplified RM system based on advance purchase controls where lower fare classes are blocked as the flight date approaches. In turn, Airline A (FSC) presents RM controls with nested protection levels that block a fare class when the associated protected capacity depletes, increasing the average fare of their offered classes. Table 1 presents the fare class structure, the advance purchase (AP), the protected capacity, and the fare.

From the base experiment, we build two extended experiments.

2.3.2. Experiment 2: entrance of new a competitor

In the second experiment, we include a new LCC carrier to the market, named Airline C. The new competitor offers a higher number of flights but a similar coverage compared to incumbent airline B, as depicted in Figure 3.

The fares presented by airline C are always the lowest in each period. This practice is an observed airline strategy to secure an initial market share (Kelemen et al., 2019). To impose this condition, the RM system presented by Airline C uses a combination of advance purchase and protected nested controls. This combination of strategies allows Airline C to always have the lowest fare available in the market and avoid selling all seats at the lowest fare (dilution). Table 1 presents the fare class structure, the advance purchase (AP), the protected capacity, and the fare. An advance purchase of 99 indicates that the class is available in any DCP if the class is still available, considering the seat protection levels (i.e., if it is not sold out).

Table 1 – Fare structure base experiment

Fare Class	AP	Seat Prot.	Fare
Airline A			
Fare Class 1	99	200	345
Fare Class 2	99	170	322
Fare Class 3	99	130	264
Fare Class 4	99	80	241
Airline B			
Fare Class 1	99	200	210
Fare Class 2	5	200	168
Fare Class 3	3	200	150
Fare Class 4	2	200	143
Airline C			
Fare Class 1	99	200	200
Fare Class 2	5	200	168
Fare Class 3	4	100	150
Fare Class 4	3	100	143

2.3.3. Experiment 3: Airline B (LCC) pricing response

To showcase the flexibility of the simulator we implement RM response strategies adopted by the incumbent carriers. Airline B's response strategy to the introduction of airline C is to implement a new pricing procedure. They define a single fare class with strict conditions (Cento, 2009), blocking the other classes, and they modify the fare across the time periods, increasing it as it gets near the departure date (Holloway, 2016).
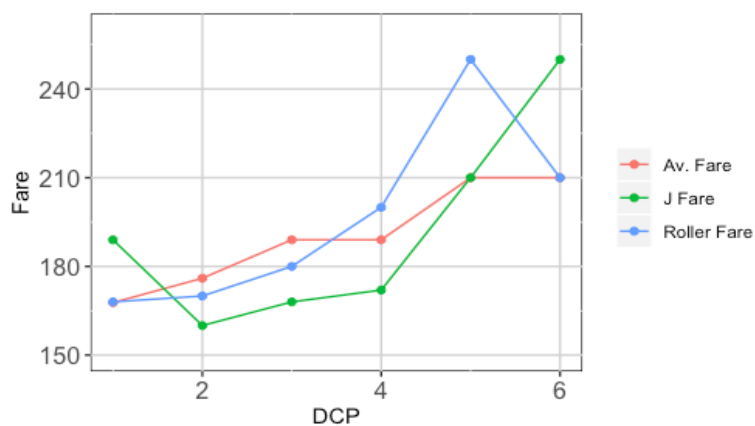

Figure 4 - Pricing response of Airline B to the entrance of airline C. Each line represents a different pricing curve.

Airline B tests three types of fare profiles adopted in the literature. The price curves follow recommendations generated in a market with two types of passengers with different willingness

to pay, that adjust their proportion across the sale horizon (Varella et al., 2017). These curves use mainly a Lo-Hi strategy (Alves and Barbot, 2009), in which discounts decrease near departure time (Holloway, 2016). The three temporal profiles of the evolution of the fare used to simulate the responses of Airline B are presented in Figure 4. The curves used exhibit subtle differences; the J curve starts with higher fares, but soon lowers the fare in the middle of the sales horizon to finally increase near the end. The roller curve shows its highest point before the last period of the horizon. The average fare presents a fare profile that increases in every passing period, imitating their own average fare imposed by the advance purchase RM controls used in experiments 1 and 2.

