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DOI
10.1016/j.tra.2021.11.010

Publication date
2022

Document Version
Final published version

Published in
Transportation Research Part A: Policy and Practice

Citation (APA)
Fukushi, M., Delgado, F., Raveau, S., & Santos, B. F. (2022). CHAIRS: A choice-based air transport simulator applied to airline competition and revenue management. *Transportation Research Part A: Policy and Practice*, *155*, 297-315. https://doi.org/10.1016/j.tra.2021.11.010

Transportation Research Part A 155 (2022) 297–315

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

CHAIRS: A choice-based air transport simulator applied to airline competition and revenue management

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A R T I C L E I N F O

Keywords:
Revenue management
Simulations
Discrete choice models

A B S T R A C T

In Revenue Management (RM) systems, information censoring and the interaction between the forecasting and optimization stages, increases the costs and complexity of performance analysis using historical data. An affordable and suitable alternative is using simulations, but appropriate behavioral models must be considered. In the following document, we discuss and test the implementation of a dynamic air transport market simulator, designed to analyze RM systems. The simulator replicates the behavior of passengers that book seats offered in multiple flights by different airlines. We use discrete choice models to replicate the demand behavior, accounting for preferences and decision rule heterogeneity, and including a temporal evolution of the preference throughout the selling horizon. To replicate the supply behavior, a number of airlines modify the price and quantity of different fare classes offered in each flight, using a variety of RM forecasting, un-constraining, and optimization techniques. The simulator allows analysts to study the economic benefit of RM systems under predefined assumptions in an artificial and controlled environment. This increases the benefits obtained by the correct selection of context-appropriate RM systems and the likelihood of successfully implementing new and complex systems. We test and showcase the simulator performance, studying the entrance of a new airline in a competitive context. We generate, 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 proposed framework.

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 (Talluri and van Ryzin, 2006, Çetiner, 2013; Li and Peng, 2007).

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https://doi.org/10.1016/j.tra.2021.11.010
Received 14 July 2021; Received in revised form 5 October 2021; Accepted 8 November 2021
Available online 2 December 2021
0965-8564/

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. One example is motivated by the introduction of the "New Distribution Capability" of the International Air Transport Association (IATA), which promises to offer specific products for individual consumers, which will allow and require the elaboration of novel complex RM techniques (Wittman and Belobaba, 2017). To see a review of the development of RM techniques, we recommend Strauss et al. (2018), Klein et al. (2020), McGill and Van Ryzin (1999), and Chiang, Chen, and Xu (2007).

Selecting an appropriate RM strategy is usually a time-consuming and complex task. The successful implementation of a RM method depends on the specific context of the airline, and 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 and 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). Likewise, multiple simulation frameworks have been proposed, validated, and applied in the air transport industry. Simulators such as the Passenger Origin-Destination Simulator (PODS), the Airline Planning and Operations Simulator (APOS) and the Revenue Management Training for Experts (REMATE), have all been used in real life applications. The widespread adoption of simulators to study revenue management systems by airlines and study groups supports the adoption of simulation techniques.

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 propose, 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 review the literature related to the simulation frameworks developed for the air transport context and, in particular, to Choice-Based Revenue Management simulations. In Section 3, we present the general framework of the simulator. In Section 4, we present an applied example of the simulator, replicating the entrance of a new competitor in an established competitive air transport market. In Section 5 we assess and discuss the obtained results. Finally, in Section 6 we present the conclusions and propose some future work.

2. Background

In this section, we begin by reviewing how RM systems work and their importance in the air transport market. We present some limitations in measuring the performance of RM systems using real data and conclude that simulations are an appropriate method to overcome them. Next, we review the main simulation frameworks developed for these contexts and compare the proposed CHAIRS methodology with the ones used in other simulators.

2.1. Revenue management and the requirement for simulations

In air transport, the service provided by an airline ensures the right to travel in a predefined space inside the plane, a seat. This seat can be associated with different sets of restrictions and benefits (e.g., fare classes), generating multiple services, which passengers acquire at different fares. Under this context, RM systems intervene in controlling the quantity, structure, and price of the offered services. RM systems are applied iteratively in several sequential periods across a fixed selling horizon (e.g., between the date the fare classes of a particular flight are made available and the departure time). In each period, the RM system recommends interventions in a two-stage process; first, it forecasts the demand behavior and then optimizes the structure, quantity, and combination of the offered products/services to maximize revenue.

To correctly assess RM systems performance, it is necessary to compare the forecast with the real demand behavior. However, in practice, it is often impossible to know the real behavior of the demand using historical data. This is due to three main conditions: a) missing data, b) interactions between different RM stages, and c) influence of external variables. Regarding missing data, airlines only have access to the bookings or reservations of passengers' that decide to acquire their services. As such, they are blind to the decision made by passengers booking on a competitor or preferring not to fly. Because of this missing information, it is impossible to describe the actual demand behavior (Cleophas, 2009).

Additionally, in real scenarios, there is an interaction between the forecasting and optimization stages of RM systems. The effect arises because RM systems aim to control the demand by modifying the characteristics of the offered products, while at the same time, they use consumers' behavior to select the optimal controls. This interaction generates two main research branches that further exemplify the problem's complexity: the effect of simultaneous determination endogeneity and the unconstraining problem.

In the presence of endogeneity, the model's parameters used to describe the demand behavior are distorted due to a correlation between the explanatory variables and the error components. This effect is related to the common use of fare or price variables in models used to describe demand. Since the demand behavior is dependent on the price and, due to the use of RM systems, the price is also dependent on the demand, the system incurs in a simultaneous determination scenario (Escobari, 2017), which produces endogeneity. Furthermore, there is usually another source of endogeneity present in the problem, produced by missing information (Mumbower et al., 2014). This type of endogeneity is generated by the incapacity of the researcher to address the complete set of variables that influence the decision process.

In the unconstraining problem, the demand observations used to forecast demand behavior need to be corrected considering the number of products available when the observation was registered. This requirement is generated by the restrictions imposed by the limited capacity offered in each flight. Since the observed demand is constrained by the RM capacity controls or the maximum number of seats assigned to each class, the historical information is not a perfect reflection of the service's demand. To obtain the "real" demand, we need to unconstrain the censored demand observations. This problem further evidences the difficulty to correctly identify and differentiate the causes from the observed changes in RM system performance and passenger behavior and has received ample attention in academic literature (for a review, see Guo et al., 2012).

We also need to consider that air travel markets are usually highly dynamic and quite sensitive to seasonal effects and changes in macroscopic conditions (Vinod, 2021; Gönsch, 2017). These dynamic conditions have been evident in recent times with the Covid-19 pandemic. However, it is generally impossible to differentiate these variables' effects using the poor data quality usually gathered in RM processes.

To overcome the difficulties described above, the literature recommends using simulations to assess RM performance (Frank et al., 2008; Cleophas, 2009). By having complete control of the demand behavior and the information generated in the simulations, it is possible to account for missing information, endogeneity, unconstraining and the variability of the scenarios. However, this requires the definition of a valid model to represent the demand behavior. In CHAIRS, we use DCM to replicate passenger behavior. A widely validated framework both in academic literature and in practical applications within the industry.

2.2. Simulations in RM

There are reputable and validated simulators currently being used in the air transport industry. Compared to these simulators' behavioral models, we believe that the models used in the CHAIRS are easier to implement while also presenting a comparable compromise between accuracy and interpretability. Both characteristics are desirable when simulating RM settings. In this subsection, we define these characteristics, justify their importance in RM simulations, introduce the alternative simulation frameworks and describe how our proposed formulation holds in relation to these abilities, when compared with the other simulators.

On the one hand, accuracy refers to the ability of the model to correctly (and precisely) represent the observed behaviors (Cleophas, 2009). This is crucial in RM simulation applications, because if the simulated scenarios closely resemble the real observed behavior, then the methods and policies tested and suggested in the simulations will be more likely to succeed when we apply them in a real competitive context. Hence, an increase in the accuracy of a RM simulation model could be directly related to an increase in revenue in an industry setting. On the other hand, interpretability refers to the ability of giving credible answers to "what if" scenarios at a disaggregated level (Han et al., 2020). The parameters and indicators used in the simulation are credible if they conform with established assumptions made with expert knowledge (Han et al., 2020). Interpretability is beneficial in RM simulations because it allows practitioners and researchers to evaluate the implementation of new strategies in hypothetical scenarios. This could be essential in supporting high-risk RM decisions proposed, for example, in projected future competitive contexts.

The CHAIRS achieves an adequate balance between accuracy and interpretability with the use of discrete choice parametric models based on the random utility maximization framework (Domencich and McFadden, 1975; Williams, 1977) to replicate the agent's behavior. The wide array of successful applications of DCM to model air transport related choices justify its use in the behavioral model of the CHAIRS. DCM accuracy in RM has been measured and presented a good fit by a variety of metrics both in CBRM and in descriptive applications. In addition, high quality information (e.g. stated or revealed preferences of passengers) can be included to estimate models that are able to account for increasingly complicated behaviors, further increasing their accuracy. Interpretability is another well-known feature of DCM. DCM considers three aspects that make the framework interpretable (Han et al., 2020). In the first place, there is a theory that supports and explains the relationship between the input and output of the model. In the second place, there is parameter level interpretability in the sense that the model parameters directly represent the marginal effect of the attributes in the decision. In the third place, we are able to easily derive widely used indicators to describe the demand behavior, such as elasticities, willingness to pay and marginal rates of substitution.

