Enhancing robustness to forecast errors in availability control for airline revenue management

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Master's Dissertation

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Abstract

Traditional revenue management systems are built under the assumption of independent demand per fare. The fare transformation theory is a methodology to adjust fares that allows for the continued use of optimization algorithms and seat inventory control methods, even with the shift towards dependent demand. Under a sell-up demand model, this marginal revenue transformation reduces the value of a specific fare by a varying margin, dependent on the upsell probability to higher fare products.

Since accurate demand forecasts are a key input to this methodology, it is reasonable to assume that for a scenario with uncertainties and disturbances it may deliver suboptimal performance. Factors such as lack or bad quality of historical booking data, inaccurate demand models, and inherent demand variability contribute to the complexity of forecasting demand in airline revenue management systems. Moreover, airlines faced striking challenges in demand forecasting during and after COVID-19, struggling to adapt to an environment characterized by unstable customer behavior, prominent schedule instability, and continuously shifting travel restrictions.

This work demonstrates, firstly, that the fare transformation theory is a theoretical dominant approach under perfect conditions, even under a varying range of input parameters. Secondly, it lacks robustness to forecast errors. A Monte Carlo simulation replicating a revenue management system under mild assumptions indicates that a forecast error of $\pm 20\%$ can potentially prompt a necessity to adjust the margin employed in the fare transformation theory by -10%. This may vary slightly according to other input parameters, such as upsell probability, expected demand, capacity, and fare structure related variables.

To capture the relationships between the optimal margin for seat availability control and input parameters, a tree-based machine learning model is employed. This model highlights the forecast error as the predominant factor, with bias playing an even more pivotal role than variance. On the one hand, when bias assumes positive values, meaning that the forecast is overestimating the real demand, the margin from the fare transformation theory needs to be adjusted down. On the other hand, with an escalating variance that signifies a progressively worsening forecast, there is a corresponding need to downwardly adjust the margin.

To validate the dominance of the predictive model under imperfect conditions, an out-of-sample study with 100 generated flights is performed for distinct scenarios. For the setting with a forecast error of $\pm 40\%$ and a possible systematic error of $\pm 10\%$, the predictive model with margin corrections outperforms the fare transformation theory in terms of expected revenue in 0.0144%. For a network carrier with thousands of flights a year, it can be an important differentiator.

Resumo

Os sistemas tradicionais de gestão de receitas assentam em pressupostos de procura independente por tarifa. A teoria da transformação de tarifas é uma metodologia que permite ajustar as tarifas de forma a que os algoritmos de otimização e os métodos de controlo de inventário embebidos continuem válidos, mesmo com a mudança em direção a uma procura dependente. Num modelo de procura caracterizado por *sell-up*, esta transformação deduz ao valor de uma dada tarifa uma margem variável, que depende da probabilidade de *upsell* para produtos com tarifas mais elevadas, resultando numa receita marginal.

Uma vez que a precisão das previsões da procura é um elemento fundamental para esta metodologia, é razoável supor que um cenário com incertezas e perturbações pode resultar num desempenho subótimo da mesma. Fatores como a falta ou má qualidade dos dados históricos de reservas, modelos de procura imprecisos e a variabilidade inerente da procura contribuem para a complexidade da previsão nos sistemas de gestão de receitas das companhias aéreas. Além disso, as companhias aéreas enfrentaram grandes desafios na previsão da procura durante e após a COVID-19, lutando para se adaptarem a um ambiente caracterizado por um comportamento incerto dos clientes, instabilidade proeminente dos horários e restrições de viagem em constante mudança.

Este projeto demonstra, em primeiro lugar, que a teoria da transformação de tarifas é uma abordagem teoricamente dominante sob condições perfeitas, mesmo com uma gama variável de parâmetros de entrada e, em segundo lugar, que carece de robustez ao erro de previsão. Uma simulação de Monte Carlo que reproduz um sistema de gestão de receitas sob pressupostos moderados indica que um erro de previsão de $\pm 20\%$ pode potencialmente levar à necessidade de ajustar a margem utilizada na teoria da transformação de tarifas em -10%. Este ajuste pode ainda variar ligeiramente em função de outros parâmetros, como a probabilidade de *upsell*, a procura esperada, a capacidade e as variáveis relacionadas com a estrutura de tarifas.

Para captar as relações entre os parâmetros da simulação e a margem ótima a aplicar no controlo das disponibilidades, é utilizado um modelo de *machine learning* baseado em árvores de decisão. Este modelo destaca o erro de previsão como fator predominante, com o enviesamento a desempenhar um papel ainda mais importante do que a variância. Por um lado, quando o enviesamento assume valores positivos, o que significa que a previsão está a sobrestimar a procura real, a margem da teoria da transformação de tarifas tem de ser ajustada para baixo. Por outro lado, quando a variância aumenta, o que significa que a qualidade da previsão se está a deteriorar progressivamente, é necessário ajustar a margem igualmente para baixo.

Para validar a dominância do modelo de previsão em condições imperfeitas, é efetuado um estudo com 100 voos gerados fora da amostra de treino para cenários distintos. Para um cenário com erro de previsão de $\pm 40\%$ e possível erro sistemático de $\pm 10\%$, o modelo de previsão com correções de margem supera a teoria da transformação de tarifas em termos de receitas esperadas em 0.0144%. Para uma companhia aérea com milhares de voos por ano, pode ser um fator de diferenciação importante.

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Contents

Acronyms and Symbols

ARM	Airline Revenue Management
BDAF	Buy Down Adjusted Fare
ARM	Airline Revenue Management
CART	Classification And Regression Trees
CI	Confidence Interval
DAVN	Displacement Adjusted Virtual Nesting
DCP	Data Collection Point
DP	Dynamic Programming
EMSR	Expected Marginal Seat Revenue
GBM	Gradient Boosting Machine
LCC	Low-Cost Carriers
MAE	Mean Absolute Error
ML	Machine Learning
OD	Origin-Destination
ODF	Origin-Destination Fare
RF	Random Forest
RM	Revenue Management
RMSE	Root Mean Squared Error
WTP	Willingness-To-Pay

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Chapter 1

Introduction

Revenue management (RM) is a strategic discipline employed by various industries to optimize pricing, inventory, and demand to maximize revenue. It involves employing data-driven techniques and sophisticated algorithms to make informed decisions about pricing, allocation, and availability of products or services. While RM finds its applications in diverse sectors, one area where it plays a particularly critical role is in the realm of airline operations.

Within the aviation industry, where market demand, operational constraints, and customer behavior exert significant influence on revenue generation, airline revenue management (ARM) systems are meticulously designed to tackle the unique challenges that airlines face in effectively managing seat inventory and executing pricing strategies. The ARM system is primarily composed of three essential components: demand forecasting, optimization, and availability control. Firstly, demand forecasting involves predicting future demand for different flights and booking classes. With this information, the optimization component aims to find the best pricing and inventory allocation strategies. Lastly, availability control involves managing seat inventory and determining when to close or open specific booking classes.

Yet, some of the theoretical dominant methods that provide a foundation for these components assume perfect input parameters. In particular, several strategies consider a perfect forecast, which is unreal due to uncertainties in factors such as market conditions, unexpected events, and changes in customer preferences, which can significantly impact demand patterns. In particular, airlines faced striking challenges in demand forecasting during and after COVID-19 (Garrow & Lurkin, 2021). With a Monte Carlo simulation that replicates the ARM system, this project aims to infer the interactions between forecast errors and the performance of a particular method for availability control: the fare transformation theory, and proposes a way to enhance its robustness to forecast errors with a tree-based predictive model.

For a greater degree of understanding, the following sections will first present the context in which the project was developed, and then deep dive into the scope of the problem, by summarizing the evolution of ARM and contextualizing the fare transformation theory within this framework. Lastly, the outline of the dissertation will be described.

1.1 Project background

This project was developed at Lufthansa Group, which is an aviation group with worldwide operations that holds a prominent position in its European domestic market. With 109,509 employees, the Lufthansa Group achieved a revenue of EUR 32,770m in the financial year of 2022. The group consists of the the segments Network Airlines, Eurowings, and Aviation Services.

The Network Airlines segment encompasses Lufthansa German Airlines, SWISS, Austrian Airlines and Brussels Airlines. Lufthansa German Airlines also incorporates regional carriers Lufthansa CityLine and Air Dolomiti, along with Eurowings Discover, which focuses on the touristic segment. Eurowings focuses on short-haul in European point-to-point routes. Aviation Services, in particular, encompasses the Logistics, MRO (Maintenance, Repair and Overhaul), and Catering divisions.

Typically, ARM analysts allocate a substantial amount of their time looking for and rectifying forecast errors. Specifically, within Lufthansa's Revenue Management department at the Munich hub, a need arose to investigate the interaction between forecast errors and margin setting in availability control. This project undertakes a comprehensive examination of this matter, and seeks to identify and understand the key factors that drive this interaction.

1.2 Project scope

Following airline deregulation, RM methods had a striking effect on the industry, contributing to revenue gains of up to $4-10\%$ (Bertsimas & Popescu, 2003). Formerly, most of the traditional ARM methods assumed independent demand for each fare class on a leg level, meaning that passengers who acquire a specific fare class are presumed to be willing to purchase solely that particular fare class. This assumption was facilitated by the fare structures based on sets of restrictions, such as minimum stay prerequisites or cancellation charges.

However, the introduction of low-cost carriers (LCC) led to the establishment of restriction-free fares, inducing prevalent demand dependencies across booking classes (Vinod, 2021). Even though independent demand was never a solid assumption, it turned to be almost impracticable. Consequently, traditional models assuming only independent demand started to overestimate low-fare demand at the expense of high-fare demand. This incentivized the systems to account for an even greater extent of low-fare demand, inciting a higher number of high-fare customers to opt for lower priced options, known as spiral down effect (Cooper et al., 2006).

To tackle this issue, novel methodologies emerged to account for demand dependencies. Among these approaches is Q-forecasting, which forecasts demand for the lowest existing fare and scales it to higher fares using an exponential sell-up function, which is a willingness-to-pay (WTP) estimate (Belobaba, 2011). This is an approach for totally dependent demand, where fare products are just different price points. This is valid if fare families are built in a way that fare products with similar restrictions are assembled in one family (Fiig et al., 2012).

In spite of the new forecasting methods, the remaining components of the ARM system still needed to be adjusted to account for demand dependencies. To solve it, Fiig et al. (2010) introduced the fare transformation theory, which allows for the use of previously developed optimization methods (either leg- or network-based), such as the bid price control later presented. This marginal revenue transformation reduces the value of a specific fare product by a varying margin, dependent on the upsell probability to higher fare products. A greater upsell probability results in a lower marginal value assigned to that fare product.

The fare transformation theory is a theoretical dominant method under perfect conditions. However, in the presence of uncertainty, it might fail to be optimal, potentially leading to overprotection and, consequently, spoilage through too low seat load factors. Even though it is recognized that demand modelling is crucial since fluctuations in demand generally have a stronger impact on revenue than any method alteration (Frank et al., 2008), it remains challenging to achieve high levels of forecast accuracy. Despite the fact that it is hard to calculate concrete values for forecast accuracy, due to the mismatch between demand forecasts and observed bookings subjected to capacity constraining and user intervention (Fiig et al., 2014), it is evident that there are many uncertainties and disturbances negatively affecting it. These can be both within ARM and beyond it. Within ARM, there is a lack or bad quality of historical booking data, which is most of the times adjusted by manual intervention of RM analysts, inaccurate demand models, when disregarding key customer decision drivers, and possibly inaccurate demand estimates. Beyond ARM, there is, for instance, the inherent demand variability, or even changing customer behavior.

On top of all these aspects, the recent global pandemic has brought up unprecedented challenges. According to Garrow and Lurkin (2021), the traditional demand forecasting approaches strongly struggled to adapt to the high schedule volatility and unstable travel restrictions. Now, all the data from this period has no value to train the algorithms due to the unstable customer behavior. Thus, it is essential to analyze the performance of the fare transformation theory across diverse scenarios characterized by escalating levels of uncertainty.

1.3 Problem statement

Bearing in mind the aforementioned context, the main objective of this project is to, firstly, model the interaction between forecast errors and margin setting in the fare transformation theory for availability control, and secondly, to enhance the robustness of this technique if necessary.

The main goal of this research study is threefold, striving to address the following questions:

- Is the fare transformation theory, in fact, a theoretical dominant method under perfect conditions?
- Is it robust to forecast errors? What other variables impact the optimal margin to apply in availability control?
- In case it lacks robustness to forecast errors, is it possible to predict an optimal margin correction under a given set of input parameters?

To answer these questions, a Monte Carlo simulation will be developed to replicate an ARM system. In terms of demand modelling, a fully dependent demand is considered for fare families with similar restrictions. Moreover, this ARM system is ruled by a bid price control, and bid prices are compared to the marginal revenue given by the fare transformation theory. Although it assumes network optimization, the simulation is done at the leg level, at a stage where the forecasted demand has already been allocated to each leg.

Furthermore, a tree-based predictive model will be applied in order to model the relationship between the input parameters, including forecast errors, and optimal margins. This approach enables a comprehensive understanding of the key variables that significantly contribute to the accurate prediction of the optimal margin.

1.4 Dissertation structure

In this section, the remainder of the dissertation is described. Chapter 2 first provides a broad understanding of the current state of knowledge on RM, especially ARM, from demand forecasting to optimization and availability control methods, and then presents an outline of the theory behind tree-based machine learning (ML) models and how to fine-tune them. Chapter 3 deep dives into the framework used in this project, pointing out which methods from the previous chapter are employed here, as well as some of the assumptions. Chapter 4 presents the results of the simulation for both a psychic and distorted forecast scenarios, stressing the implementation of sensitivity analysis to input parameters. Chapter 5 generates simulated data for a range of input parameters, and develops a tree-based ML model to predict the optimal margin correction to adjust the fare transformation theory. Moreover, it validates the findings with an out-of-sample study. Lastly, the final chapter displays the main conclusions, and suggests opportunities for future research.

Chapter 2

Literature review

This chapter primarily aims at providing a comprehensive understanding of the current state of knowledge on RM, in particular ARM. A process overview is provided including the key concepts and techniques used in ARM, such as pricing strategies, capacity steering, and demand forecasting.

Furthermore, some of the state-of-the-art ML techniques are analyzed, especially decision trees-based methods, which have been successfully applied in the context of ARM, while providing a review on the theoretical background and methods of evaluation, and discussing their potential benefits and challenges.

2.1 Airline revenue management

RM is a strategic business practice that seeks to maximize revenue by managing the pricing and availability of products or services in response to fluctuations in demand. Selling a product or a service implies two fundamental amounts: (i) an immediate revenue equivalent to the price and (ii) an opportunity cost of the discarded capacity, that may come at the expense of future revenue opportunities, as demand may increase, and prices may rise (Bitran & Caldentey, 2003). Thus, there is a trade-off between selling to high-valuation customers and waiting too long to make a sale. If a business waits too long, it may end up with remaining inventory that could have been sold to lower-valuation customers.

Furthermore, RM had a significant impact on both traditional industries, like airlines, hotels, and car rentals, and non-traditional ones, such as retail, telecommunications, and healthcare. In general, RM has the potential to improve the profitability of businesses across a wide range of industries. Chiang et al. (2006) provide a review of the most relevant documentation on RM strategies for each industry.

2.1.1 Conditions for applying revenue management

The implementation of RM practices to optimize revenue and profitability depend on the presence of certain business conditions. These are presented by Talluri and Van Ryzin (2004b) as follows:

- **Demand variability** is a core concept behind RM techniques, which are designed to optimize revenue by adjusting prices based on fluctuations in demand. When looking at the demand for air travel, there are noticeable fluctuations that occur due to different drivers such as holidays, seasons, day of the week, and time of day. Even when accounting for this seasonality and trends, it can be difficult to accurately predict the demand for a specific flight.
- **Perishable products or services** need to be offered. When the product or service being sold has a finite lifespan, it is critical to maximize revenue from available inventory. Naturally, once a flight has been realized, a seat cannot be sold anymore.
- **Capacity constraints** make it critical to allocate available resources to maximize revenue. This is related to the concept of production inflexibility: if a company has the ability to easily and inexpensively adjust the supply of their product or service to match changes in demand, then managing demand becomes less complex. When committing to fly a certain flight from A to B, with a given capacity, airlines show a highly inflexible production.
- **Segmentation opportunities** allow for distinct segments of customers with different price sensitivities. When all customers place the same value on a product and exhibit similar purchasing behavior, there is limited opportunity to leverage differences in their WTP, preferences for various products, and changes in their purchasing behavior over time. Airline customers have significantly different behaviors, according to when they book, their flexibility and the value they assign to that specific travel.
- **Price discrimination opportunities** arise from customer segmentation, making it possible to identify and target customers who are willing to pay more for a particular product or service. In this sense, prices should not be perceived as a signal of quality. Even though airlines might assume distinct positions regarding price and quality, customers usually do not directly link the ticket price with the quality of the flight.
- **Proportion of fixed and variable costs** is characterized by high fixed costs (in the case of airlines, capital costs, fuel, wages). Therefore, a company can sell a product or service with low costs and still profit. One additional passenger in an aircraft creates additional considerable revenue, but low variable costs.
- **Information systems infrastructure** must be able to cope with the high amount of data needed to depict and model the demand, in order to accurately forecast it and then optimize revenue. Airline industry was one of the first industries to offset almost entirely to electronic selling and distribution, with the establishment of the Global Distribution System in the 1960s (for more information, see Marie Emmer et al. (1993)).

2.1.2 Process overview

RM systems have standard designs, including key components, information flows and controls. According to Talluri and Van Ryzin (2004b), the process typically consists of three primary steps:

estimation and forecasting of demand, optimization of several levers, and availability control, as shown in grey in Figure 2.1, where fares from pricing and demand are considered an input to the model.