3. RESULTS AND DISCUSSION

In this section, we present the results obtained in the simulations. We showcase the flexibility of CHAIRS by analyzing the demand and the airlines behavior. First, we describe the demand behavior observed in the simulation, focusing on the interpretability, the accuracy and the credibility of the observed behavior. Second, we consider the aggregate results of each operator, and explain them using the RM configuration present in each scenario. We consider aggregate and disaggregated measures to analyze individual and group behavior.

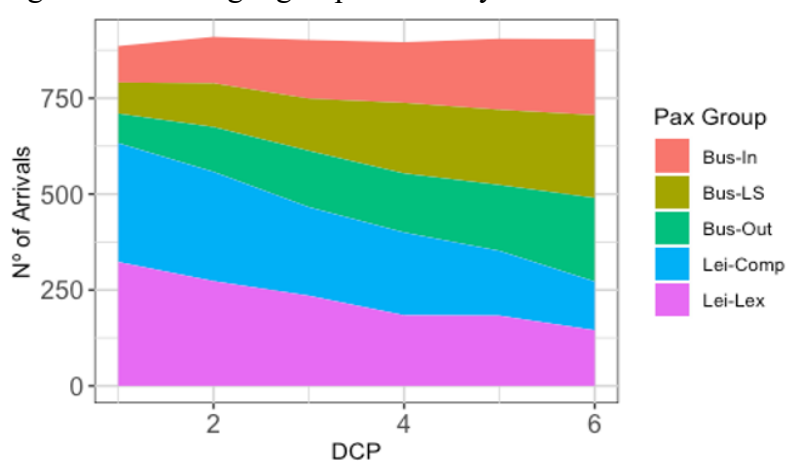Figure 5 – Passenger group arrivals by DCP

Figure 5 - Passenger group composition arriving in each DCP.

We control and analyze the possible sources of variability by repeating each experiment scenario 30 times. Since the RM controls imposed and the network configuration are deterministic, they don't change between repetitions, hence the airline's behavior cannot account for the variability of the results. The variability of the results is instead linked to the stochastic behavior of the demand; composed by the volume of the demand, the order of arrivals of the passenger belonging to different groups and the random components of the DCM. These three sources are credible and interpretable. We restrict the variability of both the volume of the demand and the passenger order of arrival (i.e., the passengers' groups) across the repetitions, leaving only the variability introduced by the random behavior of the DCM framework.

We first analyze the demand behavior obtained in the simulations. Figure 5 presents the passenger groups arriving across the DCP. Since we control the demand volume and the passenger groups arrivals, the demand composition is constant across repetitions. We can see that leisure passengers, composed of groups 4 and 5, are the majority at the start of the selling horizon (DCP 0). However, business passengers increase as the date of flight departure approaches, becoming the predominant group near the end. The greater proportion of business passengers produces an increase in the average willingness to pay. As such, we can correctly replicate a temporal evolution of the preference.