2.3. CHAIRS comparison to other simulators

Our proposed simulator presents similarities and differences when compared with other well-known simulators. Belobaba and Hopperstad (1999) implement, with the cooperation of several Airlines, the Passenger Origin-Destination Simulator (PODS). This tool aims to study different RM systems in a controlled environment. The validations and applications of PODS in the literature are abundant. (Belobaba and Wilson, 1997) analyzes the performance of RM systems using the PODS, while Carrier (2003) details how the simulator works. Several RM methodologies have been implemented and tested in the PODS (Skwarek 1996, Zickus, 1998; Lee, 2000). Recently, PODS has also been used to test CBRM performance in both stages (Carrier and Weatherford, 2015).

Regarding the generation of the volume of demand, PODS simulates passenger's decision by first generating the potential demand at an Origin-Destination market level. It defines two passenger groups: leisure and business. The average number of passengers is based on real data, and it uses random deviations to generate variations across departure days. In CHAIRS, we use a disaggregated approach that applies an homogeneous Poisson arrival function to define the stochastic potential demand for each period. We also consider leisure and business passengers, assigning each traveler to one of these groups using a latent class membership model. With the use of the latent class model formulation, we are able to include covariates, such as time periods or average fares in the market, that modify the probability of observing passengers of specific groups. Thus, improving the interpretability of our model.

Regarding the passenger choice model, in PODS passengers decide between alternatives using a three-step process. First, each passenger is assigned a decision window, characterized by a width and a position during the day, that represents the earliest and latest convenient departure time. Second, a maximum willingness to pay is defined for each passenger. Third, a group of dis-utilities are assigned to account for the aversion to fare restrictions, schedule inconvenience, connecting paths (as opposed to non-stop flights) and the least preferred airline. The first two steps are used to eliminate unsuitable alternatives, while passengers select the alternative that presents the higher utility obtained in the third step. Consequently, we believe that PODS formulation resembles an elimination by aspects procedure. In CHAIRS, we use a compensatory approach that uses covariates to design an appropriate utility function that accounts for departure time and price preference. We add new covariates to account for class restrictions and benefits and assign a quality attribute to account for favorite airlines. Similar to PODS, our simulator is capable of accommodating taste heterogeneity and also of replicating complex substitution patterns, but we use a latent classes approach and a Nested Logit formulation to achieve this. We believe that using a compensatory model improves the interpretability of the simulator because it allows us to directly account for marginal rates of substitutions between every attribute.

On the other hand, Doreswamy et al., (2015) showcase a successful application of a simulator to test the implementation of RM systems. The researchers calibrated the simulator using real airline controls as a reference and reported the benefits that the use of these tools present. The simulator is developed by SABRE and is coined Airline Planning and Operations Simulator (APOS). The simulator is capable of supporting RM decisions, network planning, and operations such as re-fleeting processes. The model accounts for unconstrained passenger behavior using historical information and aims to obtain the primary demand for the products offered along with parameters to account for spill and recapture behavior. APOS uses a non-parametric MNL model to replicate the choice behavior (Ratliff et al., 2008; Vulcano et al., 2012). The non-parametric models are usually easier to calibrate and more accurate than parametric formulations, because they do not account for the different attributes of the alternatives. However, this also reduces the model's interpretability, restricting the ability of the researchers and practitioners to modify alternative attributes (covariates) to represent passenger behavior in new hypothetical scenarios.

The Revenue Management Training for Experts (REMATE) is a simulator implemented by Lufthansa and the universities of Paderborn, Heidelberg, Kaiserslautern and the Freie Universität Berlin. It is based on the principles defined by Frank et al. (2008). This simulated environment presents the opportunity to control in a manual way the policies imposed by RM systems. The simulator is able to account for different types of passengers and complex strategic behaviors (e.g., delay the purchase). The model is used to support strategic decisions and training in Lufthansa and for application driven theoretical research by the universities (Gerlach et al., 2013). The simulator is continually improving so there are conflicting descriptions of its functionality (Gorin et al., 2012; Zimmermann, 2014; Gerlach et al., 2013). However, we know that REMATE uses a non-homogeneous piecewise constant Poisson process to generate demand volume and a discrete choice model to replicate choices. Which should make APOS similar to the CHAIRS in both accuracy and interpretability.

In the last subsections, we have established that it is advisable to test the performance of RM systems, including forecast and optimization processes, using simulations (Frank et al., 2008) and reviewed the established simulators currently used in the industry and highlight the similarities and differences of the alternative frameworks compared to CHAIRS.

3. Literature review

In this section we review the applications of DCM as a valid way to model passenger behavior. We gather methodological recommendations of their use in similar applications and identify the contributions of our formulation. We summarize the developments presented in the literature, focusing on similar behavioral models as the one presented in CHAIRS.

3.1. Discrete choice models

DCM are a mathematical representation of individual behavior when faced with a discrete, mutually exclusive, and exhaustive set of alternatives (Train, 2009). The decision process is represented by a mathematical formulation that is calibrated using observations made in the same choice context (real and/or hypothetical). The output of a DCM is the probability that the decision maker will choose a particular alternative.

In DCM, two main classes of models are defined according to the formulation used to describe the choice behavior. The first group, called parametric models, requires the proposal and validation of a clear functional form to explain the decision process. The second group, coined non-parametric models, makes no assumptions about the data structure that drives the decision. Due to their fixed structure and increased number of parameters, parametric models usually show less predictive performance and are more challenging to calibrate than non-parametric ones. However, parametric formulations allow researchers to use covariates to explain the choice behavior. This enables them to study the effects of the introduction of new alternatives and the change in specific attributes of the alternatives. This formulation presents clear advantages in simulation contexts.

Descriptive applications of DCM have been used to model passenger behavior in airlines (Cho et al., 2017), itinerary (Lurkin et al., 2017) and fare class choices (Wen and Chen, 2017). Since the focus is on explaining the decision process, descriptive applications mainly use parametric models. The vast number of descriptive implementations include the use of different models, such as multinomial logit (Escobari and Mellado, 2014), nested (Garrow and Koppelman, 2004a) and cross-nested logit (De Luca, 2012), mixed logit (Tsai and Chen, 2019), ordered extreme value models (Lurkin et al., 2018) and generalized extreme value formulations (Coldren and Koppelman, 2005a). We also observe different stratification considerations (Carrier, 2008) the introduction of complex time-dependent behavior (Freund-Feinstei and Bekhor, 2017), and even the use of decision rule heterogeneity (Gonzalez-Valdes and Raveau, 2018). However, descriptive applications of DCM only provide the associated probability of choosing each alternative. To define passenger behavior, it is also necessary to obtain the number of individuals that will face the choice decision. We turn to RM applications to define a validated method to overcome this challenge.

3.2. Choice based revenue management systems

The application of DCM to define user behavior in RM settings starts with introducing choice-based revenue management (CBRM) systems (Talluri and van Ryzin, 2006). CBRM is a new family of techniques that can account for passenger behavior dependent on the characteristics of the offered alternatives available in the chosen scenario. They present a wide array of benefits and have been studied in detail in the literature (Weatherford and Ratliff, 2010; Musalem et al., 2017; Strauss et al., 2018). One of the main benefits of CBRM is that it overcomes the independent demand assumption, which supposes that the demand for different products is independent of the set of offered products. This assumption has been invalidated in recent times (Wang, 2015), mainly due to the introduction and adoption of online distribution platforms and the market penetration of airlines with unrestricted fare structures (Garrow, 2016).

In a CBRM system, historical data is used to calibrate a DCM. At the start of each of the selling periods, the DCM forecast the demand for a set of offered products. These demand forecasts then feed an optimization model to obtain the optimal distribution of products presented to the consumers for the duration of the period. As opposed to descriptive applications, the focus of DCM in CBRM systems is to provide high-quality inputs for the optimization stage of RM. As such, CBRM applications favor the use of non-parametric models because of their superior prediction accuracy.

CBRM systems include some successful applications that showcase the validity of the assumptions and are the main inspiration for our simulation framework. Vulcano et al. (2010) propose a CBRM system and test its performance using a mix of real and synthetic data for a major U.S. airline. The researchers calibrate a parametric multinomial logit (MNL) model using data from an origin-destination market (New York-Florida). They use simulations to validate their results with synthetic data generated by assuming that the MNL model calibrated represents the real passenger behavior. The simulation uses a homogeneous Poisson model to obtain the total number of passengers, and a choice-based stochastic gradient optimization procedure (Van Ryzin and Vulcano, 2008) to select appropriate protection levels. Dai et al. (2014) expand the simulation framework proposed by Vulcano et al. (2010) to test the performance of CBRM methods in a competitive Chinese market. They calibrate MNL, Nested Logit and Mixed Logit models using real data to define passenger behavior. They propose a simulation framework that includes competition, no-show and go-show behavior, taste heterogeneity, discontinuous demand responses and temporal evolution of preference. Finally, Newman et al. (2014) proposed an estimation procedure that allows working with revealed preference censored data, obtaining the parameters of an MNL model for choice behavior and a Poisson arrival model. They use a synthetic population to validate the proposed methodology in the context of hotel room revenue management. The simulations consider a parametric MNL model to replicate the choosing behavior between rooms and use a systematic taste variation approach to include temporal evolution of the preference for the price.