These systems need to collect and preserve the appropriate historical data, such as demand, including request times and requested fares, availabilities, cancellation and no-show rates. Just with this data, it is possible to proceed with the step of estimation and forecasting, which entails not only estimating the parameters of the demand model and forecasting demand based on these parameters, but also predicting other relevant quantities, such as no-show and decrementing rates.

With the information from forecast, optimization is possible, and it involves identifying the optimal set of controls, such as allocations, prices, markdowns, discounts, and overbooking rates, that can be applied until the next round of re-optimization. Finally, the availability control step implies implementing the optimized controls to regulate the sale of inventory. This can be done through the company's own channels or through shared distribution channels, such as Global Distribution Systems.

This process is done cyclically with a certain frequency that depends on factors such as the amount of data, the volatility of the business, the forecasting and optimization methods. Airlines commonly divide their 360-day booking cycle into data collection points, which are also known as DCPs. These DCPs are defined by a specific number of days before the scheduled departure of the flight. By pinpointing these DCPs, airlines establish a discrete booking curve (Walczak et al., 2012). DCPs do not need to contain fixed time intervals, with the most general rule in industry considering decreasing lengths, that allow for increasing granularity and the refining of forecasts and optimization as customer arrival rate increases.

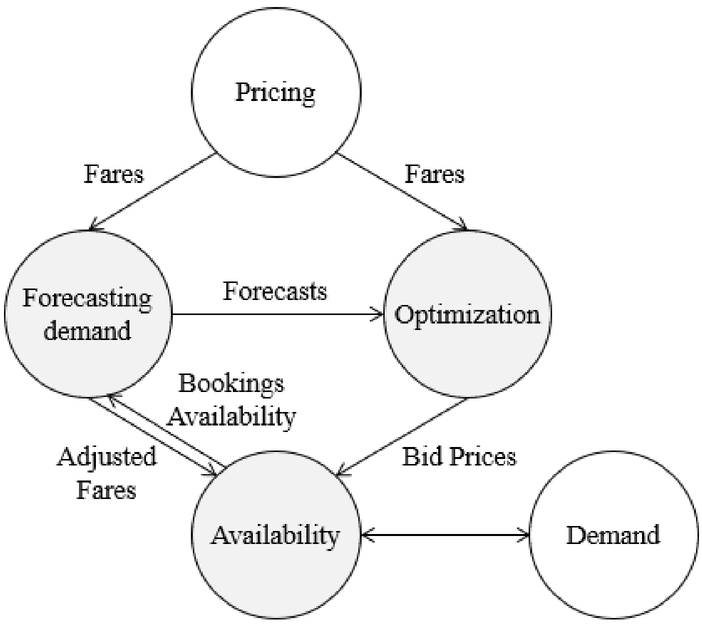

Figure 2.1: RM process overview, adapted from Rauch et al. (2018)

In the upcoming subsections, a comprehensive outline will be presented regarding the aforementioned key stages of the RM process, namely demand forecasting, optimization, and availability control.

2.1.3 Demand forecast

Conventional ARM systems assume independent demand models, meaning that the demand for a particular fare class in a certain itinerary is not influenced by the availability or price of other fare classes, nor by other itineraries. This assumption was mainly enabled by the fare structures at that time, which consisted of a variety of fare products, each with distinct restrictions such as minimum stay prerequisites, advance booking, non-refundability requirements and cancellation/alteration charges. Thus, if a passenger is willing to buy a certain fare, there is no chance of selecting a lower fare, another itinerary, or even another airline (Fiig et al., 2010).

The first RM forecasting systems were mostly based on time-series methods. Lee (1990) discusses the use of methods such as moving average, autoregressive integrated moving average, or exponential smoothing. Later, more complex techniques emerged, ranging from Bayesian forecasting, which is particularly valuable when there is no historical data, to Kalman filter or even neural networks (Talluri & Van Ryzin, 2004a).

Since past bookings are constrained by the availability control of inventory, they are not accurate as input data for the forecasting systems and, thus, need to be submitted to a process designated as demand unconstraining. Guo et al. (2012) provide an overview on unconstraining techniques. Some of the most basic methods include the Naïve methods, which offer as solutions ignoring censored data (not advisable, since it leads to demand underestimation), discarding the censored data, or filling censored data with plausible values, such as the mean. Inversely, some of the best-performing methods are the Booking Profile, proposed by Wickham (1995), which is a deterministic method that assumes that the unconstrained booking profile is independent of the demand level, and other statistical methods based on the Expectation-Maximization, firstly introduced by Dempster et al. (1977). These methods aim at using Maximum Likelihood Estimation by going cyclically through two steps until convergence: the E-step, where censored observations are replaced by the sample mean, and the M-step, which calculates a new sample mean and variance.

Even though independent demand was never an absolutely accurate assumption, most of the aforementioned RM techniques were developed considering this. However, with the introduction of LCC in the 1990s came along the establishment of restriction-free fares, leading to prevalent demand dependencies across booking classes (Vinod, 2021). While the initial LCC model incorporated completely unrestricted fares, representing 100% of sell down to the lowest available fare, it originated afterwards hybrid models, where multiple fares are assigned identical restrictions and, therefore, are not independent, producing a nearly 100% sell down.

With the rapid growth of LCC, the distinction between dependent and independent demand became an increasing focal topic. Boyd and Kallesen (2004) approach this issue, showing the potential danger of a mismatch between the forecast and the actual demand model. For that, the concepts of priceable and yieldable demand are used, with the former representing the fully dependent (price-oriented) demand, and the latter referring to the totally independent (product-oriented) demand. In this sense, traditional models considering yieldable demand overestimate low-fare demand at the expense of high-fare demand if the actual demand is priceable. That encourages the system to consider even more low-fare demand and, thus, even more high-fare customers to buy down. Cooper et al. (2006) model this mathematically as a spiral down effect.

Therefore, it is utterly important to better understand demand dependencies. Whereas for independent demand it is enough to forecast the volume component, for dependent demand a probabilistic component must also be modelled in order to mimic customer preferences. In this context, a distinction between upsell and choice models should be made regarding customer behavior. Upsell models consider that a customer requests a higher priced product with a certain upsell probability if there is no availability for the required one. The independent demand model is a particular case of the upsell model, where the upsell probability is zero. In this case, customers are generated separately for each fare product, and leave if the product is not available. Choice models focus on simulating specific consumer purchasing behaviors. In general, these methods involve an unlimited number of parameters, allowing to model various decisions, from distinct fare products to several departure times, or even other carriers (Frank et al., 2008).

With regards to upsell models, the primordial approaches to tackle dependent demand used a simplification of fully restriction-free fares, where different products represented only distinct price points. The main goal was to undertake the spiral down effect. For that, Q-forecasting was introduced as a method to forecast demand for the lowest existing fare and scale it to higher fares, by using a WTP estimation, i.e., an upsell probability. Belobaba (2011) poses the estimation of these parameters as a major challenge mainly due to volatility and sparseness of historical upsell behavior. Guo (2008) provides an overview of upsell estimation methods, namely direct observation, inverse cumulative and forecast prediction. However, when looking into Q-forecasting, it is not completely accurate to consider that passengers will always buy the lowest available fare (fully price-oriented demand). Bearing this in mind, hybrid forecasting was developed to allow for a separation among priceable and yieldable demand. In this case, historical bookings are considered yieldable demand only if the next lower booking class is available.

Choice models are a broader approach to model dependent demand, and aim at estimating a choice element, while disregarding the volume element. Usually, discrete models are applied, with special focus on random utility models. These models rely on the assumption that the decision-maker has a perfect discrimination capability. However, the analyst is expected to have insufficient information and, thus, uncertainty must be considered. So, the utility is modeled as the sum of a deterministic and a zero-mean random components. Some of the state-of-the-art techniques include the multinomial logit and nested logit models. Both rely on the logit model, which is characterized by considering the errors of the random parcel to be independent and identically Gumbel distributed, with the latter being an extension of the former allowing for correlations amongst possible choices (Bierlaire, 1998).

According to Fiig et al. (2014), most of the previously mentioned methods miss a key component for evaluation: a forecast accuracy metric. Without it, airlines end up relying on indirect methods, notably revenue results. That violates the guidelines provided by Cleophas et al. (2009), which claim that the RM system should be evaluated by each of its parts and not as a whole. Quantifying forecast accuracy is a significant challenge, mainly due to past bookings constraining derived from RM controls blended with human input.

The traditional approach for accuracy measurement involves leveraging the demand forecasts used in optimization, since at that point, without RM controls, demand is unconstrained. Consequently, in order to calculate forecast accuracy, real unconstrained observations are required and, thus, constraining needs to be reversed. However, this is only possible for independent demand. Reciprocally, in a dependent demand model, the optimization requires constrained demand forecasts as an input for each of the possible control policies since the availability of a class affects the demand for other class. Fiig et al. (2014) present a method that measures forecast accuracy by comparing the real bookings that took place under the actual control with the constrained demand for the precise same control. As a result, forecasts for all RM controls need to be saved, since it is impossible to know in advance which one will be practiced at the moment of the bookings. With that, regular error measures are applied, such as mean deviation, mean absolute deviation, mean squared error, or coefficient of variation.

2.1.4 Optimization

Generally, RM optimization models can be segregated into two prominent dimensions: deterministic versus stochastic models, and single- versus multiple-product cases. Regarding the former, deterministic models assume that the seller has perfect knowledge concerning demand, which is a significant oversimplification, especially in industries where demand is hard to predict, just like in airlines. However, deterministic models can be an effective approximation for stochastic models (in some cases they are asymptotically optimal), while easier to analyze. Within the second differentiation, the case of multiple products has a greater level of complexity, and its study gained more attention after major progresses occurred in the single-product case. The higher complexity of the multiple-product case is mainly due to product substitution and demand correlation. In this case, a wider list of products is preferable for demand skimming, but complicates the optimization problem (Bitran & Caldentey, 2003).

The first approaches for optimization of seat inventory in airline context aimed to solve the problem of multiple fare products for a single leg and refer back to Littlewood (1972). The reputed Littlewood's rule considers that all fares fall into two categories: high yield (r_1) and low yield (r_2), i.e., $r_1 > r_2$. If the only objective is to maximize revenue, then, given a high yield demand (D_1) and a remaining capacity (C), low yield passengers should be accepted as long as the condition in in Equation (2.1) is met.

$$r_2 > r_1 \times P(D_1 > C) \tag{2.1}$$

This indicates that there is an optimal protection limit for the high yield customers. Whereas Littlewood's rule is restricted to two fare classes only, Belobaba (1987) extends it to multiple fare classes in the Expected Marginal Seat Revenue (EMSR) model, that attempts to dynamically generate booking limits for various fare types. This is done for nested fares classes, in which the fare class inventories are arranged in a way that a high fare request is never refused as long as any seats remain available in lower fare classes. Since higher classes have access to unused seats from lower classes, the goal is to find protection levels for higher classes and booking limits for the lower ones.

Later on, when comparing his prior work to the optimal booking limits proposed by Curry (1990), Belobaba (1992) realizes that the EMSR can retrieve sub-optimal nested booking limits below the second highest fare class as a result of neglecting joint revenue functions of higher fare classes. To tackle this issue, EMSRb is proposed as a method that combines the forecasted demand distributions for higher fare classes in the booking limits calculation.

Still on the single leg framework, Lee and Hersh (1993) introduce a dynamic programming (DP) model. Whereas the aforementioned methods use a probability distribution to characterize the demand for each booking class, this new approach models the demand as a stochastic process in a discrete time horizon, with the restriction that at most one customer can arrive per period. Throughout the time horizon, demand intensity for each booking class is modeled by a certain request probability, that may vary with time. In this sense, demand arrival is characterized by a Poisson process, which is widely used in literature, mostly due to the memoryless property of the exponential interarrival distribution (McGill & van Ryzin, 1999).

In the 1990s, network RM systems, or origin-destination (OD) controls, started to arise. Smith and Penn (1988) propose a virtual nesting approach as a control framework that allows to approximate a market class control. For that, leg buckets are created with itineraries that flow over that leg, according to their relative values: groups of similarly valued itineraries are clustered. This way, the availability of a given itinerary is always established from the leg bucket availabilities, considering the availability for connecting markets as the minimum availability across the covered legs.

In the traditional virtual nesting approach, OD itineraries were assigned to virtual buckets based on total itinerary ticket revenue. However, under this method, long-haul itineraries with higher revenues were prioritized over short-haul ones with lower revenues, which does not certainly mean a maximum network revenue (Williamson, 1992). To mitigate this issue, the Displacement Adjusted Virtual Nesting (DAVN) was created, in which the real value of connecting itineraries for each specific leg can be obtained by deducting the displacement costs associated with consuming one seat in the remaining legs from the total fare.

An alternative method for OD control in the network optimization setting is the bid price control, pointing out some of the primordial techniques and concepts developed by Williamson (1992). Firstly, the concept of shadow price is noteworthy: it refers to the incremental network revenue that would be reached if a certain constraint was increased by one unit, ceteris paribus. Secondly, it is important to introduce the simplest representation of the network problem, as a deterministic linear program. Considering a set of fares (revenues) and seat allocations for each origin-destination and fare class (ODF), r_{ODF} and x_{ODF}, respectively, a capacity C_j for each flight leg j, and a deterministic maximum demand for each ODF such that $D_{ODF} = \mu_{ODF}$, the linear programming model is given by Equation (2.2).

$$\begin{aligned} \max_{x_{ODF}} \quad & \sum_{ODF} r_{ODF} x_{ODF} \\ \text{s.t.} \quad & \sum_{ODF} x_{ODF} \leq C_j, \forall_{ODF \in j}, \forall_j \\ & x_{ODF} \leq D_{ODF}, \forall_{ODF} \end{aligned} \tag{2.2}$$

However, there are some flaws with the linear programming model. In the first place, the optimal solution is obtained for a non-nested inventory, meaning that seats destined for an ODF are only available for that ODF and, thus, any unsold seats remain empty. Furthermore, this solution misses the stochasticity of demand, by modeling it with the expected value, which disregards forecast errors. Talluri and van Ryzin (1998) provide a review on bid prices, showing that they are asymptotically optimal as leg capacities and sales increase, and present other methods for their calculation, such as a probabilistic nonlinear program that captures the randomness of the demand, and heuristics approaches applying EMSR.

In a twofold work, Gallego and van Ryzin (1997) and Talluri and van Ryzin (2004) propose a DP method for bid price determination. The main difference to previous works is the consideration of sell-up or buy-down, typical from a dependent demand that assumes unrestricted fare structures. In this sense, the goal is to determine the lowest class available. Similar to Lee and Hersh (1993), an arrival of passengers through a Poisson process is considered, meaning that the past bookings only relate to future demand by absorbing a seat, which allows for a DP formulation and, thus, for the Bellman equation formulated in Equation (2.3).

$$V_t(x) = \max_{S \subseteq N} \left\{ \sum_{j \in S} \lambda \ P_j(S)(r_j + V_{t-1}(x-1)) + (\lambda \ P_0(S) + 1 - \lambda) V_{t-1}(x) \right\}, \tag{2.3}$$

where $N = \{1, ..., n\}$ is a set of fare products, $S \subseteq N$ a subset of fares, r_j the revenues from each product $j \in N$ such that $r_1 > r_2 > ... > r_n$, $P_j(S)$ the probabilities of choosing product $j \in S$ when the fares S are offered ($j = 0$ denotes the no purchase decision), and $V_t(x)$ the value function (maximum expected revenue) from periods t, $t-1$, ..., 1 for seat index x.

Yet, in practice, the network DP is impossible to solve for real airline networks due to the curse of dimensionality (Rauch et al., 2018). Instead, a common method in industry is to apply first a heuristic decomposition to reduce the state space, and just then apply DP to single legs. This heuristic that aims at network optimization usually considers a deterministic linear program to calculate the displacement costs for each leg (similar to the DAVN method), and decomposes the network, usually by prorating the OD fare to the enclosed legs (see Appendix A for an illustrative example). Just then, the DP is solved at leg level to consider the stochasticity of demand.

2.1.5 Availability control

According to the inventory control defined in the optimization, the next step is to regulate the sale of seats, i.e., whether or not to accept reservations, in response to the actual demand. When referring to point-to-point carriers, protection levels and booking limits are widely used and they can easily be converted from one form to another. Protection levels aim at protecting a certain number of seats due to potential future requests for a given fare class, whereas booking limits impose bounds in the amount of seats to sell in a given fare class.

A bid price control is substantially different. While considering network effects, bid prices represent the opportunity cost of one seat in a given leg, usually for each compartment. Originally, literature stated that a certain fare should only be available when its value exceeds the bid price. However, Fiig et al. (2010) introduce the fare transformation theory, which supports the idea that the bid price (considered a marginal opportunity cost) should be compared to the marginal revenue instead. The main goal is to maximize revenue for a variety of fare structures, including the case of fully unrestricted ones, for which the marginal revenue is modelled in Equation (2.4) by an upsell probability $psup_k$ for each fare $k = 1, \ ..., \ n$, with demand D_k and revenues $r_1 > r_2 > ... > r_n$, as follows:

$$r\prime_k = \frac{r_k \, D_k - r_{k-1} \, D_{k-1}}{D_k - D_{k-1}} = \frac{r_k \, psup_k - r_{k-1} \, psup_{k-1}}{psup_k - psup_{k-1}}. \tag{2.4}$$

Basically, the fare is being subtracted by a price elasticity cost, to take into consideration the possible risk of buy-down under dependent demand. This is why marginal revenue can also be called buy down adjusted fare (BDAF). In this sense, as the customers' WTP rises, the price elasticity cost also rises and, thus, the BDAF decreases. Now, comparing this BDAF to a given bid price, it is more likely inferior, leading to a faster closing of lower fare classes.

In the end, real demand produces bookings if the selected inventory control accepts the request. These observations are stored as past data and will serve as input to the next iteration. The offline RM systems of forecasting and optimization need to provide frequent updates to the real-time RM inventory control to keep up with the pace of incoming bookings and learn from new trends.