Figure 6 shows the bookings observed according to the departure time of the flights of each airline for one representative repetition of experiment 2. The differences in the demand composition are due to departure time and fare differences. Due to differences in willingness to pay, leisure passengers, which are mainly price-sensitive leisure (Domaico, 2007), prefer airlines B and C. Thus, we can see that airline A, the FSC, focuses mainly on business passengers (Wehner et al., 2018). Additionally, we can see a clear preference of inbound and outbound passengers for early and late departure times respectively. This behavior is consistent with the continuous approximation of departure time valuation of the passengers.
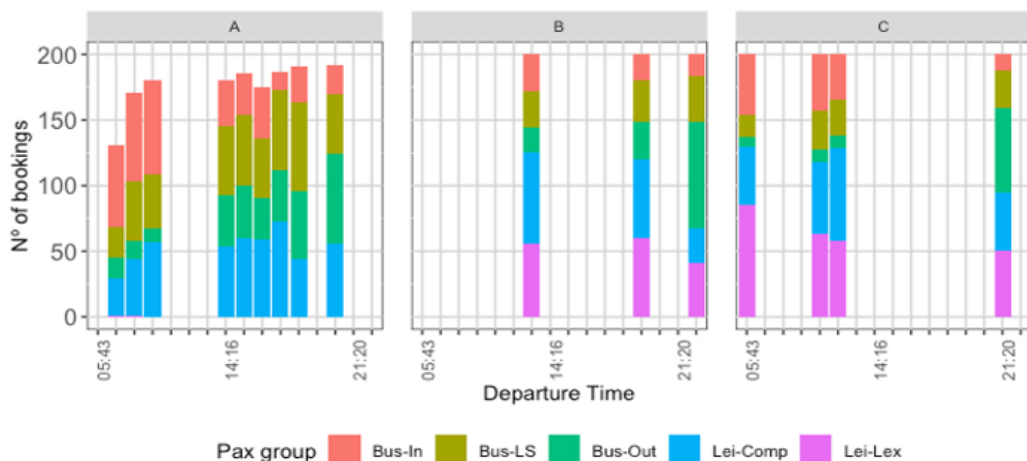

Figure 6 - Each bar represents a different flight, separated into the three airlines. Passenger group bookings according to the departure time of the flight.

Table 2 – Airline revenue per flight by experiment

	1	2	3-I Roller	3-I J	3-I Average
Airline A	$59.308 ($413)	$52.085 ($909)	$51.976 ($858)	$52.114 ($827)	$51.884 ($756)
Airline B	$32.409 ($179)	$34.509 ($210)	$35.123 ($775)	$32.932 ($987)	$34.189 ($893)
Airline C	-	$33.407 ($108)	$33.154 ($137)	$33.276 ($121)	$33.164 ($136)

Tables 2-4 presents the aggregated results of all the repetitions for every experiment. We compare the average revenue divided by the number of flights, the average fare, and the average load factor (LF; the average percentage of occupied capacity) of the airlines. Numbers in parentheses depict the associated standard deviation. We first analyze the results of experiments 1 and 2, the base case and the introduction of new competition. In experiment 1,

airline A obtains a higher revenue by flight and a higher average fare compared to B. However, airline A leaves some idle capacity on its flights, achieving an average LF of 98%. In experiment 2, due to the entrance of airline C, airline A reduces its LF, average fare and revenue by flight. However, for airline B the effect is the opposite, and the introduction of Airline C is favorable.

Table 3 – Airline average booked fare by experiment

	1	2	3-I Roller	3-I J	3-I Average
Airline A	$303 ($0,98)	$294 ($0,88)	$296 ($1,17)	$296 ($1,20)	$296 ($1,06)
Airline B	$165 ($1,72)	$177 ($0,81)	$196 ($0,40)	$186 ($2,09)	$189 ($0,26)
Airline C	-	$170 ($1,07)	$169 ($1,33)	$170 ($0,83)	$169 ($1,28)

Table 4 – Airline load factor by experiment

	1	2	3-I Roller	3-I J	3-I Average
Airline A	98,2% (0,6%)	87,4% (1,4%)	87,2% (1,2%)	87,4% (1,3%)	87,1% (1,1%)
Airline B	100% (0%)	99,8% (0,4%)	87,0% (1,8%)	89,2% (2,5%)	88,4% (2,2%)
Airline C	-	100% (0%)	100% (0%)	100% (0%)	100% (0%)