There are other investigations that use the assumptions of CBRM to test RM system performance using different DCM formulations but a similar simulation framework. Vulcano et al. (2012) propose a CBRM demand behavior model estimation procedure that accounts for censored data. The proposed methodology uses a non-parametric MNL and a non-homogeneous Poisson arrival model to describe the primary demand, spill, and recapture behaviors shown by a group of passengers. A simulation is used to validate the CBRM system. Since the DCM used is non-parametric it only presents a magnitude associated with each alternative (the utility). Berbeglia et al. (forthcoming) tests the predictive and revenue performance of multiple DCM, including MNL, Nested Logit, Mixed Logit, Markov chain, exponomial and rank list-based models using synthetic and real data. They implement a simulation procedure in which they replicate passenger behavior using a non-parametric rank list-based (i.e. stochastic preference) model.

Our work expands upon the current research by focusing explicitly on the simulation procedure. We gather the assumptions validated by Vulcano et al. (2010) to generate the number of passengers that face the decision. We introduce competitive scenarios and use a mixed logit model to replicate taste heterogeneity in departure time and price sensitivity like Dai et al. (2014). Moreover, we incorporate the following new features to the simulation framework:

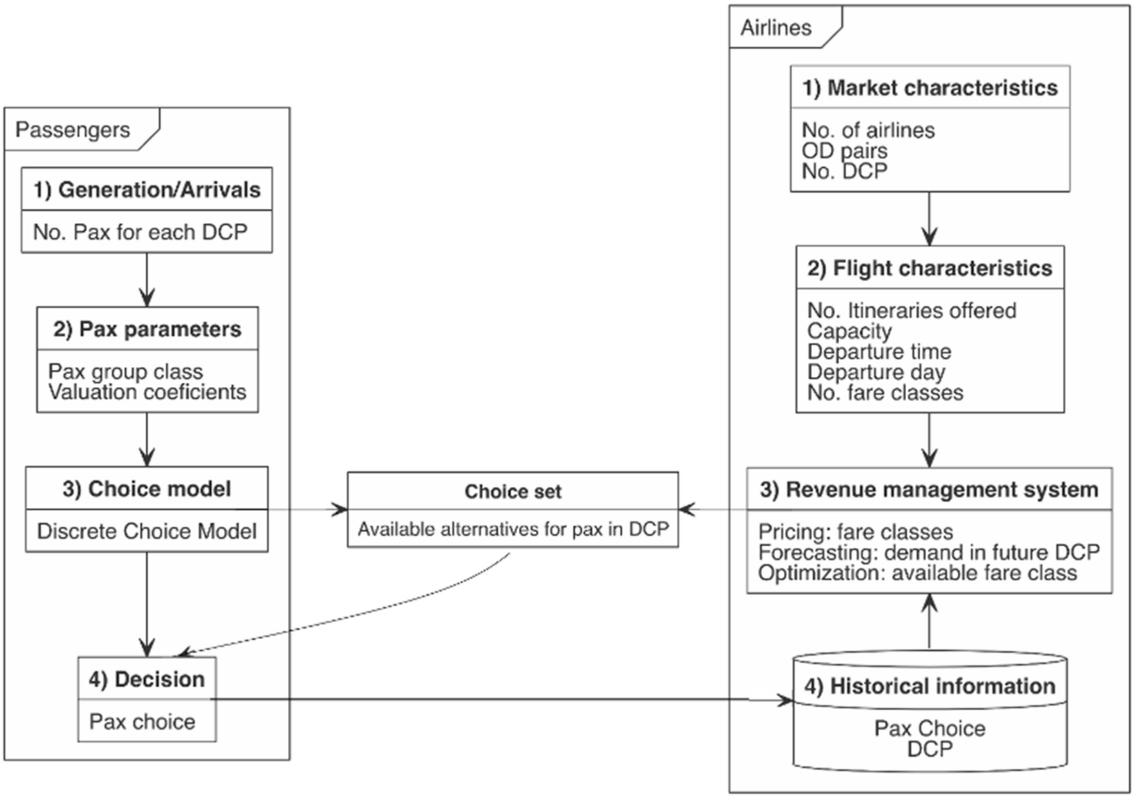

Fig. 1. Interaction between passenger and airline simulation modules.

– We use a continuous approximation of departure time valuation.
– We introduce a latent class approach based on a combination of mixed logits and Nested Logits to account for different groups and replicate taste heterogeneity.
– We account for the temporal evolution of the preference by modifying the probability of the group membership model across time.
– We allow control over pricing and implement pricing procedures that modify the fare according to demand behaviors or time periods.
– We replicate the effect of the loss of information observed in competitive scenarios.

Using DCM to replicate passenger behavior, we develop a simulation tool capable of characterizing almost any competitive air transport market and the use of multiple RM systems in an accurate and interpretable way. This tool can be used to measure the performance of multiple methodologies defined for the forecast and optimization stages of RM systems.

4. Simulation framework

In this section, we introduce the CHAIRS simulation framework. We simulate the interaction between two modules that represent a dynamic and competitive air transport market: i) one module that replicates the behavior of a group of airlines, ii) another module that represents the demand behavior of the passengers. These modules are presented in Fig. 1. Both modules interact during a predefined sale horizon. This horizon is further divided into a known number of periods (i.e., Data Collection Points, DCP). After the simulation reaches the end of the last DCP, the flights depart. In the following sections, we will explain the way each of these modules works.

4.1. Passengers' module

This module replicates the demand behavior and considers 4 stages: 1) generation/arrivals of the passengers, 2) definition of individual and group parameters, 3) designation of the passenger choice model and 4) the final decision of the passenger between every alternative.

In 1) the generation/arrival stage, we define the number (volume) of passengers that will face the decision to book a flight in each DCP. The number of passengers is obtained as a random variable from a homogeneous Poisson process with an arrival mean of λ (Newman et al., 2014), which could depend on macroeconomic variables like the average fare in the market. This parameter is difficult to obtain in real applications because there is usually no evidence of no choice behavior in the air transport context. The probability of getting k arrivals during a DCP is given in equation (1):

$$Pr(X = k) = \frac{\lambda^k e^{-\lambda}}{k!} \tag{1}$$

After defining the number of passengers, in stage 2) we assign to each one a set of parameters that will control their preference between alternatives. These parameters, paired with the alternative's attributes, generate a utility associated with preferring each alternative. The parameters are mainly valuation coefficients, that assign value to each of the attributes that define the choices. The parameters are randomly obtained from known distributions to replicate heterogeneous behaviors. We can define multiple passenger groups by sampling their attributes from distributions that are different between groups but equal between passengers of the same group. The assigned parameters will vary according to the choice model in use. Thus, the utility function can take any functional form.

In stage 3), we define the choice model for each passenger. Considering the passenger group, we assign compensatory and non-compensatory choice behaviors. As discussed earlier, we use the Random Utility Maximization paradigm to replicate passenger choices. In this formulation, we assume that passenger q will prefer alternative i if it has the maximum utility between every alternative (set A) as shown in equation (2).

$$U_{iq} \geq U_{jq} \quad \forall j \in A(q) \tag{2}$$

This utility is only known by the individual, so we add randomness in the behavior by dividing the utility in an observable part (V) and an error component (ε) (equation (3)). By assuming that the error component belongs to certain distributions, we can define a probability associated with choosing each alternative (equation (4)). For example, by assuming that the error distribution is i.i.d. Extreme Value (type I), this probability will present a closed form, and we would obtain the renowned MNL model. With a modification in the error component, we would obtain different probabilities associated to each choice (e.g., we could assume a normal distribution for a probit model). We could also include additional error terms (with different distributions), to account for other correlation (i.e., substitution) patterns. However, models of the logit family were chosen for this application because of the convenience of the closed form of the probability and the successful application of these models in the air transport literature.

$$V_{iq} + \varepsilon_{iq} \geq V_{jq} + \varepsilon_{iq} \quad \forall j \in A(q) \tag{3}$$

$$P_{iq} = Pr\left\{\varepsilon_{iq} - \varepsilon_{iq} \geq V_{jq} - V_{iq}\right\} \quad \forall j \in A(q) \tag{4}$$

Finally, in stage 4) Decision we apply a random procedure to obtain the final choice between the available alternatives using the probability associated by the model defined in 3). It takes as input the parameters and choice model of each passenger, and the available fare classes offered by every airline and returns the passenger choice between the fares, or the decision not to fly. The decision is instantiated sequentially for each passenger that arrived in the period, and after each choice, the inventory of the airline is updated.

4.2. Airline's module

We simulate the behavior of each airline using a 4-stage process: 1) Market characteristics, 2) Flight characteristics, 3) Revenue Management systems and 4) Historical information.

In 1), the market characteristic stage, we define the main attributes of the market. We detail the extension of the network, the number of competing airlines, the origin-destination pairs that the airlines will serve, and the number of available fares for each one. Additionally, we detail the sale horizon and the number of DCP used in the simulation.

In 2), the Flight characteristics stage, we define the specific characteristics of each airline's fleet and network. We use this stage to specify the number of itineraries offered, the capacity of each flight, and the departure day and time.

In stage 3) RM systems we characterize the fare classes structure and availability across time, and their dynamic control using RM systems. The RM systems implemented in the simulation replicate in a simplified way their real-life counterparts. They intervene in the offered products using three submodules, one for pricing, one for forecasting and another one for optimization.

In the pricing submodule, we define the offered fare classes (i.e., a fare and a set of restrictions and benefits). This module creates the products that the passengers will choose from. In the simulation model, we implemented a function that inserts different classes to the Airlines, using as input the characteristics that we want them to have. The fare classes, availability, and price and service restrictions characteristics can be easily changed across periods, and across flights using different mechanisms, allowing us to replicate dynamic pricing procedures (Wittman and Belobaba, 2018, 2019). The only restriction imposed by the simulation model is that the classes need to be defined according to comparable attributes across Airlines.