2.2 Tree-based machine learning models

The field of ML has witnessed significant advancements in recent years, particularly in the realm of tree-based models. Tree-based ML algorithms have emerged as powerful tools for solving complex problems and making accurate predictions. Since Chapter 5 will employ both a random forest (RF) and a gradient boosting machine (GBM), a comprehensive understanding must be provided.

This section firstly delves into the intricacies of decision trees as the foundation for RF and GBM, and secondly deep dives into the suggested models. These algorithms have garnered immense attention and popularity due to their ability to handle both classification and regression tasks, while exhibiting remarkable performance and robustness.

2.2.1 Decision trees

Trees are hierarchical structures originating from a single node and extending into multiple branches, according to a specific set of rules. This is an intuitive principle, since it attempts to mimic, in a simplified version, the human decision-making process. Extending this concept, regression and classification trees are powerful ML methods used to construct predictive models from data, by iteratively splitting the domain and constructing simple predictions within each partition. The resulting structure can be visualized as a decision tree, where each node represents a split based on a specific feature, and each leaf node corresponds to a prediction.

Classification trees are specifically designed for dependent variables that have a finite number of unordered values. They aim to minimize prediction errors by considering the misclassification cost. On the other hand, regression trees are tailored for dependent variables that have continuous or ordered discrete values. In regression trees, prediction errors are typically measured using the squared difference between the observed and predicted values.

For the classification task, with a set of training data corresponding to p predictor variables, X_1, ..., X_p, and a class variable Y that encompasses values 1, 2, ..., k, the goal is to identify a model for estimating the values of Y given new X values. Figure 2.2 provides a comprehensive example for $p = 2$ and $k = 3$. Essentially, Loh (2011) summarizes this problem as the three following steps:

1. Start at the root node.
2. For each X, find the split $\{X \in S\}$ that minimizes the sum of the impurities for the child nodes (S represents a subset of data points or observations that satisfy a condition related to X). Select the split with minimum impurity.
3. If a stopping criteria is met, exit. Else, execute step 2 for each child node.

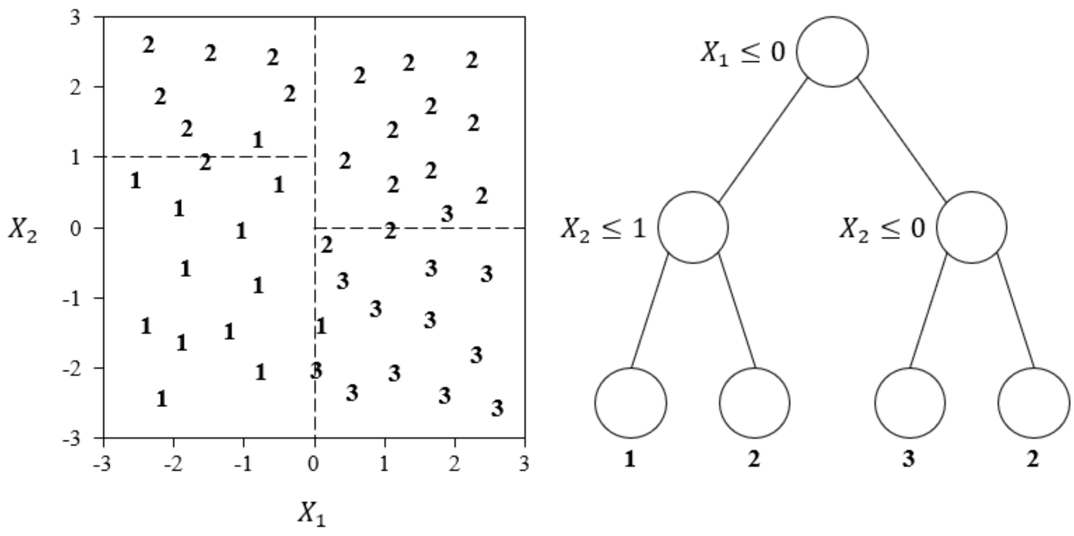

Figure 2.2: Classification tree exemplification, adapted from Loh (2011)

Classification and regression trees (CART) is a tree algorithm presented by Breiman et al. (1984) that implements this methodology. It comprises two main steps: growing an extremely large tree and pruning it. The problem of growing a tree too deep is that it can overfit the training data (high variance), meaning that the predictions for training data will be very accurate, whereas for new input data they might be inaccurate. On the other hand, growing an extremely short tree is also not an option, since the model will fail to predict precisely, both for training and new data (high bias). This is the bias-variance trade-off. Therefore, CART proposes to firstly grow the tree, and secondly prune it to a reduced proportion to minimize the estimation of the misclassification error.

The pruning is based on cost-complexity, seeking to find the optimal combination of model complexity and predictive accuracy. It evaluates different candidate trees by assigning a cost to each one, which considers not only the misclassification error, but also a complexity parameter that penalizes the size of the tree. The selection of the complexity parameter is typically performed through the use of cross-validation, in which available data is divided into multiple subsets (folds), and the complexity parameter that yields the best average performance across the folds is selected. To tune multiple hyperparameters simultaneously, there are strategies such as random search, grid search, or optimization algorithms. The cost-effectiveness of these optimization frameworks is determined by the searching strategy, that establishes the set of parameters to be investigated, and the performance estimation strategy, that defines the set of parameters to be discarded (Akiba et al., 2019).

In addition to classification, CART can also be employed for regression. A regression tree is comparable to a classification tree, but the Y variable has continuous or ordered discrete values, resulting in the need for a regression model to be fitted to each node. This generates stepwise constant models by using the node mean of Y as predicted value (Loh, 2014). Regarding the impurity function, while classification trees use the Gini index, which measures the probability of incorrectly classifying a randomly chosen element in the node if it was randomly labeled according to the distribution of classes, regression trees use the sum of squared deviations about the mean.

One key feature of decision tree models is the ability to retrieve importance scores for each predictor. In CART, this is achieved through surrogate splits, which refer to additional split rules that are used as alternatives when the primary split cannot be applied or is not informative enough (Loh, 2014). Surrogate splits can quantify the contribution of each variable in making accurate predictions within the decision tree by measuring the reduction in impurity or the decrease in the sum of squared errors (depending on the task: classification or regression) when using a particular surrogate split instead of the primary split. The larger the improvement, the more important the predictor variable is considered.

2.2.2 Random forests

Despite some advantages, such as simplicity, which makes it easy to explain to people, visual interpretation, and ability to handle classification tasks, singular decision trees lack some accuracy when compared to other regression and classification tasks, and can be very sensitive to input data (James et al., 2013).

To tackle this issue, it is essential to present the concept of bagging. Introduced by Breiman (1996), bagging predictors is a technique for producing multiple variations of a predictor by generating bootstrap replicates (random samples) of the training set, and utilizing them to obtain an aggregated predictor. The aggregation involves averaging the predictions for numerical outcomes and employing a majority vote for class predictions. The use of bootstrap replicates helps introduce diversity and capture the variability in the training data, leading to improved accuracy in the aggregated predictor. For decision trees, since training data may cause significant perturbations in the constructed predictor, bagging mitigates this by using the average or mode of many predictors.

However, even though it improves accuracy when compared to a single decision tree, bagging still poses one major challenge. Since the criteria for the splitting based on the variable that minimizes the sum of the impurities is the same for each decision tree generated, the trees will most likely be highly correlated, considering that similar splits will occur. Random forests, with a minor adjustment, are able to decorrelate the trees (Breiman, 2001). The process is essentially similar to bagged trees, but each tree uses only a random selection of features to split each node. By forcing each split to consider only a subset of the predictors, random forests lead to a substantial reduction in variance.

The maximum number of random features to consider in each split is, therefore, considered a hyperparameter of the model. Even though there are some guidelines to choose it, such as the square root rule that considers the square root of the total number of predictors, it is always recommended to test different values empirically using cross-validation.

2.2.3 Gradient boosting machines

Boosting was introduced by Friedman (2001) and, just like bagging, it is an approach to improve the predictions resulting from not only decision trees, but many other statistical learning methods for classification and regression. As bagging, boosting also combines many decision trees in order to create a single predictive model. However, whereas in bagging trees are independent from each other, considering that they are built on bootstrap replicates of the training set, in boosting the trees are grown sequentially. For boosting, each tree is not modelled on a random sample, but in a modified version of the dataset.

Instead of fitting a single large tree to the training data, which could lead to overfitting, boosting takes an alternative approach by constructing many smaller decision trees. Each tree learns slowly from the previous ones. The process for regression begins by fitting a tree to the original training dataset and calculating the corresponding residuals, which might be squared deviations, absolute deviations, or a combination of both through the Huber loss function. Then, a new tree is fitted to the residuals. This iterative process continues, updating the residuals at each step with the new tree, until the desired number of trees is reached. The successive trees are gradually incorporated into the boosted model to produce the final output. This approach helps mitigate overfitting and allows the model to learn from the errors and weaknesses of previous trees, leading to improved overall performance.

Boosting has three main hyperparameters: number of trees, shrinkage parameter and number of splits in each tree. Firstly, contrary to bagging, boosting may overfit if too many trees are considered. Thus, it is crucial to carefully select the number of decision trees with cross-validation. Secondly, the shrinkage parameter is a learning rate, and the right value depends on the problem data. Very small values can lead to the necessity of a high number of trees. James et al. (2013) present 0.01 and 0.001 as typical values. Finally, the number of splits in each tree regulates the complexity of the ensemble model.

2.3 Final considerations

Chapters 3 and 4 will focus on developing and implementing a robust Monte Carlo simulation to model and analyze the complex ARM system. By incorporating the probability distribution for the demand, the goal is to study multiple variations of margin setting in the fare transformation theory within availability control. Random samples are generated and converted to expected revenues after going through the ARM system. Through statistical analysis of the simulation results, the objective is to evaluate the performance of the fare transformation theory and the potential application of margin corrections to achieve the optimal expected revenue.

In the context of forecasting, two scenarios are considered. Firstly, a psychic forecast is derived with known demand parameters. The goal is to assess the theoretical dominance of the fare transformation theory. Secondly, a distorted forecast is considered. The forecasting method to be employed is an average of past flights, since the goal is just to include the inherent forecast error. The unconstraining method is a Naïve technique that discards the censored data. With regards to optimization, the bid price control is applied. Bid prices are obtained from the expected revenues, which are calculated through a dynamic program with backward induction.

Chapter 5 will employ both an RF and a GBM models, seeking to predict an optimal margin correction for the fare transformation theory for a certain set of parameters under adverse conditions. To enhance the bias-variance trade-off, hyperparameters are tuned with an optimization algorithm that reduces the search space. Ultimately, the selected model is used to derive feature importance scores, providing insights into the parameters that significantly influence the performance of the fare transformation theory.

Chapter 3

Simulation framework for expected revenue derivation

The use of simulation has become increasingly popular in RM as a means to test and validate new concepts and methods. However, the inherent assumptions can significantly impact the results. Despite the importance of topics such as simulation setup and input data, there are no established standards or universal tools for developing an RM simulation.

This chapter outlines the framework for the proposed Monte Carlo simulation to derive expected revenues, which is introduced by Figure 3.1. In compliance with Chapter 2, the three main steps of the ARM system are highlighted in grey: (i) forecasting, (ii) optimization, and (iii) availability control. In order to initiate the simulation, input settings have to be loaded, namely the expected demand parameter of the Poisson distribution for the lower fare class, the upsell probability to higher fare classes, the capacity and the fare structure.

The forecaster first needs to discretize the booking horizon in such a way that no more than one request arrives per time step. Hence, based on the expected demand parameter, the calculation of the number of time steps is carried out to meet this requirement with a defined level of certainty. With this, the expected demand, and the upsell probability, the forecaster is able to generate a probability matrix, with request probabilities for each booking class and time step. Then, a bid price control is implemented on the optimization stage. Resorting to the probability matrix and fare structure, bid prices are calculated for each time step and seat index with a dynamic program, which is further detailed later in Figure 3.3. From this point forward, the Monte Carlo simulation is initiated, and for each run a set of requests is created according to the respective Poisson arrival process and the upsell probability. Then, for each request, the BDAFs from the fare transformation theory are compared to the bid price for the current time step and seat index in order to determine the lowest availability. Based on that, the request is either accepted or denied, and the total revenue is updated accordingly. Ultimately, the expected revenue is the average across all runs.

The next sections will deep dive into the steps of demand modelling and forecasting, optimization, and availability control, as well as the approach to define the desired confidence level for the Monte Carlo simulation, while highlighting some of the employed assumptions.

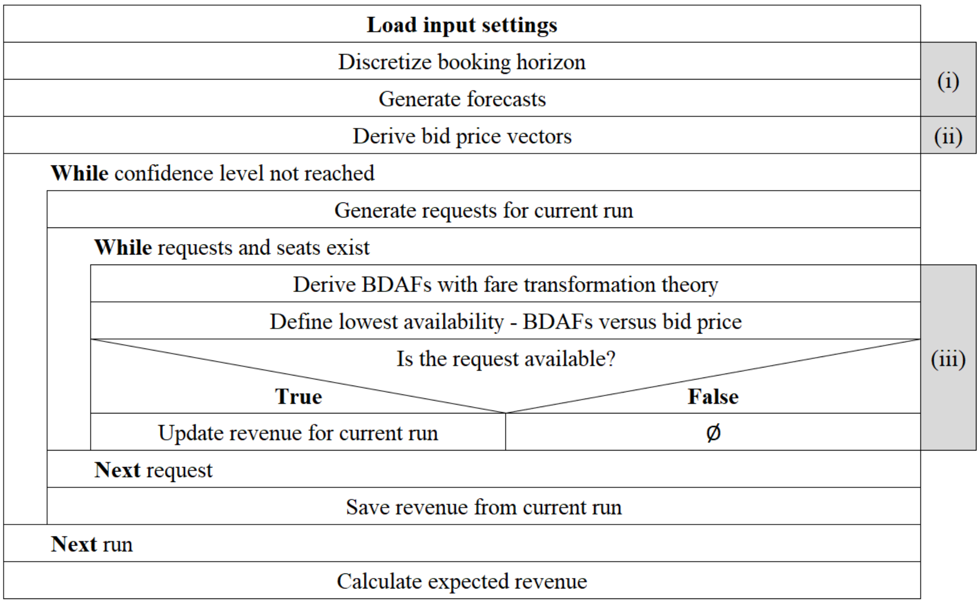

Figure 3.1: Simulation framework

3.1 Demand

Modeling customer demand is an essential component of a simulation, given that the variability in demand typically exerts a higher impact on revenue outputs than any alteration to the methodology (Frank et al., 2008). Thus, it is indispensable to integrate the random features of demand and ground them in prior historical data to achieve a high-quality simulation that closely mirrors reality.

3.1.1 Demand generator

Following the work by Fiig et al. (2012), fare families are considered, which are built in a way that fare products, or booking classes, with similar restrictions are clustered into one family. Hence, within each fare family, the fare products are undifferentiated, meaning that demand is fully dependent and customers will always buy down to the lowest available fare. To model it, an upsell model is employed.

In order to incorporate demand's stochastic nature into the simulation model, a Poisson arrival process is implemented. This way, for each fare family with booking classes $k = 1, \ldots, n$, sorted by fares in such a way that $r_1 > r_2 > \ldots > r_n$, a global homogeneous Poisson arrival process with expected value λ is considered for the minimum fare (n). As a consequence of the dependent demand model within each fare family, the Poisson arrival process for the lowest available class k can be modelled, generally, as $\lambda psup^{n-k}$, where $psup$ represents the probability of a customer requesting a higher priced booking class (k) if there is no availability for the demanded one (n).

At each point in time t, the simulation needs as an input the probabilities P_k^t that a customer requests the lowest available fare product k, since the dependent demand model considers that every customer who arrives will request the lowest available price point. The goal is, then, to discretize the booking horizon in such an extent that, at maximum, one request arrives per time interval. For that, the booking period is first divided into DCPs, each of which encompasses a set of requests following the abovementioned Poisson arrival process. Current practices to define the DCP structure - number of DCPs and time ranges - aim at including an approximately equal proportion of demand in each DCP, while assuring a constant arrival rate throughout a DCP interval.

Following a similar approach to Lee and Hersh (1993), each DCP is then divided into smaller time intervals of equal length, each of which follows a Poisson process with an expected number of bookings proportional to its length. Hence, the global Poisson process for a certain DCP, i.e., a given time range of the booking horizon, is further subdivided into an amount of reduced time intervals such that Equation (3.1) is satisfied.

$$P(x > 1) < \varepsilon, \tag{3.1}$$

where x is the random variable representing the number of requests that arrive during a time interval. ε should be negligible and, by examining Figure 3.2 and following a similar reasoning to the elbow method, $\varepsilon = 0.01$ is selected since it indicates a cutoff point where the additional returns in terms of $P(x > 1)$ are not worth the additional computational cost, given that the time complexity for each simulation to process the defined amount of time intervals is $O(n)$.