Airline B benefiting from the entrance of a new competitor is a counterintuitive result that can be explained by further examining the booking behavior. Figure 7 depicts the demand composition of the bookings across the selling horizon for each airline for experiments 1 and 2. We find that in experiment 1 airline B capacity depletes early in the sale horizon (DCP 4). Airline A RM system takes advantage of this situation by reserving seats for high-fare classes in the final periods. As such, we could argue that the good performance of A is linked to presenting a greater number of seats available and being able to offer their products with low competition. In experiment 2, with the entrance of the new competitor, and by not adjusting the RM system, the capacity protection now harms Airline A, leaving it with lower occupation, revenue and average fare. On the contrary, the introduction of an assured lower fare presented by Airline C allows this airline to capture low-fare passengers that previously booked mainly on airline B (Lei-Lex and Lei-Comp). Due to this fact, Airline B can now better administer its capacity to capture high-fare passengers, increasing the average fare paid and its revenue.
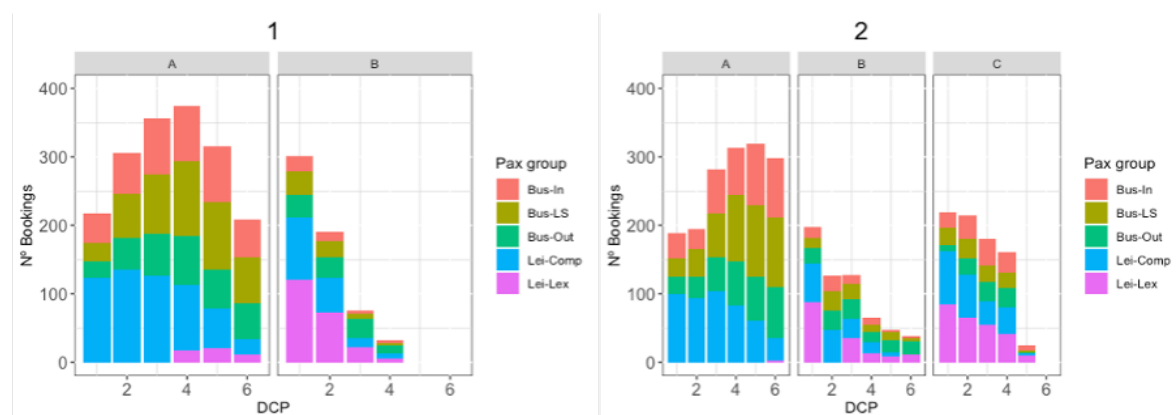

Figure 7 - Group bookings by DCP of each airline in experiments 1 and 2

In experiment 3 we observe the effect of the implementation of different RM strategies as a response to the introduction of C. Experiment 3-I presents the response to the pricing procedure

implemented by B. Table 2 shows that every curve profile implemented by airline B improves its average revenue per flight compared with experiments 1 and 2, but that the Roller curve profile is superior. These changes, presented in Table 2-4, are statistically significant and consistent and cannot be attributed to the inherent variability of the simulation. The increase in revenue is accompanied by a decrease in the final LF, which is explained by an increase in the average fare paid. We can further examine the effect of the new pricing procedure. Figure 8 presents the booking composition of airline B for representative repetitions of the different experiments. We can see that the pricing curves implemented restrict the booking of low-fare passengers during the beginning of the selling horizon compared with experiment 2. The best performing curves, Roller and Average, present a similar booking composition that peaks in price just before the final DCP. The peak in price coincides with a peak in the passenger bookings in the roller and average profiles. Using the Roller curve, airline B is able to capture more bookings in the last DCP.
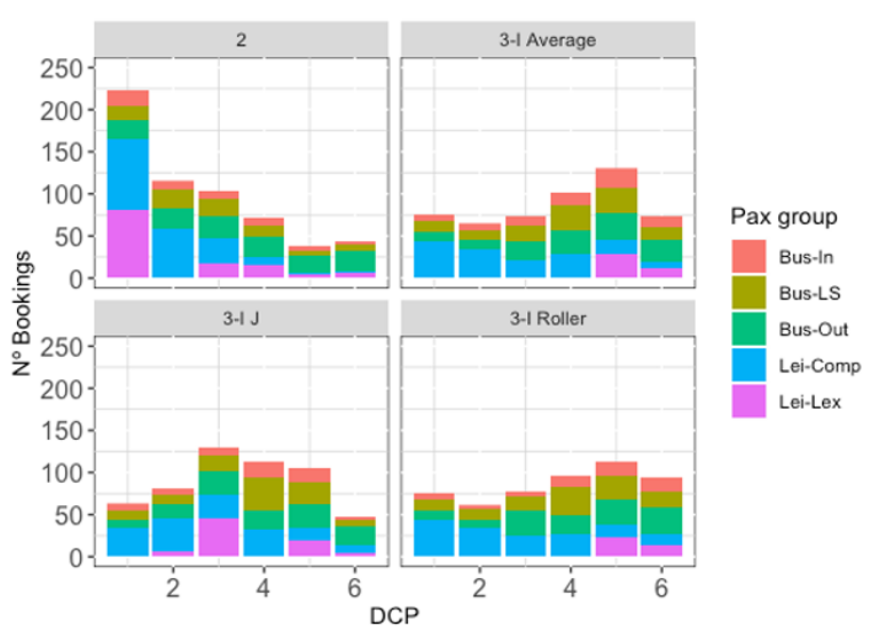