The forecasting submodule uses simulated historical information to predict the future behavior of the demand, this is used as input for the optimization module. The forecasting submodule obtains past booking information from the decision stage of the passenger module. The access to the information presents several filters to replicate real applications. The most important is that an Airline can only access the bookings made on their own flights. As such, airlines are blind to the no booking behavior or the preference for products offered by the competition. In response, the forecasting submodule also accounts for demand unconstraining. Our simulator can use various unconstraining methods to obtain the "real" demand using censored demand observations.

The optimization submodule assigns the number of protected seats that maximize the revenue using the demand forecast, the fare structure, and the seat availability per class as input. The optimization procedure can be applied after each choice, but it is not recommended due to the computational burden. Instead, after each choice, we only update the availability of the class if the passenger exhausts the protected capacity. Thus, the information related to the class-protected seats, fare, and associated characteristics is transmitted usually at the start of the period. The simulator has a flexible configuration that allows users to modify the imposed RM controls directly or include different pricing and optimization methodologies to automate the procedure. This flexible architecture allows us to test different RM strategies.

The RM module (3) interacts directly with the class availability submodule, which collects the controls imposed by the RM systems of each airline and defines the currently available fare classes for each passenger at any time. This submodule works as a distribution platform and can be altered to simulate special distribution capabilities (e.g., modify the available classes according to specific passengers' groups).

Finally, in 4), the historical information stage, we record every booking made in the decision stage, ordering them according to the period and the sequence that the choices were made. The database contains the sale period, the class, the flight number, the itinerary, and the Airline. We also include an id associated with each passenger. This database is accessed by the forecasting and optimization modules to check seat availability or historical booking behavior.

4.3. Simulation run description

Algorithm 1 presents the functional layout of the simulation. A specific simulation run considers the complete sale horizon. We can do multiple runs of a specific simulation. At the start of the simulation, we define the market and flight characteristics along with the demand volume. Then, for each period of the sales horizons, we first assign the parameters and choice model for every passenger arriving at the period. Next, we define the available fare classes for each airline using different forecasting and optimization RM techniques. Finally, we process the request of the passengers in a first come first served ordered procedure. This consists of checking the available classes and then instantiating the decision for each passenger, updating the historical information with the choice. Once every run of the simulation is completed the model output is generated and saved.

```
Algorithm 1- Simulation run
Initialize Market Characteristics.
Initialize Flight Characteristics.
Initialize Generation/Arrivals.
for (set of periods before flight) do:
  Initialize/define individual & group parameters.
  Initialize/assign choice model.
  for (set of airlines) do:
    Initialize RMS.
  for (set of initialized passengers) do:
    Initialize/Check Class availability/Choice set.
    Initialize Decision.
    Initialize Class booking or no flight.
    Update historical information.
Save simulation run information.
```

5. Case study: Simulation of the introduction of a new competitor in an established air transport market.

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.

5.1. 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 adjusts the availability and price of their fare classes across the time periods, implementing different 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. CHAIRS was implemented using R language (R Core Team, 2019). The discrete choice models used were implemented using Apollo (Hess and Palma, 2019).

5.2. 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 (Boyd and Kallesen, 2004; Dresner, 2006; Gilbert and Wong, 2003), 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 (5):

$$V_i = \beta_{fare}*fare_i + b_1*sin(\frac{2\pi*DT_i*60}{1440}) + b_2*sin(\frac{4\pi*DT_i*60}{1440}) + b_3*sin(\frac{6\pi*DT_i*60}{1440}) + \\ + j_1*cos(\frac{2\pi*DT_i*60}{1440}) + j_2*cos(\frac{4\pi*DT_i*60}{1440}) + j_3*cos(\frac{6\pi*DT_i*60}{1440}) + \beta_q*Q_i \quad (5)$$

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 and So, 2018; Zhang, Lin, and Newman, 2016). The fare valuation parameters are obtained from itinerary choice DCM found in the literature (Coldren and Koppleman, 2005a,b). The valuation of the departure time uses 6 parameters (Ben-Akiva and 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 (Zeid et al., 2006; 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.

The temporal evolution of the preference across the sale horizon has been widely documented in the literature (Drabas and Wu, 2013; Wen and Chen, 2017; Morlotti et al., 2017). To simulate a similar effect, we modify the passenger mix across different periods. In CHAIRS, it is possible to associate a class membership probability to each arriving passenger. The probability can be defined as a function of any variable present in the simulation or even other simulated variables associated with passenger characteristics. Hence, it is possible to use a latent class logit model to define the class membership.

In our proposed example we will use a simplified approach, in which the probability is a function of the DCP. 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 each DCP (i.e., for leisure passengers the proportions for DCP 1–6 would be 70%, 62%, 54%, 46%, 38% and 30%). In the last period (DCP6) leisure passengers will be 30% and business 70%. We also tested different configurations for the proportion of the leisure-business passengers' mix, such as 60%-40% and 90%-10%. We found that if the proportions invert at the last DCP increasing in a linear way, the results are similar but not identical. Note that under any of these configurations, the total number of business and leisure passengers, considering every DCP, is expected to be the same. As such, we considered that a 70%–30% mixture that increased in a linear way, was a representative scenario.

The main difference between leisure and business passengers is their fare valuation parameter (Chang and Sun, 2012; Jung and 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 use the same fare valuation coefficients used in equivalent nested logits models applied by Lurkin et al., 2018. That is, −0.068 and −0.051, respectively. The researchers found the parameters were consistent across time and space.

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 (Chang and Sun, 2012), but follow the "long stay" profile, not showing a particular preference between morning or noon flights. Fig. 2 presents these three profiles; the x-axis represents the departure time, and the y-axis is the utility associated with each time.

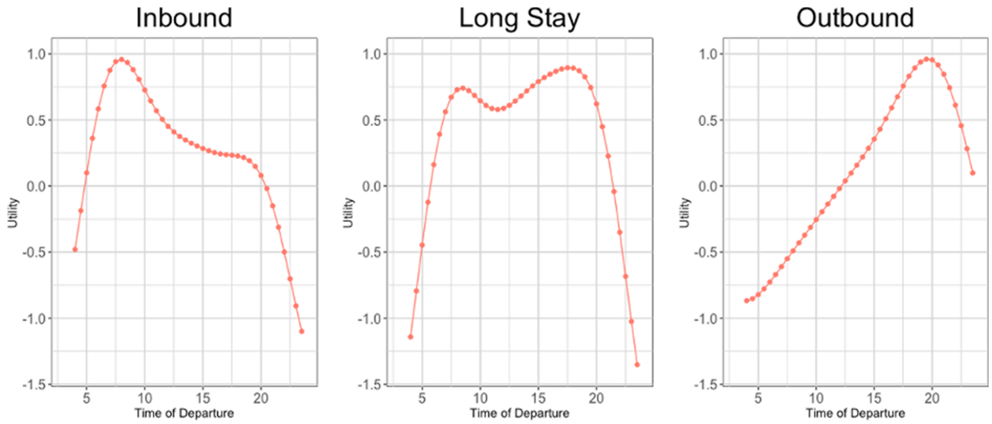

Fig. 2. Departure time valuation.

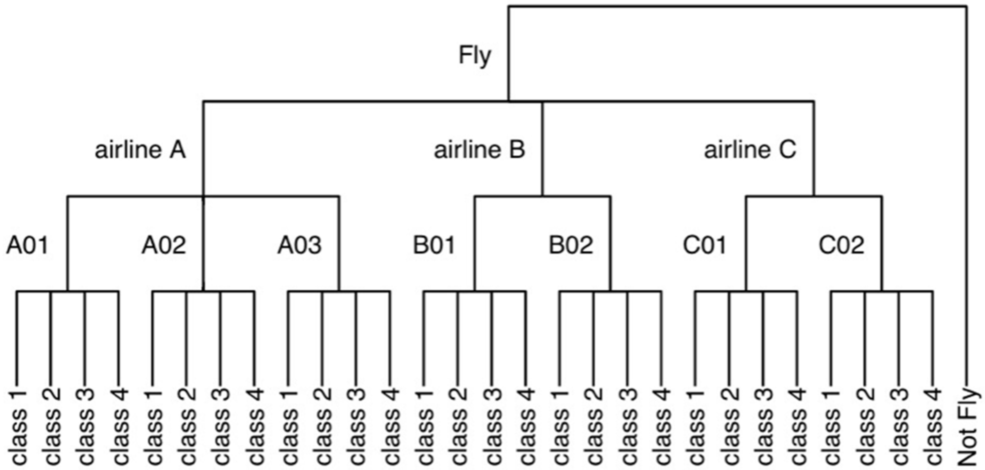

Fig. 3. Compensatory fare class choice model.

Finally, we assign a choice model to each passenger. We propose two different models to represent a compensatory (Wu and So, 2018; Gonzalez-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 Fig. 3. There is evidence to support the use of this structure in the literature of DCM applied to itinerary and fare-class choices (Coldren and Koppelman, 2005; Lurkin et al., 2018). The parameters used to implement the choice model for each of the passengers' groups is presented in Appendix A.

5.3. *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.

5.3.1. *Base experiment*

In the base experiment, two carriers compete in a unique origin destination 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. Fig. 4 presents the departure time of each flight operated by each airline. In the base experiment, only airlines A and B are present.