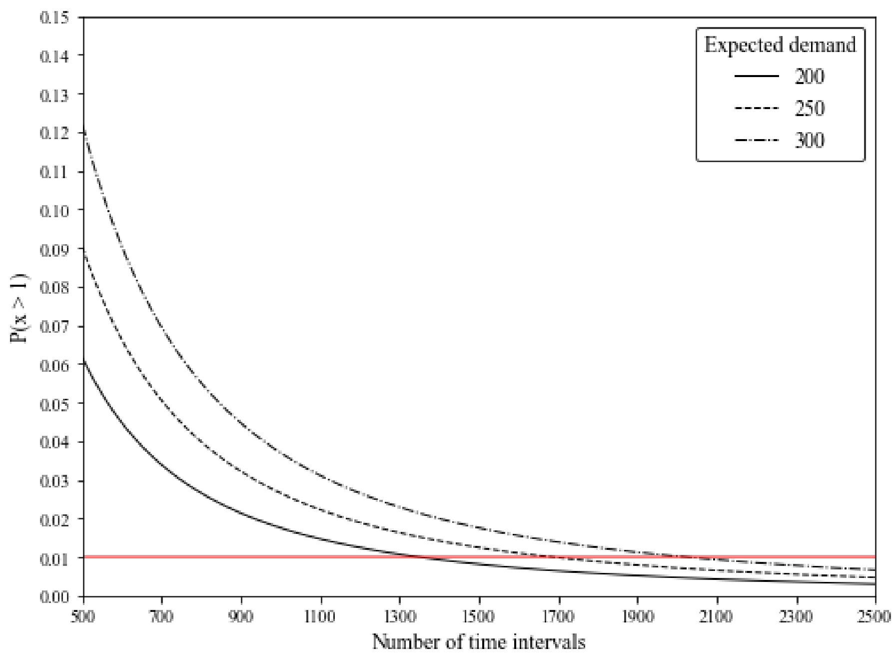

Figure 3.2: Impact of number of time intervals in $P(x > 1)$

Note that Figure 3.2 is computed for the expected demand values that are used as an input for the simulations in next chapters. Even though the time intervals division occurs at each DCP, under the assumption that demand is equally divided per DCP, the plot would look identical, just by calculating the ratio of the expected demand and number of time intervals per number of DCPs.

3.1.2 Demand forecasting

In the context of forecasting, the objective is to contrast and evaluate two distinct scenarios: one characterized by a psychic forecast and the other by a distorted forecast. Theoretically dominant approaches, such as the fare transformation theory previously mentioned, are developed in a risk-neutrality scenario, disregarding robustness to variation in input parameters. They might, however, fluctuate significantly, since there are many uncertainties in ARM - among others, the lack or bad quality of historical booking data, which is most of the times supplemented by manual intervention of RM analysts (Zeni, 2003); inaccurate demand models, when disregarding key customer decision drivers; inaccurate demand estimates: as the network complexity increases, forecasting and optimization require more time, which slows down the updating of demand estimates and inventory controls, leading airlines to either neglect forecast accuracy by selecting simpler and faster methods, or updating too infrequently.

Firstly, since demand is modelled artificially in the simulation, a psychic forecast can be derived (Cleophas et al., 2009). In this case, the forecast encompasses perfect information regarding the Poisson arrival distribution, volume of demand and customer choice behavior represented by an upsell probability. However, in numerous studies, using a psychic forecast may be subject to debate or even deemed impossible. Actually, the primary motive for conducting forecasts is due to uncertainty concerning actual demand. Assuming the psychic forecast as given tends to artificially enhance forecast accuracy and diverge from reality (Frank et al., 2008). Nevertheless, it still proves to be highly beneficial in assessing the consequences of forecast errors and establishing the theoretical superiority of a particular optimization approach, as will be shown in Chapter 4.

Secondly, considering this aspect, a distorted forecast is applied. Since the main objective is to analyze the performance of theoretically dominant optimization and availability control approaches under adverse conditions, the goal should not be to create a very accurate forecast, but just to include the inherent error. Hence, it is not required to apply a state-of-the-art forecasting methodology and, thus, a simple average of historical flight events is calculated. For that, a certain amount of flights is generated, with the corresponding customer arrivals according to the respective Poisson arrival process and upsell probability. Lowest availabilities are arbitrary, and from there booking curves for each booking class are derived. With that, probabilities of requesting a certain booking class are calculated after an unconstraining process. Again, the goal is not to have a sophisticated unconstraining method and, therefore, a simple Naïve technique is considered, which discards the censored data by, for each class, dividing the number of bookings only by the amount of time intervals where that class was available, while reflecting demand dependencies.

To finalize, in both cases the simulation considers a static forecast, meaning that the forecast is fixed at the start of the simulation, and is used for all runs without updating. An alternative approach would be a dynamic forecast, which is updated with the information of previous runs. The dynamic forecast aims at capturing the interaction between past bookings and changes in forecast and optimization. However, since in this simulation the customer behavior is the same across the successive runs, there are no benefits in recalculating the forecast.

3.2 Optimization

The optimization process is done at leg level. It assumes that a precedent network decomposition as in Appendix A has been done, through a linear program, to calculate the displacement costs for each leg and, consequently, the adjusted fares. Other than the adjusted fares, the optimization step uses as input data a probability matrix, either psychic or distorted, derived in the forecasting step, as well as the amount of time intervals and capacity.

As previously stated, the methodology employed in the simulation is a bid price control. A bid price is a net value for an incremental seat on a particular flight in the airline network (McGill & van Ryzin, 1999). In order to calculate it, firstly, expected revenues $V_t(x)$ for each combination of time intervals to departure t and remaining capacity x need to be determined, according to Equation (2.3). As a result, bid prices can be calculated as in Equation (3.2).

$$\Delta V_t(x) = V_t(x) - V_t(x-1) \tag{3.2}$$

Accordingly, expected revenues are first derived through DP with backward induction. Starting with null revenues from the end of the problem (left hand in Figure 3.3), i.e., departure time, until the beginning of the booking horizon (right hand in Figure 3.3), the objective is to calculate, for each amount of available seats, the expected revenue up to that moment, in line with the booking/no booking decisions for each booking class availability, characterized by the probability matrix returned by the forecasting step. To clarify, booking class availability means for each possible decision of lowest booking class available, which may vary during the DP.

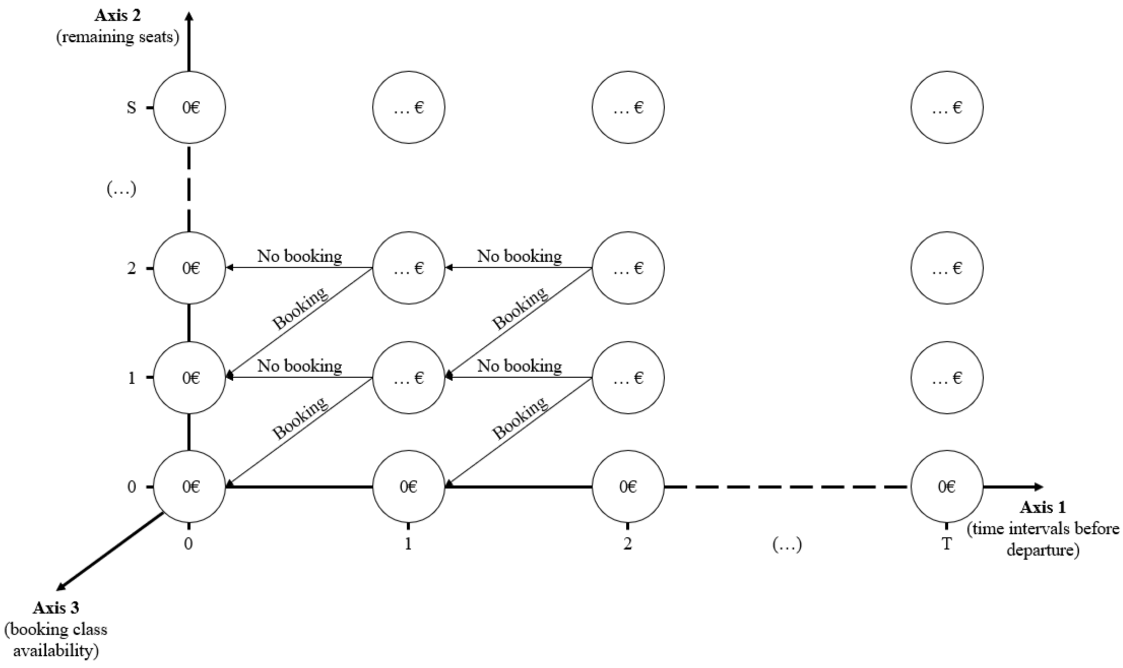

Figure 3.3: Schematic representation of the dynamic program

To avoid confusion in Figure 3.3, booking class availability is just represented by its axis. However, it is worth mentioning that here, at each time interval, for a certain amount of seats left, the expected revenue for each booking class availability depends not only on the expected revenues for that booking class availability on the previous step, but for all the booking class availabilities, since the maximum values are used. Briefly, the maximum values for the same number of seats left and for one less available seat on the previous step are required to calculate this amount. In the end, the expected revenues are the maximum values across booking class availabilities, and bid prices are computed with Equation (3.2). Algorithm 1 provides a structured, step-by-step representation of this explanation.

Algorithm 1: Optimization with DP

Data: $NrTimeSteps(T)$, $ProbMatrix(P)$, $Capacity(S)$, $FareStructure(F)$
Result: $BidPriceVector(\Delta V)$
$V \leftarrow zeros(S,\ T,\ length(F))$;
for $t \leftarrow 1$ **to** T **do**
  for $s \leftarrow 1$ **to** S **do**
    $V[t,\ s,\ :] \leftarrow P[t-1,:] \times (max(V[t-1,\ s-1,:]) + F) + (1 - P[t-1,:]) \times max(V[t-1,\ s,:])$;
  end
end
$V\prime \leftarrow V.max(axis = 3)$;
$\Delta V \leftarrow V\prime.diff(axis = 2)$;

3.3 Availability control

Following the fare transformation theory proposed by Fiig et al. (2010), bid prices are then compared to the BDAF, represented in Equation (2.4), instead of absolute revenue. A booking class will only be available if its BDAF is higher than the bid price. Assuming an exponential sell-up, if the interval between fare levels is constant, the upsell probability is also constant, and the BDAF can be formulated, generally, as $r_k - margin$, where *margin* is a constant.

The fare transformation theory accounts for the potential risk of buy-down under dependent demand modelling. However, in situations where the input parameters are highly uncertain, for instance, a significant forecast error, the BDAF can lead to the closing of a considerable amount of lower classes, which might not be optimal if the forecasted demand is not correct. To tackle this issue, the simulation seeks to study the relevance of this *margin* on the calculation of the BDAF, by computing different scenarios, where *margin* is adjusted by a factor δ in Equation (3.3).

$$r\prime_k = r_k - margin \times (1 + \delta) \tag{3.3}$$

The scenarios are evaluated and compared in order to, firstly, validate the theoretical dominance of the fare transformation theory under a psychic forecast scenario, and secondly, verify if, in fact, the forecast error can have a negative impact in this approach.

3.4 Stopping criteria

For the sake of computational time, it is crucial to properly analyze the simulation output data. It is expected that, after a certain point, the additional reduction in variance is not worth the number of extra simulations it requires. Therefore, running a simulation with an arbitrary number of runs can be detrimental. On the one hand, if the number of runs is insufficient, the random variable being estimated might end up with a large variance and, thus, differ significantly from the corresponding true measure. On the other hand, if the number of runs is excessive, a large amount of time might be spent with few additional benefits (Law & Kelton, 1982).

In this sense, it is essential to define a stopping criteria that regularly assesses the accuracy of the simulation. One technique for doing so is to construct a confidence interval (CI) for the true measure of the performance. The stopping criteria to be employed is based on the method of Lavenberg and Sauer (1977), which is only possible due to the regenerative property of the simulation, meaning that the stochastic process restarts itself from a probabilistic perspective at certain time points. The proposed procedure in Equation (3.4) is to implement a sequential stopping criteria such that the half-length of the $100(1-\alpha)\%$ CI falls below a sufficiently small value γ.

$$z\left(\frac{\alpha}{2}\right) \times \frac{\sigma}{\sqrt{N}} < \gamma \tag{3.4}$$

Then, the half-length of the CI needs to be computed after each additional simulation run. Note that here, the sample mean of the random variable expected revenue is considered to tend towards a normal distribution according to the Central Limit Theorem, since thousands of independent and identically distributed simulation runs are executed. Furthermore, since multiple scenarios are evaluated (previous section), the maximum value for the half-length of the CI is considered. With regards to the threshold for the half-length of the 95% CI ($\alpha = 0.05$), $\gamma = 0.2$ is selected, following a similar approach to the derivation of ε in Equation (3.1). Again, a reasoning based on the elbow method is adopted for the definition of γ. Appendix B plots the curve for the base set of parameters of the simulation, which will be presented later in Chapter 4, as well as for other upsell probabilities, which revealed to be one of the variables that impacted the CI the most.

3.5 Assumptions

In any complex decision-making process, assumptions play a critical role in shaping the outcomes and reliability of the results. Within the context of ARM, simulations, including the one hereby introduced, rely heavily on a series of underlying assumptions that serve as the foundation upon which the models are built.

By presenting and critically examining the considered assumptions, this section strives to gain a deeper understanding of their implications and ultimately enhance the effectiveness of RM strategies. Similar assumptions can be found, among others, in Bitran and Caldentey (2003), Rauch et al. (2018), Fiig et al. (2010), Fiig et al. (2012), and Lee and Hersh (1993), and are as follows:

- There are no explicit costs associated with the production of the final product. This is not a very restrictive assumption since, in fact, the cost of selling one additional seat is negligible (low variable costs against high fixed costs).
- The seller is risk-neutral. The goal is to maximize revenue without considering the variance of the expected revenue, which is an accurate hypothesis for airlines controlling thousands of flights a year.
- Each compartment is treated as a separate flight with fixed capacity. Even though current industry practices account for capacity sharing among compartments if demand justifies so, this simulation only works on compartment level. This is not limiting since capacity sharing generally just resorts to a mix of bid price vectors between compartments, which still need to be calculated first at a compartment level.
- Fare families are characterized by a set of restrictions in such a way that they are independent of each other. Within each fare family, products are undifferentiated and, thus, just different price points.
- An exponential sell-up is considered: $D_k = D_n \ psup_k = D_n \ exp(-\beta(r_k - r_n))$, according to the notation in Equation (2.4). This means that for a set of fares arranged in equal increments, the upsell probability and the margin in Equation (3.3) are the same for any fare products.
- The upsell probability is treated as a constant across time. Even though it may vary along the booking horizon, the main objective of the simulation is to understand the impact of different magnitudes of values.
- Cancellations, no-shows, upgrades, multiple seat bookings, competition, and cross-price elasticity of demand are ignored for the sake of simplicity.

Chapter 4

Current state

This chapter presents the results of the simulation framework developed in the previous chapter. The objective is twofold: (i) prove the theoretical dominance of the fare transformation theory proposed by Fiig et al. (2010) in a psychic forecast scenario; (ii) prove that the accuracy and reliability of forecasting play a pivotal role in the performance of this theory.

Thus, the following sections will start by introducing the parameters to be used as input for the simulation, and thereafter the results for different scenarios will be presented and evaluated on crucial performance metrics, especially expected revenue.

4.1 Simulation parameters

In order to test and evaluate the scenarios, it is essential to establish a set of well-defined parameters that govern the behavior and interactions within the simulated environment. Table 4.1 summarizes the input base values that will be used for the simulation.

Table 4.1: Parametrization of the simulation

Parameter	Value
Expected demand	250
Capacity	175
Fare structure	[500, 400, 300, 200, 100]
Upsell probability	0.2
δ	[-0.50, -0.51, -0.52, ..., 0.49, 0.50]
ε	0.01
α	0.05
γ	0.2

Demand follows a Poisson distribution in each DCP, and overall demand across all booking horizon is considered to be equally distributed by DCP, which allows to divide the whole booking horizon in smaller time steps. Total expected demand and capacity attempt to replicate possible real values for a short-haul flight. A compartment with five booking classes (fares) is considered, with the given upsell probability between them. To test different availability control alternatives, 100 equally spaced scenarios from 50% up to 150% of the original margin are compared. Finally, ε, α and γ are defined as previously stated for the computation of the number of time steps and simulations.

4.2 Psychic forecast

This section presents an analysis of the simulation results obtained under the assumption of a psychic forecast. The goal is to evaluate the performance of the fare transformation theory under an ideal scenario.

Initially, the number of time steps is computed. For the proposed expected demand and ε, 1683 time steps need to be considered in order to comply with Equation (3.1). Taking this into account, the forecaster is able to produce a psychic forecast. The probability of booking/no booking for the lower class is straightforward to derive from the Poisson distribution with an expected value corresponding to the total demand across all booking horizon divided by the number of time steps. When the lowest availability corresponds to higher booking classes, the probabilities are calculated by accounting for the upsell probability. This results in a probability matrix, for each time step and each lowest available class.

The expected revenues and bid prices are then computed, and can be seen in Appendix C. From there, the Monte Carlo simulation can be performed by generating a new set of decisions of booking/no booking from an equivalent Poisson demand. With that and the bid prices, for each time step and number of available seats, a transaction occurs only if the BDAF is greater than the bid price. The output for each margin correction in displayed in Figure 4.1.