Figure 8 - Group bookings by DCP for airline B in experiments 2 and each of the pricing responses.

Table 5 – Group monetary value of departure time modification from 21:57 to 13:40

	Bus-LS	Bus-Out	Bus-In	Lei-Comp	Lei-Lex
Util. Difference	1,014	-0,444	0,817	1,014	1,014
Monetary value	-$198,84	$87,09	-$160,23	-$149,13	-$149,13

To support pricing decisions, we can study the substitution rates between the alternatives attributes. Table 5 depicts the monetary value that each group of passengers is willing to pay for a change in departure time. We obtain a discrete rate of substitution estimating the difference in utility for a specific variation of the departure time and dividing it by the fare valuation parameter. For a change from a departure time of 21:57 to 13:40 we obtain that business long stay and inbound passengers are willing to pay more than leisure passengers. We can also conclude that for business outbound passengers the change has a negative effect, while

inbound passengers are willing to pay almost \$160 to fly in the new departure time. As such, airline B could charge double for their tickets in departure time 13:40 and still be a competitive alternative for two groups of business passengers.

4. CONCLUSIONS

We presented and implemented CHAIRS, an RM environment simulator based on DCM. CHAIRS incorporate new features such as using a continuous approximation of departure time valuation, introducing a latent class approach based on a combination of mixed logits and NL to account for different groups and replicate taste heterogeneity. CHAIRS also accounts for the temporal evolution of the preference and allows control over pricing by implementing dynamic pricing procedures. Finally, it allows replicating the effect of the loss of information observed in competitive scenarios. We showed that CHAIRS is an efficient and low-cost approach to explore and test RM strategies. We discussed how CHAIRS is able to account for specific behavior observed in airline, itinerary and fare class choices. We tested CHAIRS by simulating a competitive scenario and assessed the interpretability and accuracy of the results.

We used CHAIRS to simulate the entrance of a new competitor in an established competitive scenario and the response of two incumbent airlines. By using a latent class model, we introduced heterogeneity in the passenger's behavior, defining different passenger groups that varied in their attribute valuation parameters and their decision rule. We modified the group membership model along the selling horizon to account for the temporal evolution of the preference. We used a nested logit model to account for airline, itinerary and fare class choices. We used a continuous function to replicate the departure time preferences of different groups of passengers. All these features allow our simulation to present interpretable results.

CHAIRS allowed us to account for the entrant airline RM strategy and to design and implement appropriate RM responses for the incumbent airlines. We tested different RM configurations that used advance purchase restrictions and seat protection levels to control the capacity assigned to multiple fare classes. We implemented different pricing procedures and identified suitable ones to benefit from the specific behavior defined for the demand.