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, 2017). 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

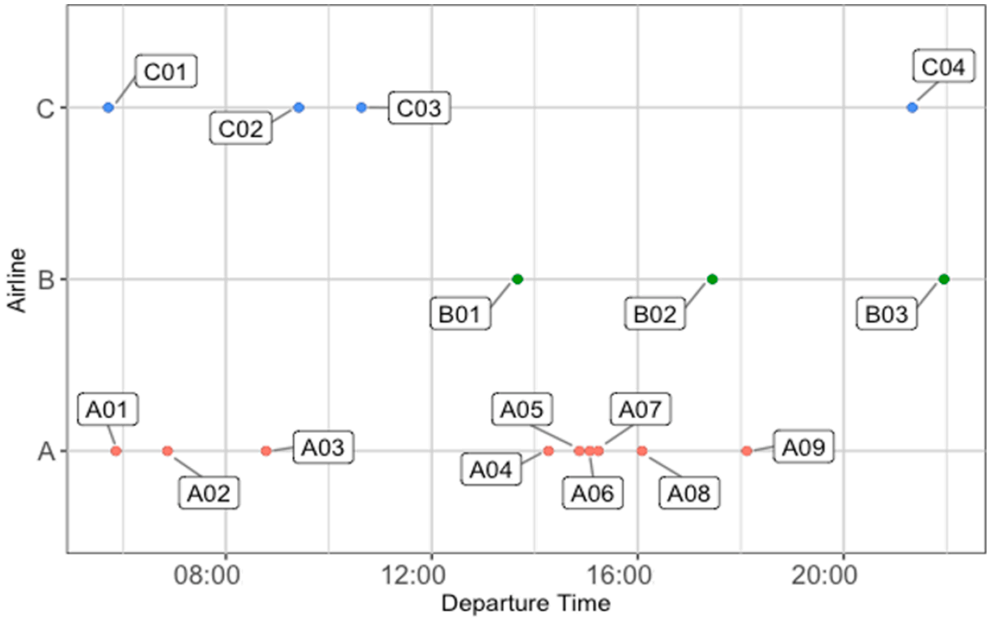

Fig. 4. Flights departure time distribution for each airline.

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

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. An advance purchase of 99 indicates that the class is available in any DCP as long as the class is still available, considering the seat protection levels (i.e., if it is not sold out).

From the base experiment, we build two extended experiments.

5.3.2. *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 Fig. 4.

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). The details of the fare classes and their characteristics are presented in Table 1.

5.3.3. *Experiment 3: Incumbents response strategies*

To showcase the flexibility of the simulator we implement two RM response strategies adopted by the incumbent carriers. The first

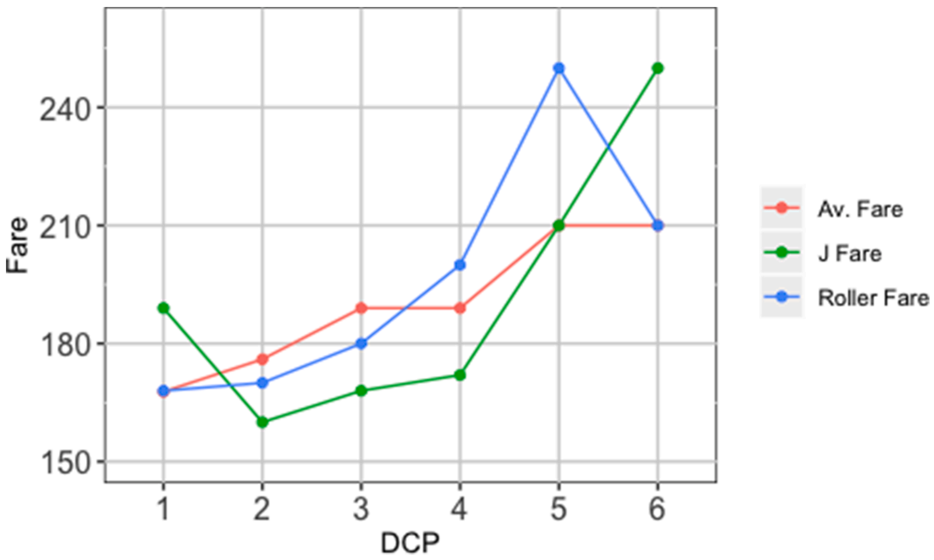

Fig. 5. Pricing response of airline B to the entrance of airline C.

strategy is implemented by airline B (LCC) and the second one by airline A (FSC). Both strategies use an RM system proposed in the literature.

5.3.3.1. Airline B (LCC) pricing response. 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).

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; Piga and Bachis, 2006). The three temporal profiles of the evolution of the fare used to simulate the responses of Airline B are presented in Fig. 5. 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.

5.3.3.2. Airline A (FSC) RM response.. With the entrance of airline C, the incumbent airline A implements a RM system based on capacity with leg-based controls. With this strategy, the airline attempts to control the availability of the classes across time. The implemented system is automated and corresponds to a classical pick-up model (Gorin, 2000) for the forecasting, paired with an EMSRb (Belobaba, 1989) procedure for the optimization. The unconstraining requirements are met using the expectation-maximization method (Zeni, 2001). These mechanisms are used at the start of each period to fix the protected capacity of each fare class.

To generate the historical information necessary to run the forecasting procedure, we consider 10 simulation runs (i.e. repetitions) of experiment 2, that present the entrance of Airline C, as ground truth. Using the booking behavior observed in these simulations we define the unconstrained demand using the pickup model and the expectation-maximization procedure.

6. 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.

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 do not 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

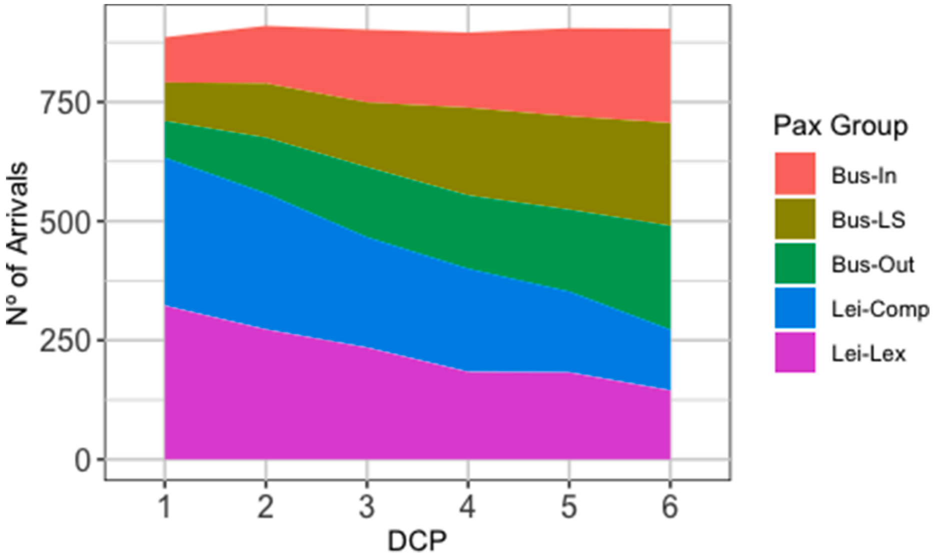

Fig. 6. Passenger group arrivals by DCP.

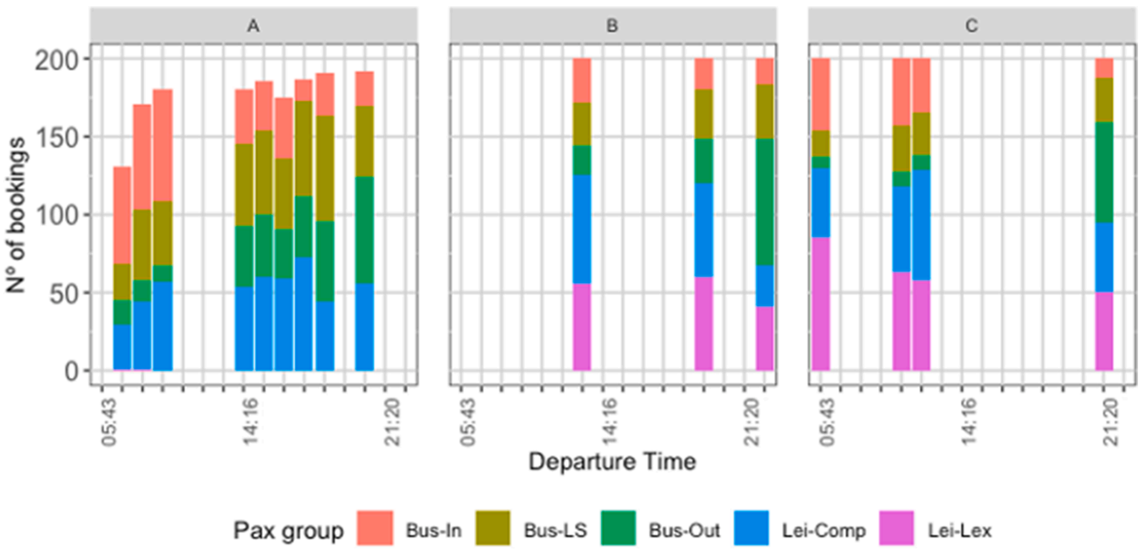

Fig. 7. Passenger group bookings by airline and flight departure time.

random behavior of the DCM framework.

We first analyze the demand behavior obtained in the simulations. Fig. 6 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.

Fig. 7 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 (Domanico, 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.

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 (i.e., the average percentage of occupied capacity) of the airlines.

Table 2
Airline revenue per flight by experiment.