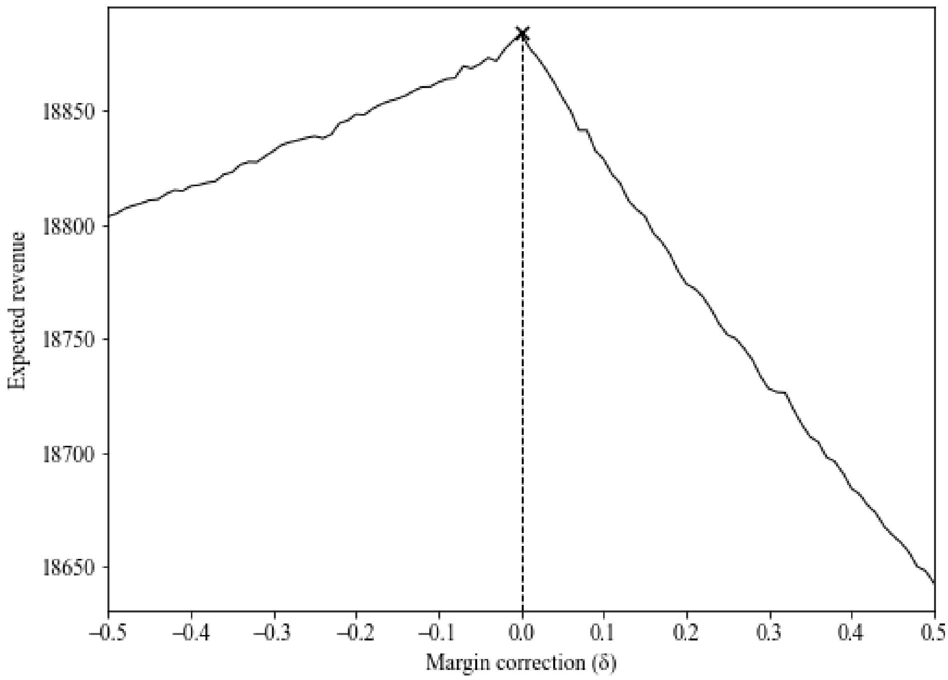

Figure 4.1: Expected revenue by margin correction for psychic forecast

As anticipated, the fare transformation theory retrieves the optimal results in terms of expected revenue under psychic forecast. Appendix D supports the comprehension of the process, showing that an aircraft does not need to be full to produce optimal revenue if higher fare tickets are sold to the right passengers. When considering the allocation of passengers across fare classes, on the one hand, corrections that decrease the margin given by the fare transformation theory ($\delta < 0$) lead to an excessively high BDAF and, therefore, a less restrictive availability. This results in a high share of the seats being allocated to low-fare customers, while capturing fewer high-fare customers. On the other hand, for corrections that increase the margin ($\delta > 0$), there are too many seats saved for high-fare customers, which in the end are not enough to cover the potential revenue from low-fare customers.

Assessing it from a different angle, Pang et al. (2015) demonstrate that, for optimal controls, bid prices do not exhibit a trend throughout the booking horizon. Alternatively, the average bid price across many demand processes is almost constant over the booking horizon. This is explained by the weighting of two properties: (i) resource scarcity effect, denoting that given a certain point in time, a reduced level of inventory results in a higher bid price; (ii) resource perishability effect, reflecting the fact that given a particular inventory level, the bid price decreases with time. Figure 4.2 plots the average bid price across all simulation runs for each time step before departure, and shows that, from a bid price quality standpoint, the margin obtained from the fare transformation theory also appears to be the most suitable. It also supports the conclusions previously reached, since lower margins display an evident upward trend due to negligence of upsell potential, resulting in premature overselling, while higher margins exhibit a downward trend due to overprotecting.

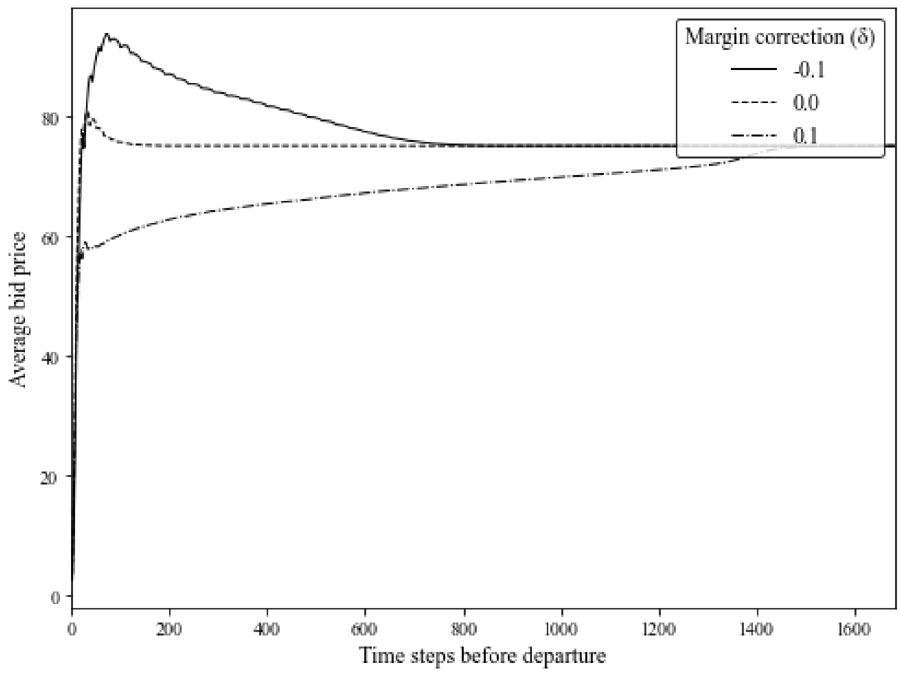

Figure 4.2: Bid price development according to margin correction

As input parameters are ad-hoc, there is a higher degree of uncertainty and, thus, it is of utmost importance to perform a sensitivity analysis on them. By doing so, it is possible to gain valuable insights into how different ranges of values for these parameters may affect the output of the simulation, in this case, the margin correction that retrieves the optimal expected revenue. This allows to assess the robustness and reliability of the results. In this sense, Figure 4.3 deep dives into the upsell probability parameter and shows that the fare transformation theory is robust to different levels of upsell potential. Appendix E presents similar studies for both expected demand and capacity, for which the conclusions are identical.

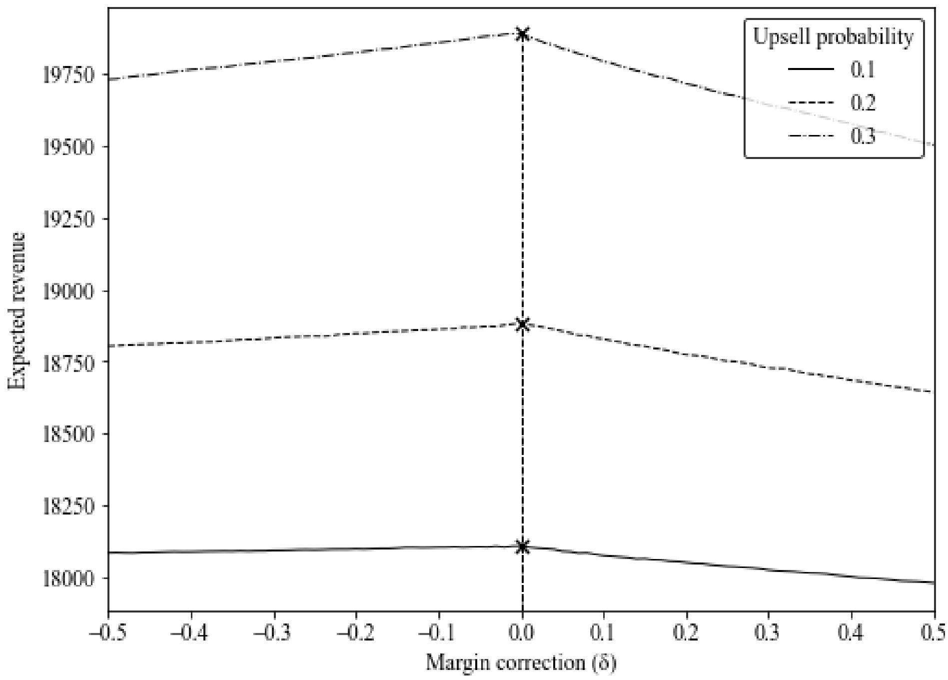

Figure 4.3: Sensitivity analysis on upsell probability for psychic forecast

4.3 Distorted forecast

Forecasting demand in airline industry is far from trivial. It might, in fact, fluctuate significantly due to many uncertainties. Some are RM related, such as lack or bad quality of historical booking data, inaccurate demand models, or inaccurate demand estimates, others are not, including the inherent demand variability, or customer behavior changes. Thereby, forecasts often deviate from actual passenger demand, and it is critical to evaluate RM strategies, as the fare transformation theory, on an unfavorable basis.

Therefore, this section replicates some of the results for a distorted forecast scenario. For that, as described in Chapter 3, 1000 flights and the corresponding set of requests across the booking horizon are created from the same demand process. The same amount of random availabilities is generated, and from there a simple ratio of demand per availability counts is calculated for each booking class. This simply disregards the censored data, meaning the time steps where booking classes are not available, which is a simple Naïve technique. The main goal is to include the inherent variability in the forecast.

Keeping all other input parameters constant, Figure 4.4 provides the results of the Monte Carlo simulation and proves that the fare transformation theory may lack robustness to forecast errors. Now, the optimal margin in terms of expected revenue is not the primary one anymore, but the one with a -13% correction. This means that the fare transformation is introducing an excessive margin in the derivation of the BDAF, leading to an overprotection and consequent loss of revenue. Even though the delta to the new optimal margin is relatively low (approximately 8 units), for a network that operates thousands of flights a year, and especially for higher yield fares, it might have a significant impact on total revenue. Besides that, poorer forecast accuracies might affect it even further.

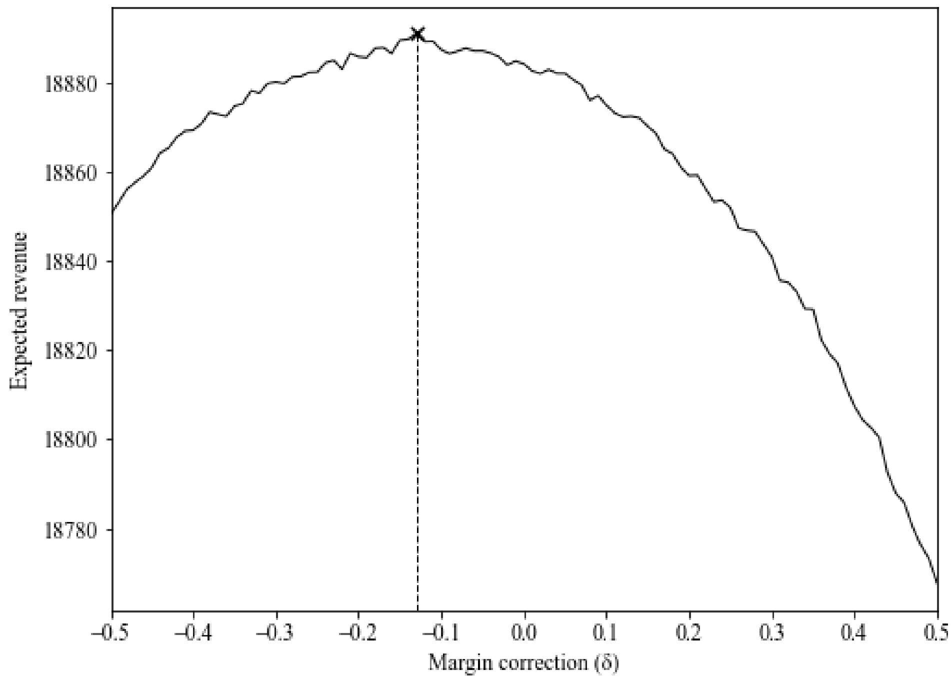

Figure 4.4: Expected revenue by margin correction for distorted forecast

For a concrete view of the impact of forecast errors on expected revenue and, thus, in the optimal margin correction, a sensitivity analysis must be performed. However, the introduction of forecast error with an average of previous flights makes it harder to quantify it. Hence, a new method to induct and quantify forecast error needs to be introduced. One way to approach the real forecast quality is to induce it by random noise. Let Δ be a matrix with equivalent dimensions to those of the probability matrix previously presented as the output of the forecaster, i.e., same number of rows as the number of time steps, and same number of columns as the number of booking classes, in the current case 1683×5. Δ is composed by random values between a lower and upper bounds for the forecast error. Then, the expected value of the Poisson demand is adjusted in line with Equation (4.1), as follows:

$$\lambda' = \lambda \times \Delta. \tag{4.1}$$

With this, the Monte Carlo simulation can run normally, preserving the remaining parameters. Figure 4.5 plots the results for three levels of forecast error, and suggests that, in fact, poorer forecast accuracies tend to lower optimal margins: forecast errors of $\pm 10\%$, $\pm 20\%$, and $\pm 30\%$ tend to, respectively, optimal margin corrections of -4%, -10%, and -17%. This may potentially be quite problematic due to the inherent complexity and volatility of the airline demand, presenting substantial challenges that need to be addressed.

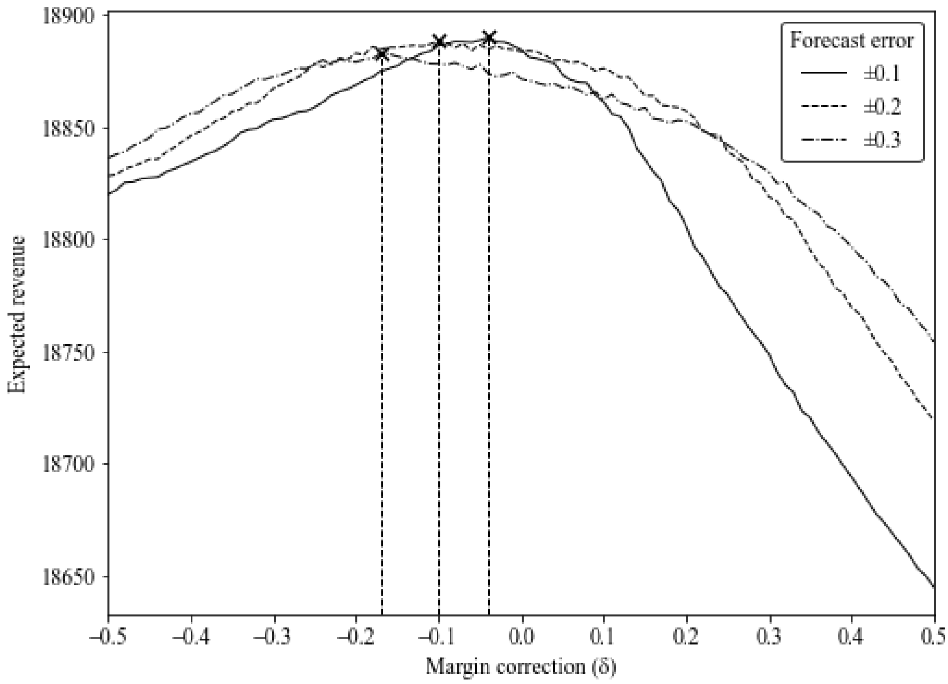

Figure 4.5: Sensitivity analysis on forecast error for distorted forecast

After testing and comparing different scenarios of forecast error, it is necessary to validate whether diverse spectrums of other parameters are now impactful. For this, the simulation is run with the same input parameters described in Table 4.1 and uses a forecast error of $\pm 20\%$. Even though the variation of input parameters does not have an impact in a psychic forecast scenario, as previously concluded, Figure 4.6 indicates that in a distorted scenario varying ranges of upsell probability can influence the optimal margin correction. Appendix F illustrates similar studies for expected demand and capacity, confirming that both variables can also influence the optimal margin. Yet, these relationships seem highly complex. Next chapter will explore nonparametric models, which offer the flexibility and adaptability required to uncover hidden patterns and nonlinear interactions that may exist among the variables.

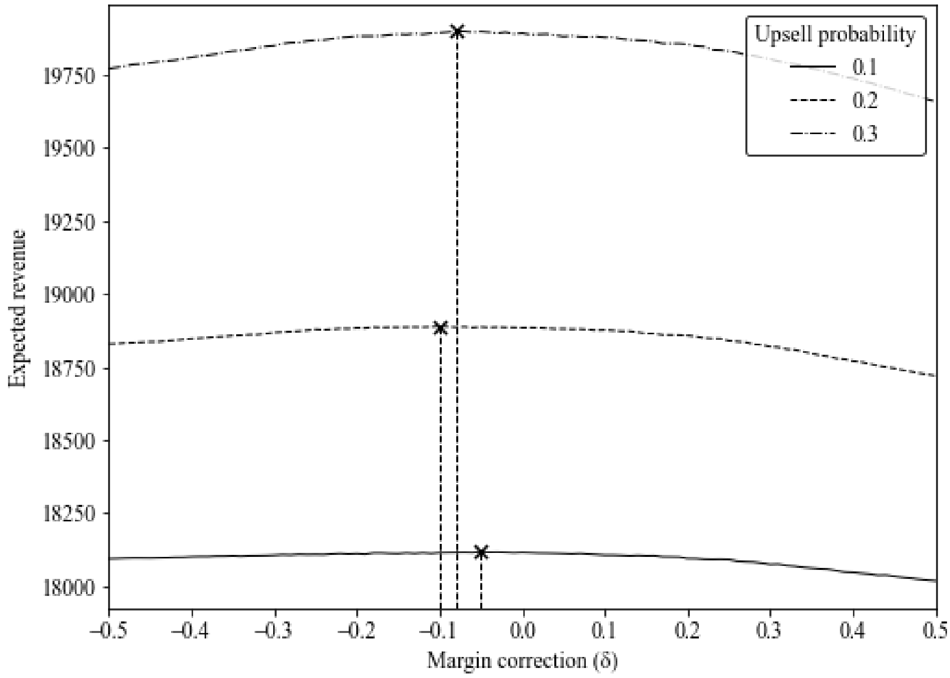

Figure 4.6: Sensitivity analysis on upsell probability for distorted forecast

Chapter 5

Improving robustness to forecast errors

In the preceding chapters, the limitations of the fare transformation theory in handling forecast errors have been thoroughly examined and substantiated. The lack of robustness of this theory have underscored the need for alternative approaches that can address the inherent challenges.

This chapter proposes a method to mitigate this. Firstly, resorting to the simulation framework previously presented, optimal margins are collected for a set of representative input parameters. Secondly, this data is used to train an ML model. The models portrayed in Chapter 2, namely random forest (RF) and gradient boosting machine (GBM), will be tuned, tested, and compared. Finally, with the top-performing model, a validation study will be conducted for a selection of flights in order to assess if the corrected margins yield, in fact, significative improvements in expected revenue, compared to the standard margins.

5.1 Data generation

As discussed in previous chapters, the proposed simulation framework is designed to retrieve the margin correction that maximizes the expected revenue for a set of parameters. Therefore, it is possible to employ it to generate a representative dataset of optimal margin corrections for a range of parameters that closely emulate the real-world. Accordingly, leveraging this simulation, synthetic data is generated according to the combination of parameters exhibited in Table 5.1.