CHAIRS presents a good compromise between modeling accuracy and interpretability. Thus, it helps with the comprehension of the studied choice behaviors and provides insight to aid in the often-intricate decision processes involved in RM. By allowing practitioners to test different scenarios and validate alternative RM strategies, it can also help in the training of RM analysts. Additionally, CHAIRS is easily applied with the current information technologies and modeling frameworks.

There are many possibilities for future work with CHAIRS. Testing increasingly complex RM systems (Strauss et al., 2018), dynamic response capabilities (Wittman and Belobaba, 2018), complex passenger decision strategies, and more heterogeneous behavior. There is also the possibility to use the simulator to train and test automated reinforced learning algorithms

capable of dynamically supporting operational decisions in complex and changing contexts. On the other hand, the creation of more advanced distribution capabilities and information technologies introduce the possibility of offering specific products according to demand characteristics. The validation and application of these new technologies will require studies on the performance of such policies in competitive environments. This will require more advanced and flexible simulation tools, like CHAIRS.

REFERENCES

Alves, C. F., & Barbot, C. (2009). Price discrimination strategies of low-cost carriers. **Journal of Transport Economics and Policy (JTEP),** *43*(3), 345-363.

Belobaba, P. P. (1989). OR practice—application of a probabilistic decision model to airline seat inventory control. **Operations Research**, *37*(2), 183-197.

Ben-Akiva, M., & Abou-Zeid, M. (2013). Methodological issues in modelling time-of-travel preferences. **Transportmetrica A: Transport Science**, *9*(9), 846-859.

Carrier, E. 2008. **Modeling the Choice of an Airline Itinerary and Fare Product Using Booking and Seat Availability Data.** PhD thesis, Massachusetts Institute of Technology.

Cento, A. (2009). Effects of LCC Entry on Pricing in Aviation. En **The Airline Industry: Challenges in the 21st Century**, 1st Ed, Physica-Verlag HD, 77-94.

Çetiner, D. (2013). **Fair revenue sharing mechanisms for strategic passenger airline alliances**. 1st Edition. Springer-Verlag Berlin Heidelberg, Vol. 668.

Cleophas, C. (2012, December). Designing serious games for revenue management training and strategy development. In Proceedings of the **2012 Winter Simulation Conference (WSC)** (pp. 1-12). IEEE.

Coldren, G. M., and F. Koppelman. 2005a. Modeling the Competition Among Air-Travel Itinerary Shares: GEV Model Development. **Transportation Research Part A: Policy and Practice** 39 (4). Elsevier: 345–65.

Coldren, G. M., and F. Koppelman. 2005b. Modeling the Proximate Covariance Property of Air Travel Itineraries Along the Time-of-Day Dimension. **Transportation Research Record** 1915 (1). SAGE Publications Sage CA: Los Angeles, CA: 112–23.

Domanico, F. (2007). The European airline industry: law and economics of low cost carriers. **European Journal of Law and Economics**, 23(3), 199-221.

Doreswamy, G. R., Kothari, A. S., & Tirumalachetty, S. (2015). Simulating the flavors of revenue management for airlines. **Journal of Revenue and Pricing Management**, 14(6), 421-432.

Dresner, M. (2006). Leisure versus business passengers: Similarities, differences, and implications. **Journal of Air Transport Management**, 12(1), 28-32.

Frank, M., Friedemann, M., & Schröder, A. (2008). Principles for simulations in revenue management. **Journal of Revenue and Pricing Management**, 7(1), 7–16.

Garrow, L. A., Jones, S. P., & Parker, R. A. (2007). How much airline customers are willing to pay: An analysis of price sensitivity in online distribution channels. **Journal of Revenue and pricing Management**, 5(4), 271-290.

Gonzalez-Valdes, F., & Raveau, S. (2018). Identifying the presence of heterogeneous discrete choice heuristics at an individual level. **Journal of choice modelling**, 28, 28-40.