	1	2	3-I Roller	3-I J	3-I Average	3-II
Airline A	$59,308 ($413)	$52,085 ($909)	$51,976 ($858)	$52,114 ($827)	$51,884 ($756)	$53,508 ($550)
Airline B	$32,409 ($179)	$34,509 ($210)	$35,123 ($775)	$32,932 ($987)	$34,189 ($893)	$33,283 ($606)
Airline C	–	$33,407 ($108)	$33,154 ($137)	$33,276 ($121)	$33,164 ($136)	$33,214 ($149)

Table 3
Airline average booked fare by experiment.

	1	2	3-I Roller	3-I J	3-I Average	3-II
Airline A	$303 ($0.98)	$294 ($0.88)	$296 ($1.17)	$296 ($1.20)	$296 ($1.06)	$286 ($0.82)
Airline B	$165 ($1.72)	$177 ($0.81)	$196 ($0.40)	$186 ($2.09)	$189 ($0.26)	$190 ($0.89)
Airline C	–	$170 ($1.07)	$169 ($1.33)	$170 ($0.83)	$169 ($1.28)	$170 ($1.19)

Table 4
Airline load factor by experiment.

	1	2	3-I Roller	3-I J	3-I Average	3-II
Airline A	98.2% (0.6%)	87.4% (1.4%)	87.2% (1.2%)	87.4% (1.3%)	87.1% (1.1%)	93.9% (0.9%)
Airline B	100% (0%)	99.8% (0.4%)	87.0% (1.8%)	89.2% (2.5%)	88.4% (2.2%)	85.8% (1.6%)
Airline C	–	100% (0%)	100% (0%)	100% (0%)	100% (0%)	100% (0%)

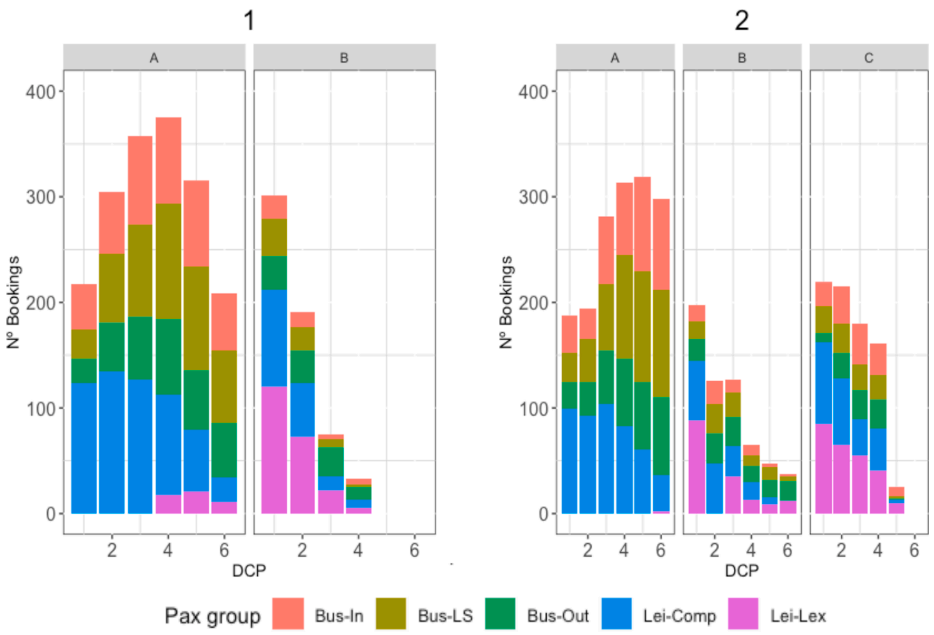

Fig. 8. Bookings by DCP of each airline in experiments 1 and 2.

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 load factor of 98%. In experiment 2, due to the entrance of airline C, airline A reduces its load factor, average fare and revenue by flight. However, for airline B the effect is the opposite, and the introduction of Airline C is favorable.

Airline B benefiting from the entrance of a new competitor is a counterintuitive result that can be explained by further examining the booking behavior. Fig. 8 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,

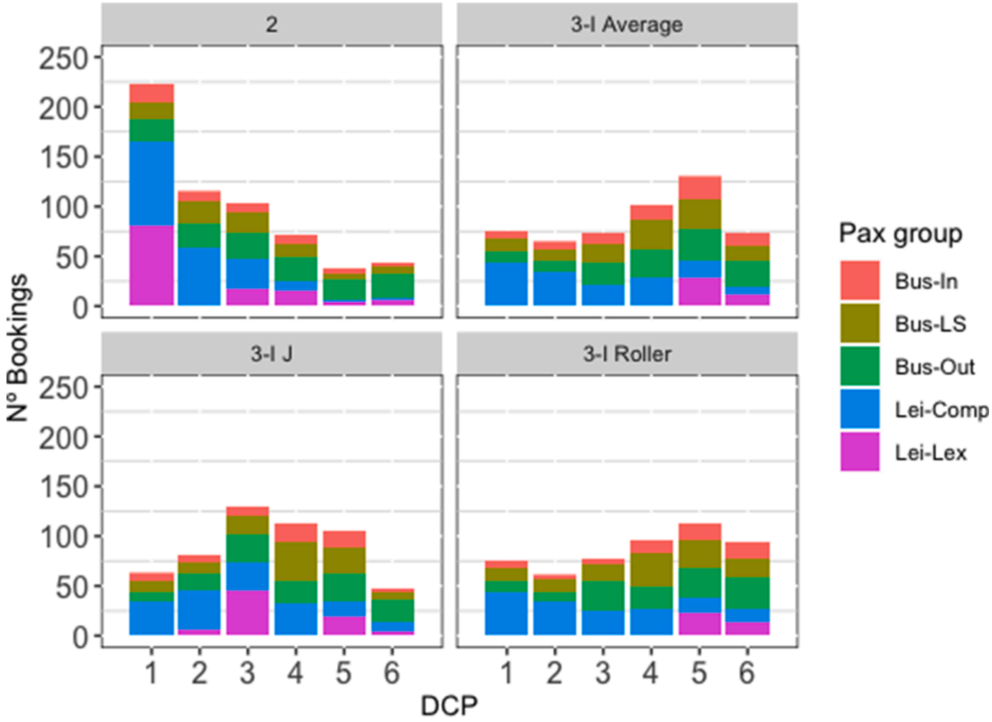

Fig. 9. Booking composition of airline B in experiments 2 and 3.

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	-$198.83	$87.09	-$160.22	-$149.12	-$149.12

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.

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 load factor, which is explained by an increase in the average fare paid. We can further examine the effect of the new pricing procedure. Fig. 9 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.

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.

Finally, in experiment 3-II we observe the results obtained by airline A by using a pick-up model to predict the demand behavior and an EMSRb procedure to optimize the capacity offered in each DCP. During experiment 3-II airline B uses the average pricing

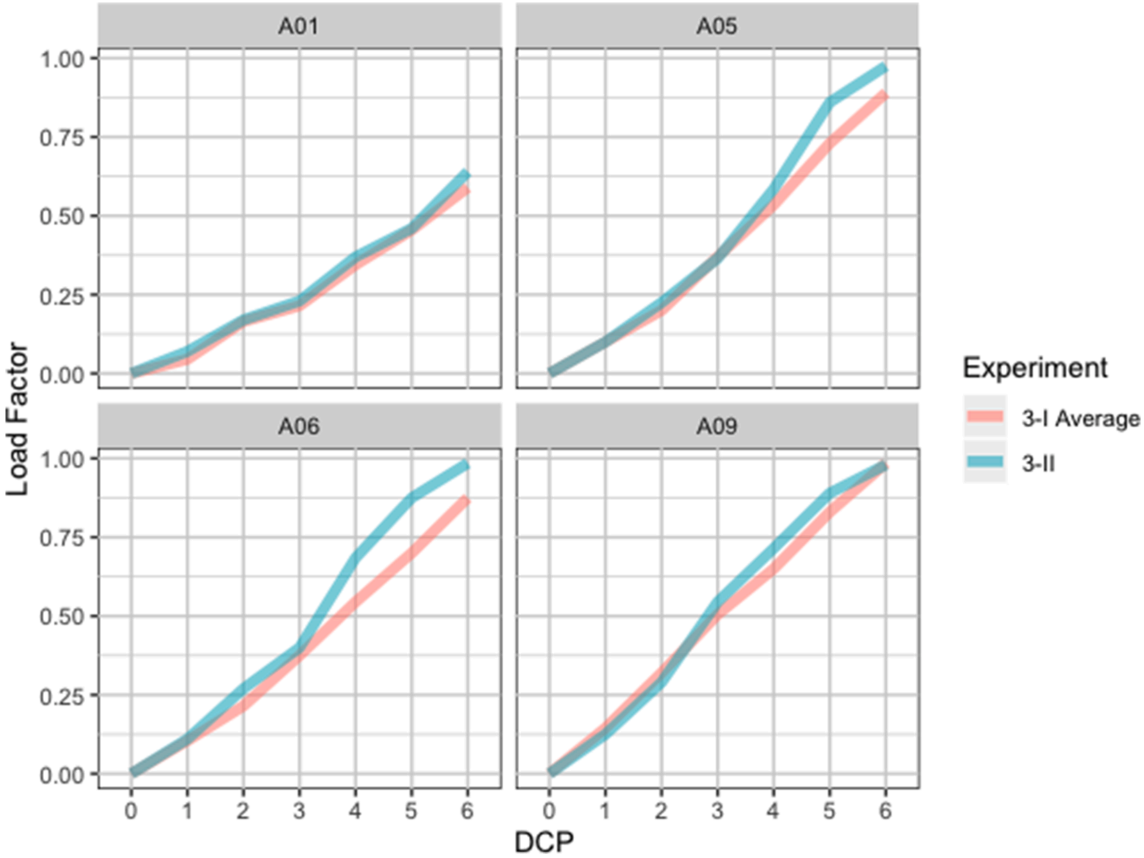

Fig. 10. Booking curve of airline A.