Table 5.1: Range of parameters for data generation

Parameter	Range of values
Forecast error	[-0.4,0.4], [-0.3,0.3], [-0.2,0.2], [-0.1,0.1], [-0.3,0.1], [-0.1,0.3], [-0.2,0.1], [-0.1,0.2]
Expected demand	200, 250, 300
Capacity	150, 175, 200
Fare structure	[300, 250, 200, 150, 100], [500, 400, 300, 200, 100], [700, 550, 400, 250, 100], [600, 500, 400, 300, 200], [700, 600, 500, 400, 300]
Upsell probability	0.1, 0.2, 0.3, 0.4

Forecast error values set the lower and upper bounds as far as ±40%, to account for the unprecedented challenges that the recent global pandemic has brought (Garrow & Lurkin, 2021). These values consider the possibility for some bias in addition to variance. For capacity, values of typical short-haul aircrafts are considered, while expected demand seeks higher values than the available capacities in order to analyze the problem with significant bid prices. Otherwise, if bid prices were null across most of the booking horizon, the margin correction would not pose significant differences (only for cases where the BDAF gets negative) and, thus, it would not be relevant for this study. Regarding fare structure, a compartment with five booking classes is always considered. The aim is to variate the minimum and maximum fares (and, thus, the step between fares) to achieve a diverse spectrum of values. For the upsell among booking classes, a representative range of values is used to account for both situations with low and high sell-up.

An exhaustive combination of the parameters is done and, therefore, 1440 data points are gathered. For each combination, the number of time steps is calculated according to the expected demand parameter. With that, the forecast error, expected demand, and upsell probability, the probability matrix is calculated in the forecaster. Then, this matrix, combined with the fare structure, capacity, and number of time steps, is used as an input for the optimizer to calculate the bid price vectors. Finally, the Monte Carlo simulation is able to run, and the margin correction that maximizes revenue is collected. If two or more margin corrections result in the maximum expected revenue, the one with the narrower confidence interval is selected. The parameters δ, ε, and γ used for the computation of, respectively, margin correction values, number of time steps, and number of simulation runs, remain unchanged and correspond to those in Chapter 4. Figure 5.1 shows the distribution of the optimal margin correction values obtained.

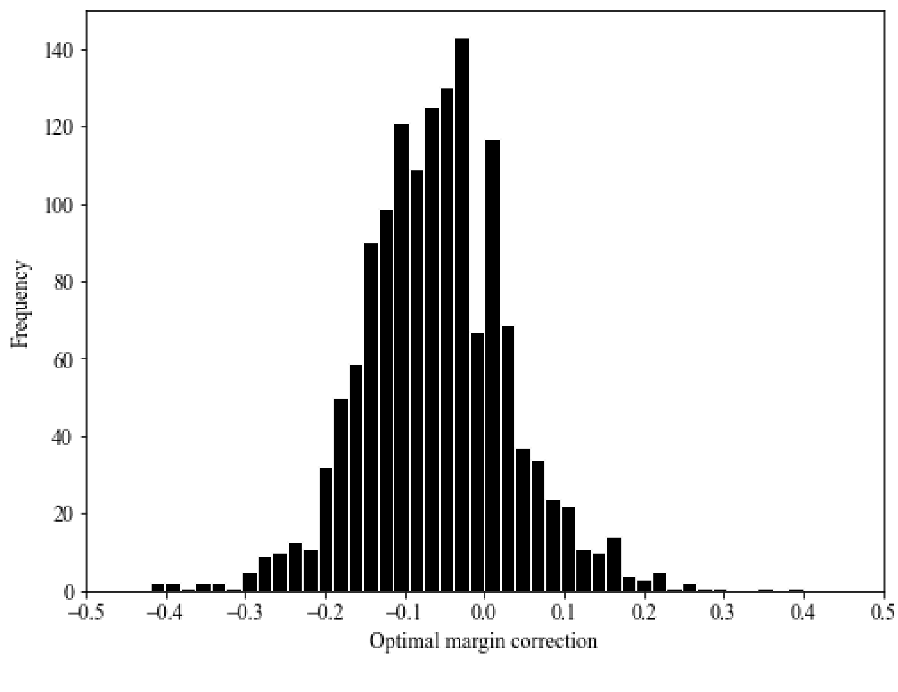

Figure 5.1: Optimal margin correction distribution

Based on the histogram of the distribution of optimal margin corrections, it is noticeable that there might be some deviations on the obtained values. The main reason for these deviations are the flatness of the expected revenue curves for some combination of parameters. Nevertheless, the objective it still to account for these interactions to ensure a flexible model with an accurate representation of the optimal margin corrections. Moreover, cross-validation will contribute to preserving the model robust to these individual deviations, while generalizing the global interactions.

5.2 Predictive model for optimal margin correction

The main objective of this section is to construct a predictive model that enhances the robustness of existing availability control strategies to adverse conditions, using the RF or GBM algorithms. By harnessing the flexibility and adaptability of these ensemble-based methods, it is possible to capture the complex interplay of various factors affecting optimal margin correction. Furthermore, one of the fundamental outcomes to retrieve from the model is the feature importance scores, meaning how significant is each parameter in the setting of the optimal margin correction.

First of all, it is necessary to convert the parameters values into numeric features to use as input for the models (Table 5.2). Regarding expected demand, capacity, and upsell probability it is straightforward since the features are equivalent to the parameter values. Concerning fare structure, it can be characterized by the minimum fare and step between fares. Since the compartment always has five booking classes, there is no need to describe the fare structure further with the maximum fare. Under these circumstances, a maximum fare feature would exhibit a strong correlation with the minimum fare and fare step features. Even though the proposed ensemble models are robust to multicollinearity, it can be harder to interpret the feature importance scores, and, thus, a maximum fare feature is not considered. Lastly, the forecast error is subdivided into two components: a bias indicator, which aims at identifying situations where the forecast is consistently inaccurate (under- or over-forecasting), and a variance indicator, that reflects how precise the forecast is.

Table 5.2: Feature engineering and labeling

Feature	Derivation
variance _indicator	Forecast error: $UpperBound - LowerBound$
bias _indicator	Forecast error: $(UpperBound + LowerBound)/2$
expected _demand	Expected demand
capacity	Capacity
min _fare	Fare structure: $min(fares)$
step _fare	Fare structure: $(max(fares) - min(fares))/5$
upsell _probability	Upsell probability

Now, it is crucial to divide the 1440 data points into training and testing sets in order to evaluate the models in an independent dataset, which mimics how well they will perform on unseen data. Furthermore, this allows to track the bias-variance trade-off. For instance, if the model performs significantly worse on the testing set compared to the training set, it suggests overfitting (variance), indicating the need for adjustments like regularization or model simplification. Since in this case the dataset is originated from a combination of ranges of parameters, the data is well balanced, and the splitting just needs to ensure that it is representative of the parameter space. This can be done with a shuffling and random sampling, while setting a random seed to ensure reproducibility and consistent results. For the split, 80% of the data is allocated for training, and 20% for testing.

The training data is then further divided into 4 subsets (folds) for k-fold cross-validation, in order to tune the hyperparameters. This way, each fold is used for validation once, meaning that for each of the 4 iterations, 60% of the overall dataset serves as input for training and 20% are employed for validation. In the end, the performances of all the folds are averaged and hyperparameters are decided upon that. Finally, the remaining 20% of the dataset is intended for final evaluation of the models.

To model the RF and GBM algorithms, the *sklearn* library in Python is employed. Moreover, for hyperparameter tuning, the *optuna* library is used, which is a hyperparameter optimization framework. In this case, a sampling strategy is applied: the Tree-Structured Parzen Estimator. A sampling strategy is known for identifying the optimal parameter combination by focusing on regions where hyperparameters yield superior outcomes. In concrete, the Tree-Structured Parzen Estimator is a Bayesian approach that models the relationship between hyperparameters and evaluation metrics using separate distributions for the parameter values associated with the best objective values, and for the remaining values (for more information, see Akiba et al. (2019)).

For model performance evaluation, two metrics are analyzed: mean absolute error (MAE) and root mean squared error (RMSE) - Equations (5.1) and (5.2). MAE is straightforward to interpret since it represents the average absolute difference between predicted and actual values. However, it gives equal weight to all errors, and does not amplify the impact of large errors. Hence, RMSE is also considered, which is sensitive to large errors, making it robust to outliers. Even though it is in the same units as the predicted values, taking the square root of the squared errors can make it more challenging to interpret directly. For this reason, both metrics are calculated and assessed. Nevertheless, for hyperparameter tuning and model selection, RMSE carries slightly more significance. This is based on the fact that the curves of expected revenue in Chapter 4 are somewhat flat and, thus, it might be worth it to penalize more larger errors, since smaller errors might not imply a significant loss of revenue most of the times.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \tag{5.1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2} \tag{5.2}$$

Initially, RF and GBM models are built with the library default hyperparameters. Looking into Table 5.3, it can be verified that whereas the GBM model shows a proper fitting with these hyperparameters, the RF model is suffering from overfitting, since training performance is significantly superior to testing performance. Thus, hyperparameter tuning is needed. According to Chapter 2, some of the most important hyperparameters are displayed in Table 5.4, with the corresponding ranges of values to test. For RF, the number of estimators, maximum depth of the tree, and maximum number of features in each split are calibrated, while for GBM, which despite exhibiting a strong fit will be further refined, the number of estimators, maximum depth of the tree, and learning rate are adjusted. For the number of estimators and maximum depth of the tree, a representative range is considered; for the maximum number of features in each split, a range from 2 to the total amount of features is tested; for the learning rate, a range between the values proposed by James et al. (2013) is examined. In this regard, the Tree-Structured Parzen Estimator from *optuna* is employed with 100 iterations, resulting in the final values displayed on the right side of Table 5.4. These optimized hyperparameters mitigated the overfitting of the RF model and, consequently, enhanced the testing performance, while for GBM the improvements were not significant (Table 5.3).

Table 5.3: Models evaluation before and after hyperparameter tuning

Dataset	Metric	Before tuning		After tuning	
		RF	GBM	RF	GBM
Train	MAE	0.0217	0.0497	0.0451	0.0490
	RMSE	0.0307	0.0683	0.0613	0.0671
Test	MAE	0.0514	0.0502	0.0497	0.0499
	RMSE	0.0734	0.0704	0.0699	0.0702

Table 5.4: Hyperparameter tuning

Hyperparameter	Range to test	Selected value	
		RF	GBM
n _estimators	range(100, 1000, step=100)	700	500
max _depth	range(1, 10, step=1)	7	4
max _features	range(2, 7, step=1)	3	-
learning _rate	range(0.001, 0.01, step=0.001)	-	0.008

Even though the models are very similar, moving forward only the RF model will be considered in order to not have duplicated information, since it has a slightly better performance. Now, the objective is to understand the relevance of each independent variable in predicting the dependent variable optimal margin correction. For that, it is possible to retrieve the importance scores for each predictor of the model. By inspecting the decrease in the sum of squared errors after the splits made using a specific feature, the RF model is able to depict the most important variables. Accordingly, Figure 5.2 indicates that the forecast error variables are unequivocally the most significant ones, especially the bias indicator. These are followed by the upsell probability, expected demand, capacity, and fare structure related variables, in this order. However, their importance scores are substantially lower.

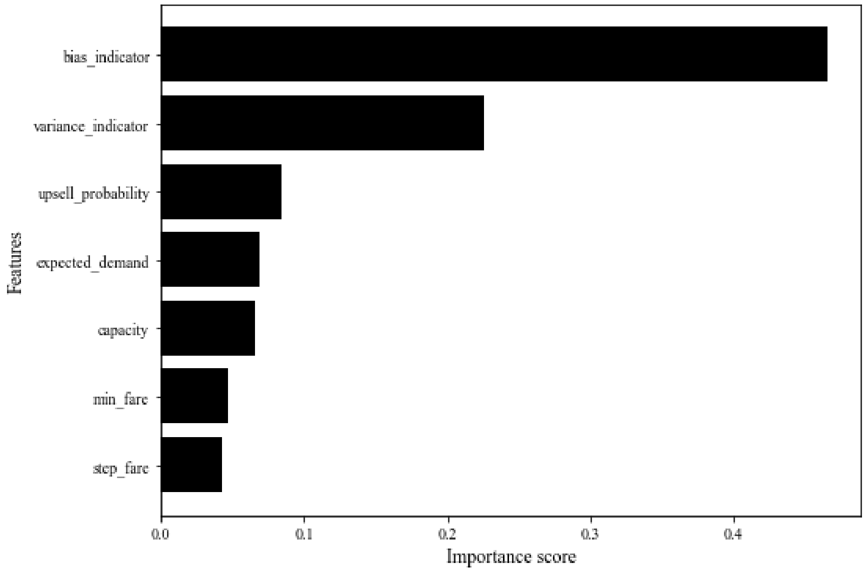

Figure 5.2: Feature importance scores

After recognizing the forecast error variables as highly important, there is a necessity to unravel their specific impact on the dependent variable. Partial dependence plots are universal methods to illustrate the marginal effect of a certain feature on the predicted outcome, after removing the influence of the other features. Figure 5.3 implements it for both the bias and the variance indicators. The findings are coherent: for the bias indicator, negative values mean that the forecasted values are lower than the real demand. Thus, the logical outcome is a trend to increase the margins, leading to lower BDAFs and, consequently, more strict availabilities. On the other hand, positive values imply over-forecasting, and the natural result is to decrease margins, causing more liberal availabilities. As for the variance indicator, as it increases, the margins need to be lower - the worse the forecast accuracy is, the less robust the fare transformation theory is.

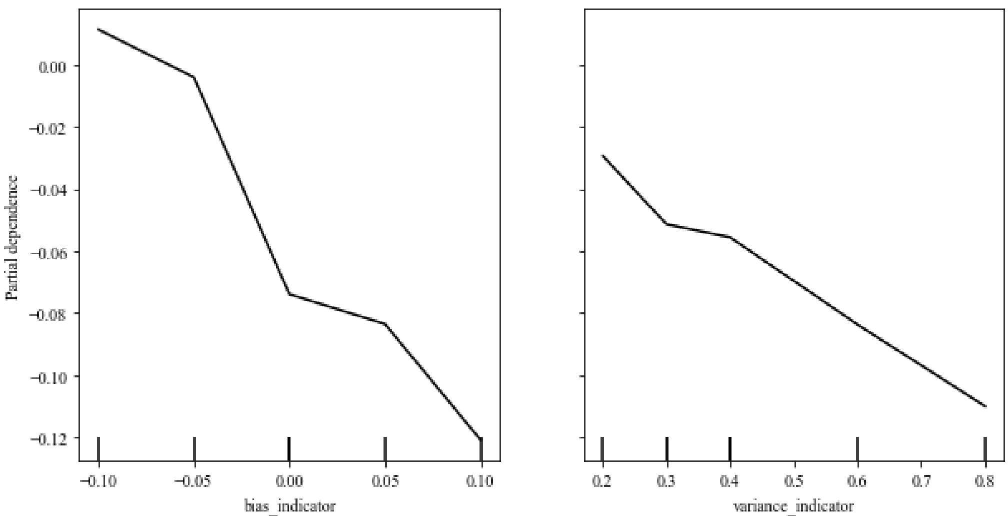

Figure 5.3: Partial dependence plots for bias (left) and variance (right) indicators

For the other less important features, Appendix G shows that, with the exception of the step between fares for which the optimal margin correction seems to increase as steps rise, it is hard to find meaningful patterns. On one side, the curves are contained in a small range of values. On the other side, the patterns do not show a clear trend.

5.3 Validation study

Even though an out-of-sample validation was already performed to assess the performance and reliability of the predictive model, it is now important to validate whether the optimal margin correction being predicted really yields a superior performance when compared to the standard fare transformation theory. Hence, this section performs another out-of-sample validation study to analyze the impact of the model in terms of expected revenue when applied to an availability control context.

It is crucial to use input parameters within the same ranges as those used during the model training. Such procedure ensures that the study reflects realistic conditions and enables a fair and accurate assessment of the model performance by evaluating it on data that closely resembles the scenarios it was trained on. Table 5.5 displays the ranges of values to consider for each feature. For the upsell probability, expected demand, capacity, and fare related features, the ranges are simply the ones considered for the training data of the model. However, here, a random value between the lower and upper bounds is calculated for each feature. Regarding the forecast error variables, three distinct scenarios with increasing inaccuracy are evaluated. Scenario A accounts only for variance, with the forecast error ranging from $\pm 10\%$ to $\pm 20\%$. Scenario B is similar, but allows the forecast error to range from $\pm 10\%$ to $\pm 40\%$. Scenario C, besides this level of variance, also considers the possibility for bias in the forecast, ranging from -10% to 10%.

Table 5.5: Out-of-sample study for predictive model in availability control

Feature	Range of values		
	Scenario A	Scenario B	Scenario C
bias _indicator	0	0	[-0.1, 0.1]
variance _indicator	[0.2, 0.4]	[0.2, 0.8]	[0.2, 0.8]
upsell _probability	[0.1, 0.4]	[0.1, 0.4]	[0.1, 0.4]
expected _demand	[200, 300]	[200, 300]	[200, 300]
capacity	[150, 200]	[150, 200]	[150, 200]
min _fare	[100, 300]	[100, 300]	[100, 300]
step _fare	[50, 150]	[50, 150]	[50, 150]

Subsequentially, 100 flights are generated, where a random value within these ranges is assigned to each feature. Then, the usual Monte Carlo simulation is applied, but now the outcome is the expected revenue for all the 100 flights. This means that each simulation runs 100 flights, and the revenue is summed up. Regarding the margin correction, only two cases are evaluated: no margin correction, corresponding to the fare transformation theory, and optimal margin correction produced by the RF model previously trained. Moreover, the stopping criteria parameter γ, that represents a threshold for the half length of the 95% CI, needs to be adjusted since now the random variable to be evaluated is the expected revenue of the 100 flights, leading to a greater variability. Thus, it would not be computationally efficient to aim for the same γ. Now, the threshold for the stopping criteria is given by $\gamma = 10$.