Gorin, T. O. (2000). **Airline revenue management: Sell-up and forecasting algorithms.** Ph.D. Thesis, Massachusetts Institute of Technology, Cambridge, MA.

Gorin, T., & Belobaba, P. (2008). Assessing predation in airline markets with low-fare competition. **Transportation Research Part A: Policy and Practice**, 42(5), 784-798.

Guo, P., Xiao, B., & Li, J. (2012). Unconstraining Methods in Revenue Management Systems: Research Overview and Prospects. **Advances in Operations Research**, *2012*, 1-23.

Holloway, S. (2016). **Straight and level: practical airline economics**. 3rd Edition. Routledge. London.

Jung, S. Y., & Yoo, K. E. (2014). Passenger airline choice behavior for domestic short-haul travel in South Korea. **Journal of Air Transport Management**, 38, 43-47.

Kelemen, M., Pilát, M., Makó, S., Rozenberg, R., & Tobisová, A. (2019). Pricing policy aspects in competitive fight between low-cost airlines on Kosice Airport. **Journal of Konbin**, 49(1), 331-342.

Klein, R., Koch, S., Steinhardt, C., & Strauss, A. K. (2020). A review of revenue management: Recent generalizations and advances in industry applications. **European Journal of Operational Research**, 284(2), 397-412.

Lawton, T. C. (2017). **Cleared for take-off: Structure and strategy in the low fare airline business**. 1st edition. Routledge. New York.

Lurkin, V., Garrow, L. A., Higgins, M. J., Newman, J. P., & Schyns, M. (2017). Accounting for price endogeneity in airline itinerary choice models: An application to Continental US markets. **Transportation Research Part A: Policy and Practice**, 100, 228-246.

Lurkin, V., Garrow, L. A., Higgins, M. J., Newman, J. P., & Schyns, M. (2018). Modeling competition among airline itineraries. **Transportation Research Part A: Policy and Practice**, 113, 157-172.

Morlotti, C., Cattaneo, M., Malighetti, P., & Redondi, R. (2017). Multi-dimensional price elasticity for leisure and business destinations in the low-cost air transport market: Evidence from easyJet. **Tourism Management**, 61, 23-34.

Perera, S., & Tan, D. (2019). In search of the "Right Price" for air travel: First steps towards estimating granular price-demand elasticity. **Transportation Research Part A: Policy and Practice**, 130, 557-569.

Smith, B. C., Leimkuler, J. F. and Darrow, R. M. (1992) Yield management at American airlines, **Interfaces**, 22, 1, 8–31.

Strauss, A. K., Klein, R., & Steinhardt, C. (2018). A review of choice-based revenue management: Theory and methods. **European Journal of Operational Research**, 271(2), 375-387.

Varella, R. R., Frazão, J., & Oliveira, A. V. (2017). Dynamic pricing and market segmentation responses to low-cost carrier entry. **Transportation Research Part E: Logistics and Transportation Review**, 98, 151-170.

Wang, J. (2015). **Choice-based Demand Forecasting in Airline Revenue Management Systems.** PhD thesis, University of Western Australia.

Wehner, C., López-Bonilla, J. M., López-Bonilla, L. M., & Santos, J. A. C. (2018). State of the art of pricing policy in air transportation: network carriers vs. low-cost airlines. **Tourism and Management Studies**, 14(3), 32-40.

Williams, H. C. (1977). On the formation of travel demand models and economic evaluation measures of user benefit. **Enviroment and Planning** 9A, 285-344.

Wu, C. L., & So, T. H. (2018). On the flight choice behaviour of business-purpose passengers in the Australian domestic air market. **Journal of Air Transport Management**, 72, 56-67.

Zeni, R. H. (2001). **Improved forecast accuracy in revenue management by unconstraining demand estimates from censored data**. PhD thesis. Graduate school-Newark Rutgers, The State University of New Jersey-Newark.