Table A1
Discrete choice model parameters for each passenger group.

Pax Type	Group Sub-class	Business Long Stay	Business Outbound	Business Inbound	Leisure Long Stay	Leisure Long Stay
Model Parameters	No Fly	1	1	1	1	1
	b1	−0.5427	−0.814	0.0417	−0.5427	−0.5427
	b2	−0.4747	−0.2373	−0.3651	−0.4747	−0.4747
	b3	−0.1771	−0.0354	−0.1362	−0.1771	−0.1771
	j1	−1.0923	−0.0109	−0.8402	−1.0923	−1.0923
	j2	−0.5272	−0.0527	−0.4055	−0.5272	−0.5272
	j3	−0.0224	−0.0224	−0.0172	−0.0224	−0.0224
	Fare	−0.0051	−0.0051	−0.0051	−0.0068	−0.0068
Scale factors	Fly-NoFly	0.9	0.9	0.9	0.9	0.9
	Itinerary	0.6	0.6	0.6	0.6	0.6
	Airline	0.75	0.75	0.75	0.75	0.75

booking profile as in experiment 3-I Average. Compared with experiment 3-I Average we can observe from Table 2 that there is an increase in the revenue obtained of around 3%. The difference could be explained by a rise in the average load factor, going from 87,1% in experiment 3-I average to 93,5% in 3-II as shown in Table 3. However, the increase in passengers does not directly translate to a higher revenue, because passengers pay on average a lower fare in experiment 3-II ($286 vs $296). These differences are presented in Tables 2–4 and are all statistically significant.

We can further analyze the performance of the RM system implemented. Fig. 10 depicts the load factor for the itineraries of airline A that presented less occupation across experiments. We analyze a specific repetition of experiments 3-I Average and 3-II for flights A01, A05, A06 and A09. We conclude that the RM system implemented helps the airline capture more passengers, especially in flights that were difficult to sell in experiment 2. The increase in load factor for A01, A05 and A06 is 5%, 8.5% and 11% respectively. For A09 we do not see a significant increase. For flights A01, A05 and A06 we can see that the EMSRb procedure allows the airline to capture more passengers. For flights A05, A06 and A09 the RM system delays some of the bookings, reserving more capacity for the final DCP.

The results presented are valid for a demand mix that includes business and leisure passengers in similar proportions. As such, these results are not directly transferable under other contexts. For example, we found that if the proportion of the passengers is fixed across the DCP, and if these proportions are extreme such as 90%-10% mixtures for business and leisure, notably different behaviors are observed. RM pricing strategies that worked for a business dominated route were not effective for leisure dominated routes. Furthermore, the introduction of the new airline had different effects, ranging from positive to negative, in the incumbent airline performance. These results were consistent with changes in the predominant passenger group.

7. 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 Nested Logit to account for different groups and replicate taste heterogeneity. CHAIRS also accounts for the temporal evolution of the preference and allows control over pricing. This is done by implementing pricing procedures that modify the fare according to demand behaviors or time periods. 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. A main advantage of the proposed framework is the possibility of designing optimal RM strategies according to disaggregate passenger behavior.

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. We assessed the performance of classic RM methods by implementing a pick-up model for the forecasting, paired with an EMSRb procedure for the optimization. The forecasting method replicated the loss of information observed in competitive scenarios.

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.

Another avenue of research that could be explored with CHAIRS pertains overbooking models. This is an interesting subject that motivated revenue management since its inception. The implementation of overbooking behavior could be achieved in CHAIRS by modifying both the demand and the supply behavior. From the demand side it would be necessary to include no-show and cancellation models. Versions of both models are presented in the air transport literature (Garrow and Koppelman, 2004b; Chiew et al., 2017). From the supply side, CHAIRS already presents a forecasting and an optimization submodule, that could be used to implement overbooking controls. Using both submodules it is possible to implement a variety of cost minimization based overbooking models, which balance spoilage and denied boarding costs of the passengers that are expected to miss the flight.

In addition, the analysis of the appropriateness of the RM procedures used can be further explored in CHAIRS. For example, we can compare the pricing behavior as the flights get closer to being full. This can be done considering the direct price of the flight or the interdependencies generated by the price and the available capacity of alternative flights. By further investigating the effect of the price of the different classes offered, analysts could gather additional insight into the pricing procedure. This would allow them to make more profitable pricing decisions.

CRediT authorship contribution statement

Mitsuyoshi Fukushi: Conceptualization, Methodology, Software, Investigation, Visualization. **Felipe Delgado:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Sebastián Raveau:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Bruno F. Santos:** Conceptualization, Methodology, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work was funded by the National Agency for Research and Development (ANID), scholarship program, DOCTORADO BECA NACIONAL/2018 - 21180796

Appendix A. Utility function parameters by passenger group

In the following appendix, we present the parameters used to represent the choice model of each passenger group. These parameters are presented in Table A1.

Reference

Alves, C.F., Barbot, C., 2009. Price discrimination strategies of low-cost carriers. J. Transp. Econ. Policy (JTEP) 43 (3), 345–363.
Baker, D.M.A., 2013. Service quality and customer satisfaction in the airline industry: a comparison between legacy airlines and low-cost airlines. Am. J. Tourism Res. 2 (1), 67–77.
Belobaba, P.P., 1989. OR practice—application of a probabilistic decision model to airline seat inventory control. Oper. Res. 37 (2), 183–197.
Belobaba, P.P., Hopperstad, C., 1999. Boeing/MIT simulation study: PODS results update. 1999 AGIFORS Reservations and Yield Management Study Group Symposium, 27–30 April, London.
Belobaba, P.P., Wilson, J.L., 1997. Impacts of yield management in competitive airline markets. Journal of Air Transport Management 3 (1), 3–9.
Ben-Akiva, M., Abou-Zeid, M., 2013. Methodological issues in modelling time-of-travel preferences. Transp. A: Transp. Sci. 9 (9), 846–859.
Berbeglia, G., Garassino, A., & Vulcano, G. (2021). A comparative empirical study of discrete choice models in retail operations. Working paper, University of Melbourne.
Boyd, E.A., Kallesen, R., 2004. Practice papers: The science of revenue management when passengers purchase the lowest available fare. J. Rev. Pricing Manage. 3 (2), 171–177.
Carrier, E., 2003. Modeling airline passenger choice: Passenger preference for schedule in the passenger origin-destination simulator. Master Thesis. Massachusetts Institute of Technology, Cambridge, MA.
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, Cambridge, MA.
Carrier, E., Weatherford, L., 2015. Implementation of MNL choice models in the passenger origin-destination simulator (PODS). J. Rev. Pricing Manage. 14 (6), 400–407.
Cento, A., 2009. Effects of LCC Entry on Pricing in Aviation. In: The Airline Industry: Challenges in the 21st Century, first ed. Physica-Verlag HD, pp. 77–94.
Çetiner, D., 2013. Fair revenue sharing mechanisms for strategic passenger airline alliances, first ed. vol. 668. Springer-Verlag Berlin Heidelberg.
Chang, L.-Y., Sun, P.-Y., 2012. Stated-choice analysis of willingness to pay for low cost carrier services. J. Air Transp. Manage. 20, 15–17.
Chiang, W.-C., Chen, J.C.H., Xu, X., 2007. An overview of research revenue management: Current issues and future research. Int. J. Rev. Manage. 1 (1), 97–128.
Chiew, E., Daziano, R.A., Garrow, L.A., 2017. Bayesian estimation of hazard models of airline passengers' cancellation behavior. Transp. Res. Part A: Policy Pract. 96, 154–167.
Cho, W., Windle, R.J., Dresner, M.E., 2017. The Impact of Operational Exposure and Value-of-Time on Customer Choice: Evidence from the Airline Industry. Transp. Res. Part A: Policy Pract. 103, 455–471.
Cleophas, C., 2009. Simulation-based analysis of forecast performance evaluations for airline revenue management. Ph.D. Thesis. University of Paderborn.
Cleophas, C., 2012. Designing serious games for revenue management training and strategy development. In: Proceedings of the 2012 Winter Simulation Conference (WSC). IEEE, pp. 1–12.
Coldren, G.M., Koppelman, F.S., 2005a. Modeling the Competition Among Air-Travel Itinerary Shares: GEV Model Development. Transp. Res. Part A: Policy Pract. 39 (4), 345–365.
Coldren, G. M., Koppelman, F., 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, pp. 112–123.
Dai, J., Ding, W., Kleywegt, A., Wang, X., Zhang, Y., 2014. Choice based revenue management for parallel flights. Available at SSRN 2404193.
De Luca, S., 2012. Modelling Airport Choice Behaviour for Direct Flights, Connecting Flights and Different Travel Plans. J. Transp. Geogr. 22, 148–163. Elsevier.
Domanico, F., 2007. The European airline industry: law and economics of low cost carriers. Eur. J. Law Econ. 23 (3), 199–221.
Domencich, T., McFadden, D., 1975. Urban travel demand: a behavioural analysis. North Holland publishing company, Oxford, England.
Doreswamy, G.R., Kothari, A.S., Tirumalachetty, S., 2015. Simulating the flavors of revenue management for airlines. J. Rev. Pricing Manage. 14 (6), 421–432.
Drabas, T., Wu, C.-L., 2013. Modelling air carrier choices with a Segment Specific Cross Nested Logit model. J. Air Transp. Manage. 32, 8–16.
Dresner, M., 2006. Leisure versus business passengers: Similarities, differences, and implications. J. Air Transp. Manage. 12 (1), 28–32.
Escobari, D., 2017. Airport, airline and departure time choice and substitution patterns: An empirical analysis. Transp. Res. Part A: Policy Pract. 103, 198–210.
Escobari, D., Mellado, C., 2014. The choice of airport, airline, and departure date and time: estimating the demand for flights. The Economics of International Airline Transport. Emerald Group Publishing Limited.
Frank, M., Friedemann, M., Schröder, A., 2008. Principles for simulations in revenue management. J. Rev. Pricing Manage. 7 (1), 7–16.
Freund-Feinstei, U., Bekhor, S., 2017. Airline Itinerary Choice in a Dynamic Supply Environment: Results from a Stated Preference Survey. J. Spatial Organiz. Dyn. 5 (4), 400–424.
Garrow, L.A., 2016. Discrete choice modelling and air travel demand: theory and applications, first ed. Routledge, New York, USA.
Garrow, L.A., Koppelman, F.S., 2004a. Multinomial and Nested Logit Models of Airline Passengers' No-Show and Standby Behaviour. J. Rev. Pricing Manage. 3 (3), 237–253.
Garrow, L.A., Koppelman, F.S., 2004b. Predicting Air Travelers' No-Show and Standby Behavior Using Passenger and Directional Itinerary Information. J. Air Transp. Manage. 10 (6), 401–411.
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. J. Rev. Pricing Manage. 5 (4), 271–290.
Gerlach, M., Cleophas, C., Kliewer, N., 2013. Airline codeshare alliances. Bus. Inform. Syst. Eng. 5 (3), 153–163.