To test and evaluate the strategies, the key indicator is the expected revenue, but data is also gathered on the number of passengers to analyze potential effects on the market share. Table 5.6 proves that, in fact, a margin correction over the fare transformation theory produces improved results for all the scenarios considered, although accompanied by different magnitudes. As expected, the positive impact increases from scenario A to C, since the forecast accuracy is decreasing and, thus, it is more crucial to correct the margins in availability control. Focusing solely on the expected values, in scenario A the margin correction strategy yields an expected revenue 0.0034% higher than the one for no margin correction; in scenario B the difference rises to 0.0093%; and in scenario C, to 0.0144%. Even though these are low percentual differences, for an airline with thousands of flights a year it can have a significant impact. Furthermore, when inspecting Table 5.7, it is also possible to assess that the margin correction strategy provides enhanced results regarding the number of passengers. By maximizing occupancy, an airline can gain a competitive edge and increase its market share.

Table 5.6: Expected revenue for validation study

Strategy	Scenario A		Scenario B		Scenario C	
	Mean	95% CI	Mean	95% CI	Mean	95% CI
No correction	3 689 785	±9.67	3 681 910	±9.61	3 650 706	±9.47
Correction	3 689 911	±9.62	3 682 255	±9.59	3 651 233	±9.43

Table 5.7: Expected passengers for validation study

Strategy	Scenario A		Scenario B		Scenario C	
	Mean	95% CI	Mean	95% CI	Mean	95% CI
No correction	17 335	±0.018	17 067	±0.018	17 651	±0.024
Correction	17 341	±0.018	17 078	±0.017	17 658	±0.023

Chapter 6

Conclusion

As discussed, the fare transformation theory is a technique to adjust fares which allows for the use of optimization algorithms and seat inventory control methods of traditional RM systems when the independent demand assumption per booking class does not hold. Under a bid price control, it defends that the bid price should not be compared with the total fare, but with the BDAF, which corresponds to the original fare deducted by a margin dependent on the upsell potential to higher fare classes. Generally, the higher this potential, the lower the BDAF is and, thus, the more frequent it becomes to close lower fare classes availability.

Even though this is a theoretical dominant approach, it is still essential to examine its robustness to uncertainties and disturbances. Specifically, demand modelling in airline industry is highly complex due to the intricate and dynamic nature of the market. Demand might vary significantly due to factors such as fluctuating customer preferences, changing travel patterns, and unpredictable external factors. Being aware of this urge, this study investigated the performance of the fare transformation theory under both a psychic and distorted forecasts, with a Monte Carlo simulation, while testing if the results are sensitive to other input parameters. Moreover, an RF model was employed to predict the optimal margin corrections under forecast inaccuracy, and a validation study was conducted to verify if this model could, in fact, yield a superior performance.

6.1 Main conclusions

By leveraging these methodologies, significant progress has been made in answering the research questions included in Chapter 1, enabling a deeper understanding of the impact of forecast errors in margin setting within the fare transformation theory.

Firstly, the Monte Carlo simulation validated that the fare transformation theory is, in fact, a theoretical dominant methodology under a psychic forecast, which mimics known input parameters. This holds not only for the base parameter values used, but also for the different ranges of values tested, showing robustness to variations in upsell probability, expected demand, and capacity. The scenario without any margin correction applied on top of the standard margin performed consistently better, with higher expected revenues, even if it meant having some seat load factor gaps.

Secondly, after introducing a forecasting method as the unconstrained average of past flights, it was proved that the fare transformation theory lacks some robustness to forecast errors. In fact, the standard margin is overestimated, leading to the premature closing of low-fare classes. However, the high-fare customers fail to arrive at the expected rate, and the expected revenue drops due to empty seats. Hence, the margin needs to be reduced to produce maximum expected revenue. Moreover, it was evident that the higher the level of inaccuracy, the more the margin needs to be adjusted down. Also, for each level of forecast error, the simulation indicated that other variables, such as upsell probability, expected demand, or capacity, might influence the optimal margin correction.

Thirdly, once the simulated data was generated and the tree-based ML models were trained and tuned, with the final selection of the RF model, it was possible to apprehend which variables impacted the most the accurate prediction of the optimal margin correction. These were, in this order, the bias indicator, variance indicator, upsell probability, expected demand, capacity, and fare related variables. The forecast variables were markedly the most essential ones, with importance scores of 0.47 for the bias indicator, and 0.23 for the variance indicator. All the remaining features had an importance score lower than 0.084. Regarding the marginal effect of each feature in the optimal margin correction, after removing the influence of the other features, when the bias indicator conveys positive values, it means that the forecast is overestimating the real demand and, thus, the standard margins retrieved by the fare transformation theory should be reduced, leading to more permissive availabilities (and vice versa); for the variance indicator, the higher it gets, the more negative the optimal margin correction has to be, meaning that the higher the forecast inaccuracy, the less robust the fare transformation theory is; regarding the remaining and less important variables there are no clear patterns, unless for the fare step, for which the optimal margin correction increases as steps grow.

For further validation, a study was conducted to assure if the predictive model was accurate enough to yield consistently better results than the standard fare transformation theory. For this end, 100 out-of-sample flights were considered. Three scenarios with decreasing level of forecast accuracy were evaluated. The results indicate that the strategy with the optimal margin correction from the predictive model steadily outperforms the fare transformation theory in terms of expected revenue. Besides that, the lower the forecast accuracy, the greater the gap between the two strategies. Scenario A considered only a forecast error from $\pm 10\%$ to $\pm 20\%$, scenario B from $\pm 10\%$ to $\pm 40\%$, and scenario C included some systematic error (bias) on top of that, allowing to shift the forecast error up or down by as much as $\pm 10\%$. Focusing only on the expected revenues, in scenario A the margin correction strategy produces an expected revenue 0.0034% higher than the one for no margin correction, in scenario B the difference rises to 0.0093%, and in scenario C to 0.0144%. Moreover, the margin correction strategy also leads to higher seat load factors, which might impact positively other indicators, such as market share.

6.2 Future research

It is now recognized that the forecast error features are the most important to predict the optimal margin correction that maximizes revenue. Yet, as discussed earlier, computing forecast accuracy in ARM is highly complex. Whereas for the traditional independent demand unconstrained bookings are compared with the unconstrained demand forecasts used in optimization, since at that point they were not subjected to RM controls, for dependent demand it is not that straightforward. For dependent demand, it depends on the control policies, since the availability of a class affects the demand for other classes. Therefore, it is argued that for the predictive model for optimal margin corrections to work properly, there needs to be a standardized method to compute the forecast errors, as the one proposed by Fiig et al. (2014), described in Chapter 2.

Still on the field of forecasting, dependent demand requires not only the forecast of the volume component, but also a choice/WTP component, in this simulation given by the upsell probability. Throughout the research, the forecast error was introduced has a whole. However, future works might be concerned about discerning the specific impact from both the volume and upsell probability sides.

Regarding the input parameters, a constant upsell probability was considered across all the booking horizon, and the fare family always accounted for five booking classes. Even though the RF model pointed that both the upsell probability and the fare related variables were less important to accurately predict the optimal margin correction, it might be worth to further study if different upsell probability distributions throughout the booking horizon, as well as a different number of booking classes impact the results.

Lastly, adjustments can be made to the simulation and predictive model in order to accommodate certain assumptions outlined in Chapter 3. This includes cancellations, no-shows, upgrades, multiple seat bookings, or even competition. Moreover, additional demand models can be studied.

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Appendix A

Network decomposition heuristic

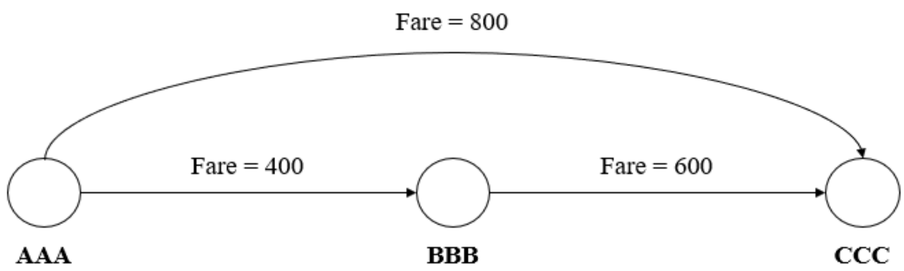

Figure A.1: Network example

Table A.1: Network specificities

OD	Fare value	Demand	Capacity
AAA-BBB	400	2	3
BBB-CCC	600	3	3
AAA-CCC	800	4	-

$$max(revenue) = 2 \times 400 + 2 \times 600 + 800 = 2800 \tag{A.1}$$

$$max(revenue)_{1\ extra\ seat\ in\ AAA-BBB} = 2 \times 400 + 600 + 2 \times 800 = 3000 \tag{A.2}$$

$$max(revenue)_{1\ extra\ seat\ in\ BBB-CCC} = 2 \times 400 + 3 \times 600 + 800 = 3400 \tag{A.3}$$

Table A.2: Network decomposition

Leg	Displacement cost connecting OD	Pseudo-fare local OD	Pseudo-fare connecting OD
AAA-BBB	$(A.2) - (A.1) = 200$	400	$800 - 600 = 200$
BBB-CCC	$(A.3) - (A.1) = 600$	600	$800 - 200 = 600$