Gilbert, D., Wong, R.K.C., 2003. Passenger expectations and airline services: a Hong Kong based study. Tourism Manage. 24 (5), 519–532.
Gönsch, J., 2017. A survey on risk-averse and robust revenue management. Eur. J. Oper. Res. 263 (2), 337–348.
Gonzalez-Valdes, F., Raveau, S., 2018. Identifying the presence of heterogeneous discrete choice heuristics at an individual level. J. Choice Model. 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. Transp. Res. Part A: Policy Pract. 42 (5), 784–798.
Gorin, T., Walczak, D., Bartke, P., Friedemann, M., 2012. Incorporating cancel and rebook behavior in revenue management optimization. J. Rev. Pricing Manage. 11 (6), 645–660.
Guo, P., Xiao, B., Li, J., 2012. Unconstraining methods in revenue management systems: Research overview and prospects. Adv. Oper. Res. 2012.
Han, Y., Zegras, C., Pereira, F. C., Ben-Akiva, M., 2020. A neural-embedded choice model: Tastenet-mnl modeling taste heterogeneity with flexibility and interpretability. arXiv preprint arXiv:2002.00922.
Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32, 100170. https://doi.org/10.1016/j.jocm.2019.100170.
Holloway, S., 2016. Straight and level: practical airline economics, third ed. Routledge, London.
Jung, S.-Y., Yoo, K.-E., 2014. Passenger airline choice behavior for domestic short-haul travel in South Korea. J. Air Transp. Manage. 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. J. 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. Eur. J. Oper. Res. 284 (2), 397–412.
Lawton, T.C., 2017. Cleared for take-off: Structure and strategy in the low fare airline business, first ed. Routledge, New York.
Lee, S., 2000. Modeling passenger disutilities in airline revenue management simulation. PhD thesis. Massachusetts Institute of Technology, Cambridge, MA.
Li, L., Peng, J.-H., 2007. Dynamic pricing model for airline revenue management under competition. Syst. Eng. Theory Pract. 27 (11), 15–25.
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. Transp. Res. Part A: Policy Pract. 100, 228–246.
Lurkin, V., Garrow, L.A., Higgins, M.J., Newman, J.P., Schyns, M., 2018. Modeling competition among airline itineraries. Transp. Res. Part A: Policy Pract. 113, 157–172.
McGill, J.I., van Ryzin, G.J., 1999. Revenue management: Research overview and prospects. Transp. Sci. 33 (2), 233–256.
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 Manage. 61, 23–34.
Mumbower, S., Garrow, L.A., Higgins, M.J., 2014. Estimating flight-level price elasticities using online airline data: A first step toward integrating pricing, demand, and revenue optimization. Transp. Res. Part A: Policy Pract. 66, 196–212.
Musalem, A., Olivares, M., Borle, S., Che, H., Conlon, C.T., Girotra, K., Zheng, F., et al., 2017. A review of choice modeling in the marketing-operations management interface. Kelley School Bus. Res. Pap. 17–60, 17–85.
Newman, J.P., Ferguson, M.E., Garrow, L.A., Jacobs, T.L., 2014. Estimation of choice-based models using sales data from a single firm. Manuf. Serv. Oper. Manage. 16 (2), 184–197.
Perera, S., Tan, D., 2019. In search of the "Right Price" for air travel: First steps towards estimating granular price-demand elasticity. Transp. Res. Part A: Policy Pract. 130, 557–569.
Piga, C., Bachis, E., 2006. Pricing strategies by European low cost airlines: or, when is it the best time to book online?. Loughborough University Department of Economics Working Paper, (2006-14).
R Core Team, 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.
Ratliff, R.M., Venkateshwara Rao, B., Narayan, C.P., Yellepeddi, K., 2008. A multi-flight recapture heuristic for estimating unconstrained demand from airline bookings. J. Rev. Pricing Manage. 7 (2), 153–171.
Skwarek, D.K., 1996. Competitive impacts of yield management system components: forecasting and sell-up models. Doctoral dissertation. Massachusetts Institute of Technology.
Smith, B.C., Leimkuhler, J.F., 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. Eur. J. Oper. Res. 271 (2), 375–387.
Talluri, K.T., Van Ryzin, G.J., 2006. The theory and practice of revenue management, Vol. 68. Springer Science & Business Media, New York, NY, USA.
Train, K.E., 2009. Discrete choice methods with simulation, 2nd Edition. Cambridge University Press, New York, NY, USA.
Tsai, T.H., Chen, C.M., 2019. Mixed Logit Analysis of Trade-Off Effects Between International Airline Fares and Fences: A Revenue Management Perspective. Curr. Issues Tourism 22 (3), 265–275. Taylor & Francis.
van Ryzin, G., Vulcano, G., 2008. Computing virtual nesting controls for network revenue management under customer choice behavior. Manuf. Serv. Oper. Manage. 10 (3), 448–467.
Varella, R.R., Frazão, J., Oliveira, A.V.M., 2017. Dynamic pricing and market segmentation responses to low-cost carrier entry. Transp. Res. Part E: Logist. Transp. Rev. 98, 151–170.
Vinod, B., 2021. An approach to adaptive robust revenue management with continuous demand management in a COVID-19 era. J. Rev. Pricing Manage. 20 (1), 10–14.
Vulcano, G., van Ryzin, G., Ratliff, R., 2012. Estimating primary demand for substitutable products from sales transaction data. Oper. Res. 60 (2), 313–334.
Vulcano, G., Van Ryzin, G., Chaar, W., 2010. Om practice—choice-based revenue management: An empirical study of estimation and optimization. Manuf. Serv. Oper. Manage. 12 (3), 371–392.
Wang, J., 2015. Choice-based Demand Forecasting in Airline Revenue Management Systems. Doctoral dissertation. University of Western Australia.
Weatherford, L.R., Ratliff, R.M., 2010. Review of revenue management methods with dependent demands. J. Rev. Pricing Manage. 9 (4), 326–340.
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 Manage. Stud. 14 (3), 32–40.
Wen, C.-H., Chen, P.-H., 2017. Passenger Booking Timing for Low-Cost Airlines: A Continuous Logit Approach. J. Air Transp. Manage. 64, 91–99.
Williams, H.C.W.L., 1977. On the formation of travel demand models and economic evaluation measures of user benefit. Environ. Plan. 9 (3), 285–344.
Wittman, M.D., Belobaba, P.P., 2017. Personalization in airline revenue management Heuristics for real-time adjustment of availability and fares. J. Rev. Pricing Manage. 16 (4), 376–396.
Wittman, M.D., Belobaba, P.P., 2018. Customized dynamic pricing of airline fare products. J. Rev. Pricing Manage. 17 (2), 78–90.
Wittman, M.D., Belobaba, P.P., 2019. Dynamic pricing mechanisms for the airline industry: a definitional framework. J. Rev. Pricing Manage. 18 (2), 100–106.
Wu, C.-L., So, T.H.H., 2018. On the flight choice behaviour of business-purpose passengers in the Australian domestic air market. J. Air Transp. Manage. 72, 56–67.
Zeid, M.A., Rossi, T.F., Gardner, B., 2006. Modeling time-of-day choice in context of tour-and activity-based models. Transp. Res. Rec. 1981 (1), 42–49.
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.
Zhang, C., Lin, Y.H., Newman, D.G., 2016. Investigating the effectiveness of repositioning strategies: The customers' perspective. J. Travel Tourism Market. 33 (9), 1235–1250.
Zickus, J.S., 1998. Forecasting for airline network revenue management: Revenue and competitive impacts. Doctoral dissertation. Massachusetts Institute of Technology, Cambridge, MA.
Zimmermann, B., 2014. Revenue management with repeated competitive interactions. Doctoral dissertation. Freie Universität Berlin, Berlin, Germany.