Appendix B

Selection of γ for computation of simulations runs

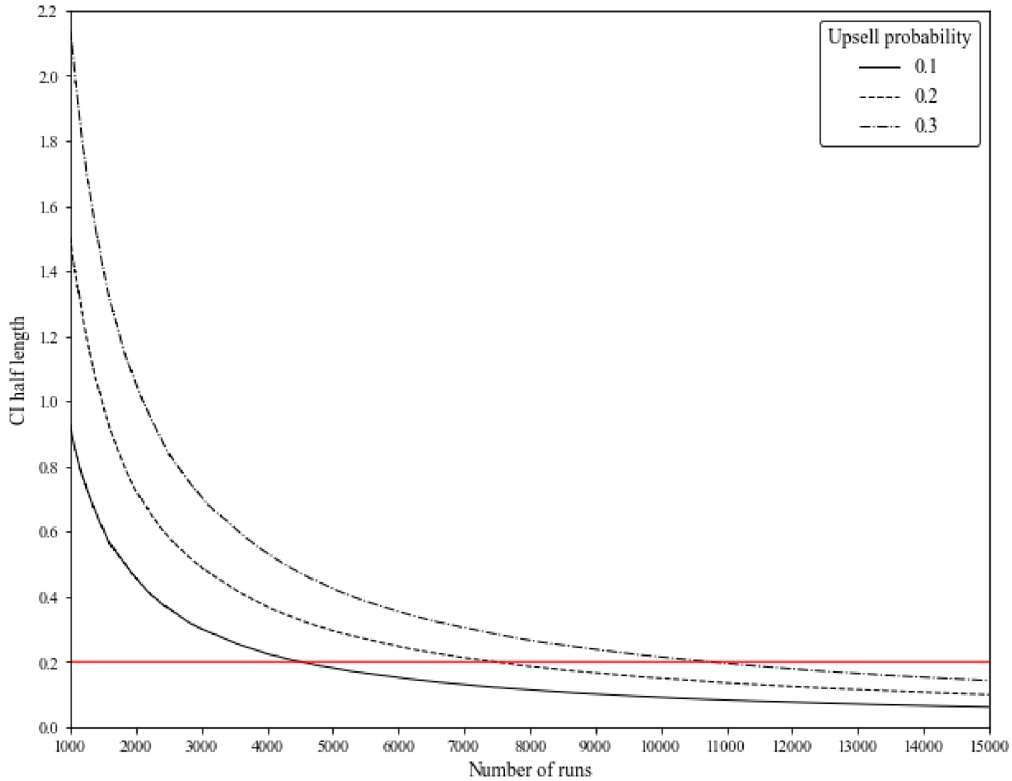

Figure B.1: Impact of number of runs on the half length of the 95% CI

Appendix C

Expected revenues and bid prices

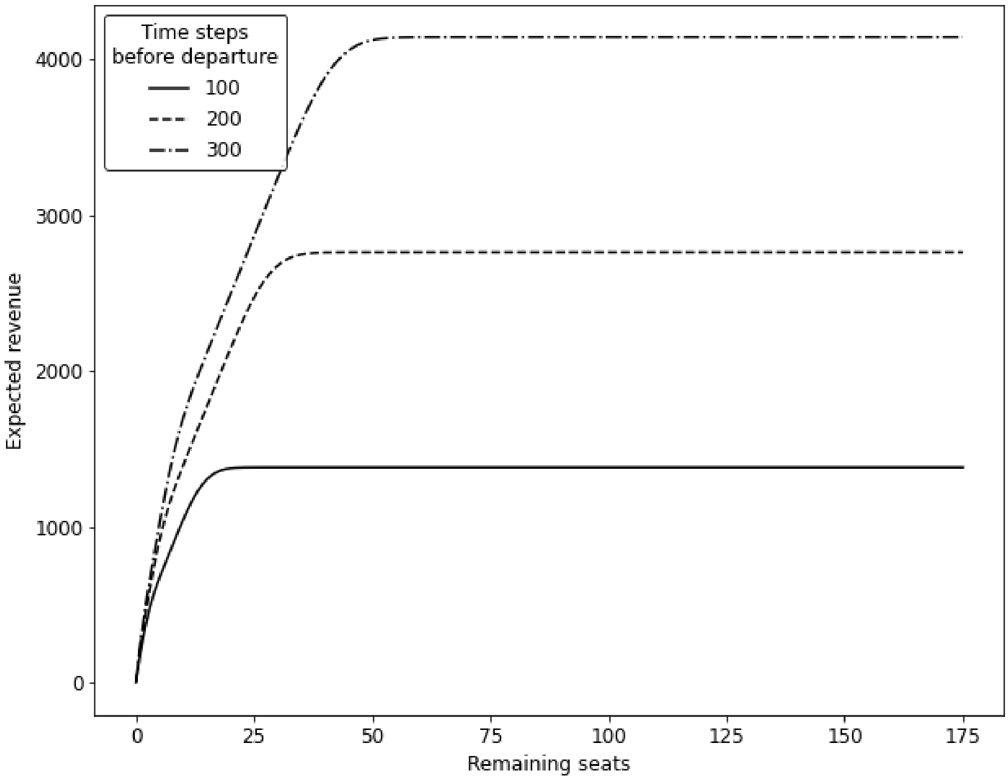

Figure C.1: Expected revenue vectors

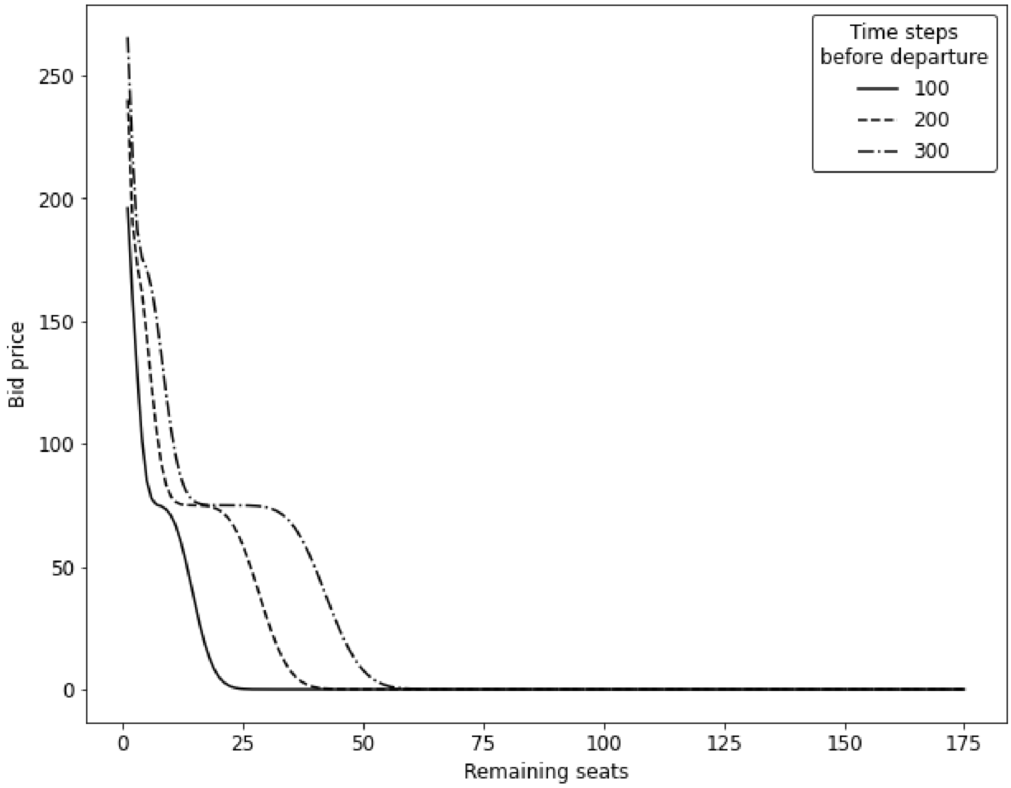

Figure C.2: Bid price vectors

Appendix D

Interaction between number of passengers and margin correction

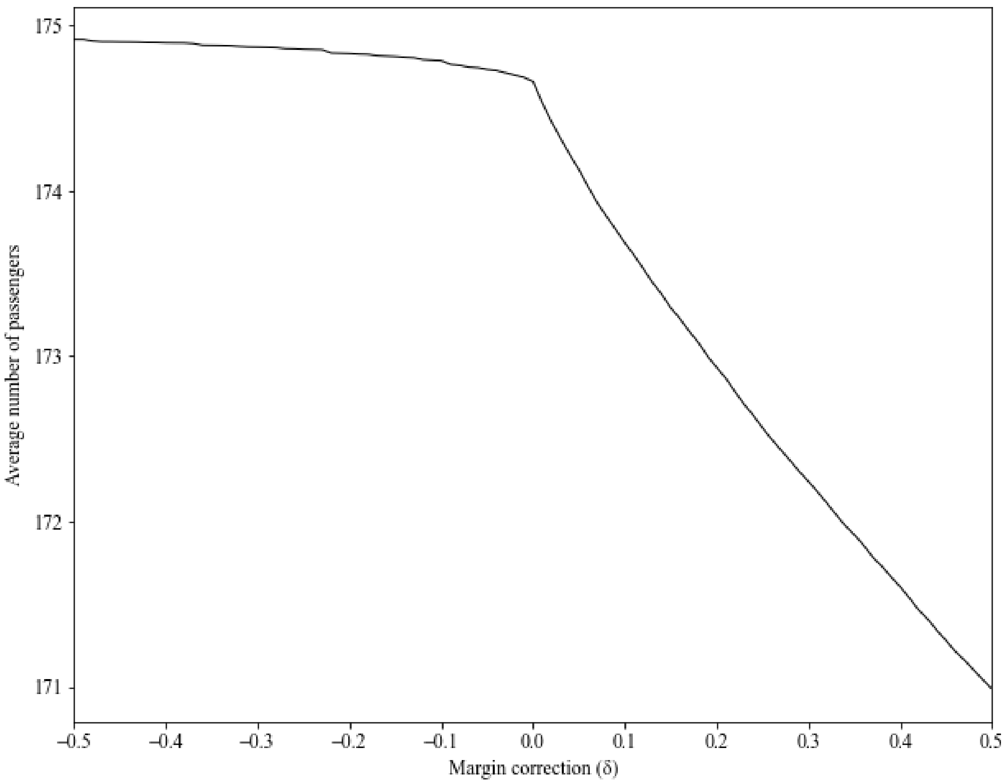

Figure D.1: Average number of passengers by margin correction

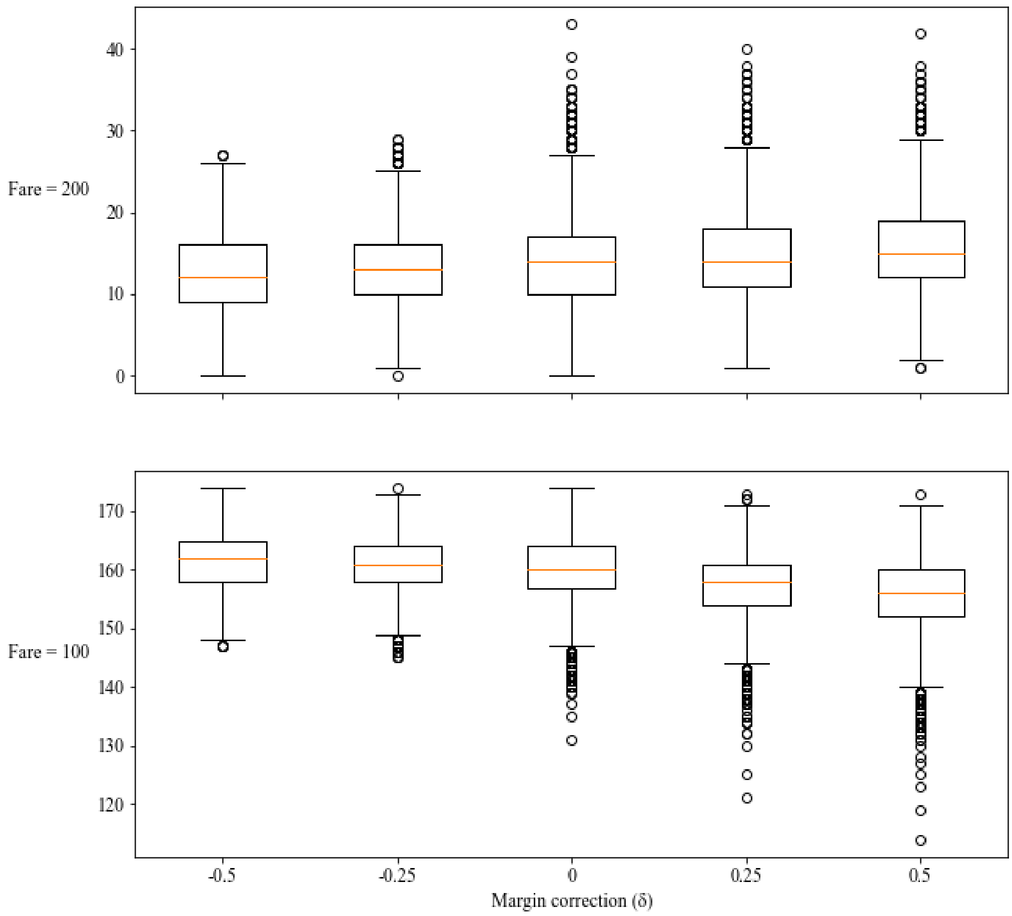

Figure D.2: Passenger distribution among lower fare classes

Appendix E

Sensitivity analysis on expected demand and capacity for psychic forecast

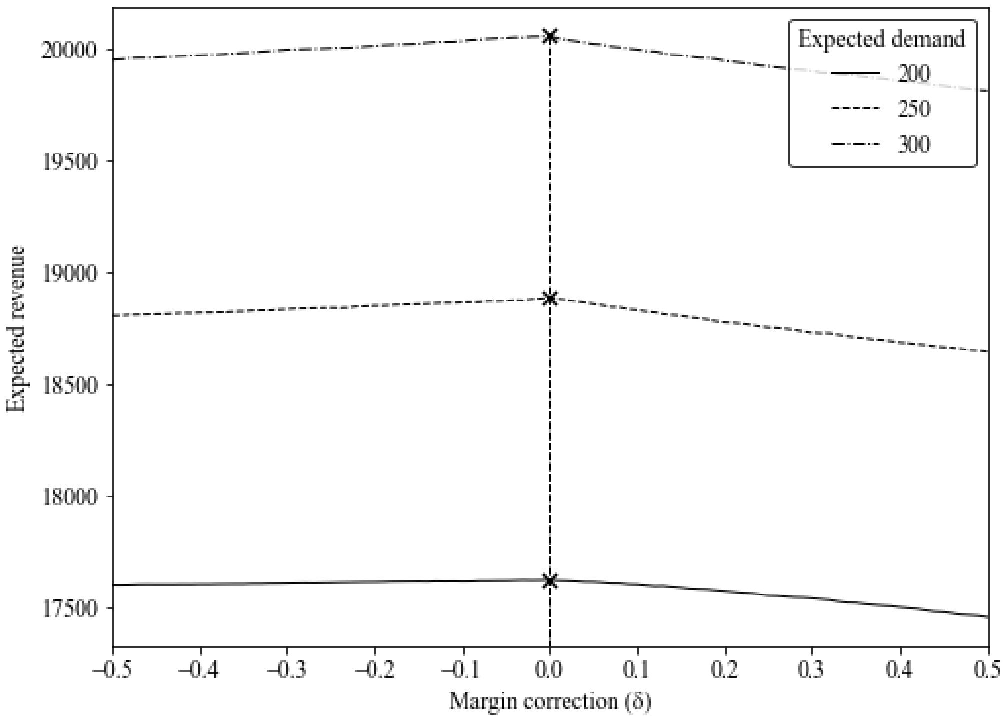

Figure E.1: Sensitivity analysis on expected demand for psychic forecast

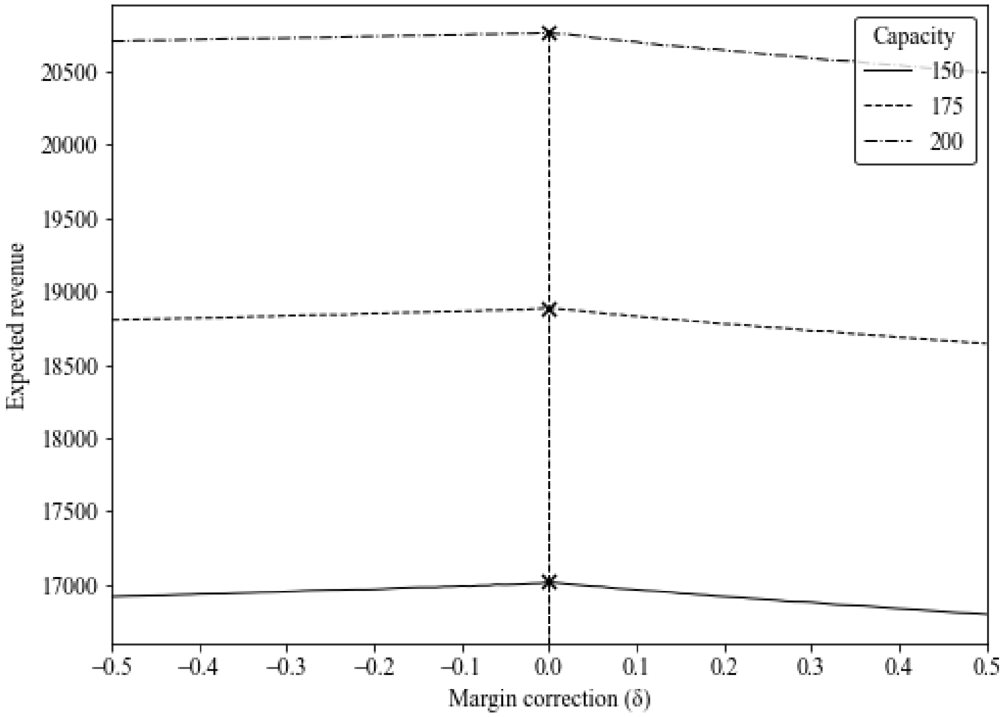

Figure E.2: Sensitivity analysis on capacity for psychic forecast

Appendix F

Sensitivity analysis on expected demand and capacity for distorted forecast

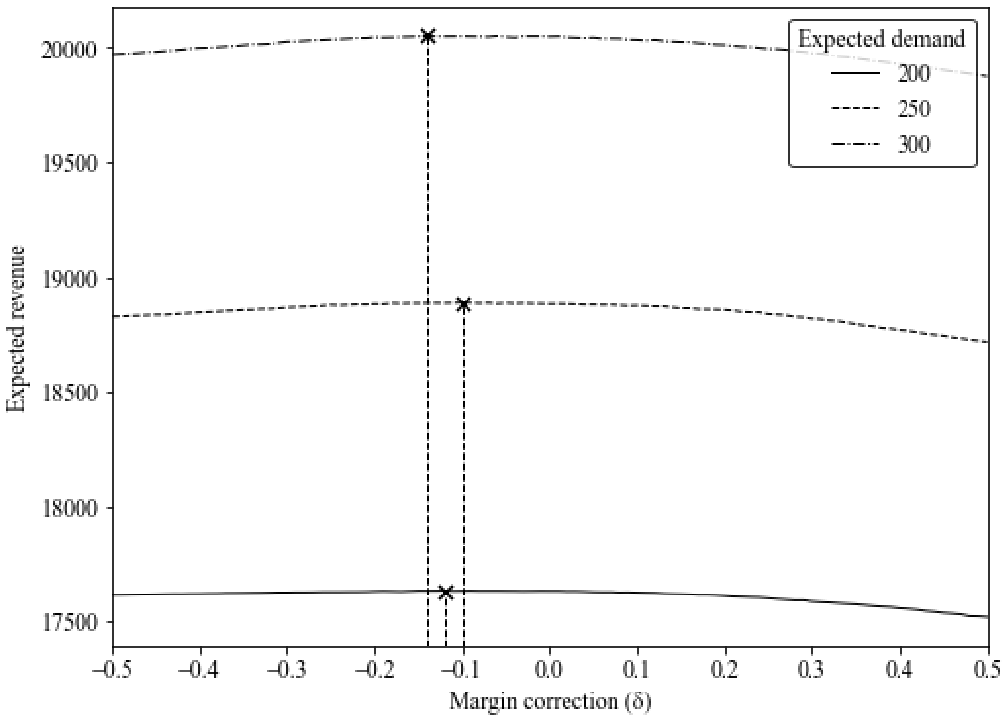

Figure F.1: Sensitivity analysis on expected demand for distorted forecast

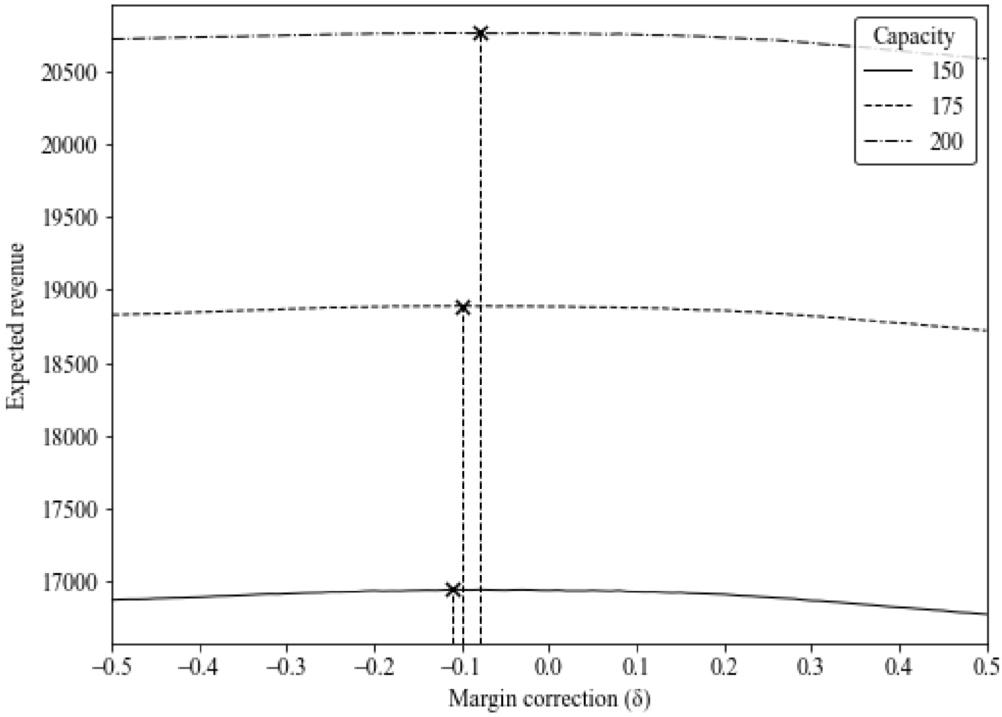

Figure F.2: Sensitivity analysis on capacity for distorted forecast

Appendix G

Partial dependence plots for upsell probability, expected demand, capacity, and fare structure related variables

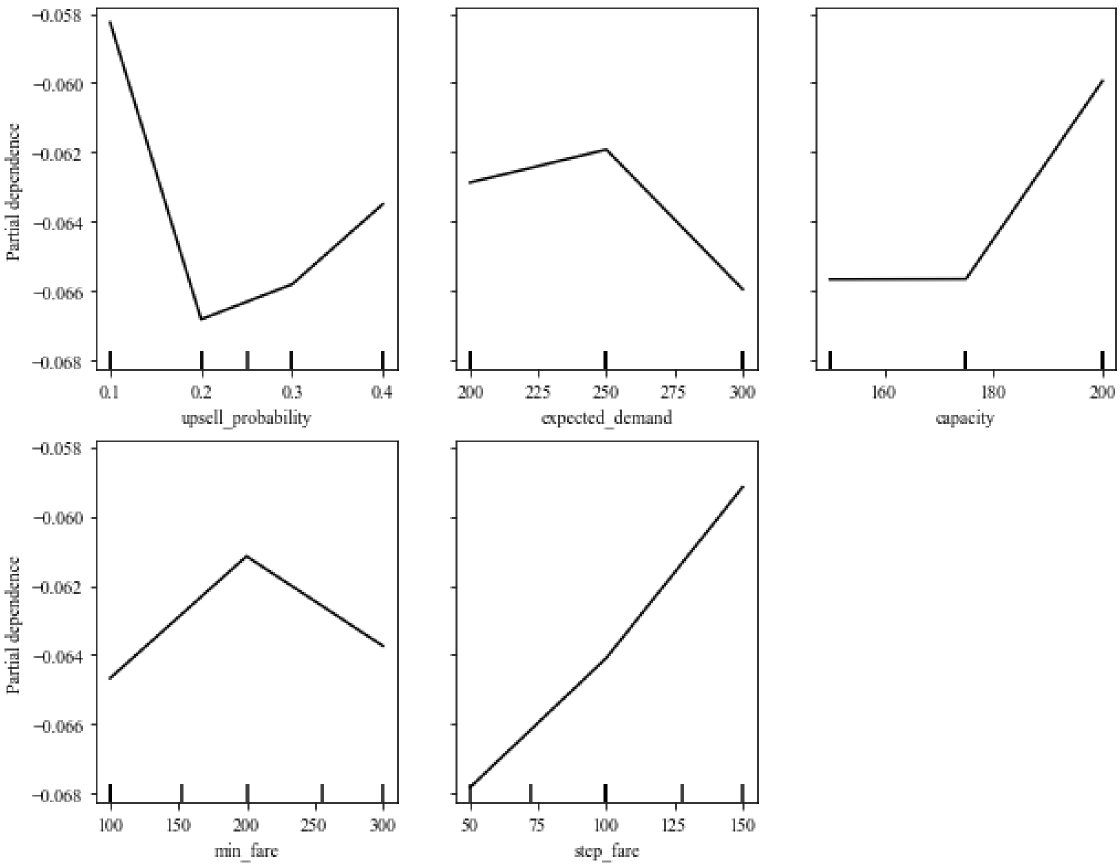

Figure G.1: Partial dependence plots for nonessential features