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Dynamic Pricing of Airline Ancillaries

Co-creating a Machine Learning Model to Price Ancillaries in the Case Company

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The purpose of this study was to improve the case company's ancillary pricing by developing a machine learning model to price ancillary products. The case company is a medium sized network airline that operates over 100 routes from its hub. Ancillaries are considered an essential part of the company's future and are integrated into the company's strategy. There are ambitious targets for growing ancillary revenue during the upcoming years which requires new innovative ways to develop ancillary business.

The main limitation in the existing pricing of ancillary services was that the pricing decisions were based on educated guesses and business experience, rather than effective utilisation of collected data. This led to relatively static prices that often did not reflect customers' willingness to pay, hence resulting in missed revenue opportunities. The focus of this thesis was on improving the pricing of ancillary services and specifically studying how machine learning can be harnessed to better target the customers with the right price.

To better understand the business problem and to be able to analyse the current state of the ancillary pricing process, interviews with the case company employees were conducted. Additionally, ancillary pricing documentation was reviewed. Existing knowledge was used to gain a better understanding of ancillaries in the airline industry and ancillary pricing, as well as how machine learning can be utilised in pricing. Existing knowledge was used to build a conceptual framework that supported the co-creation process of the machine learning model that made the outcome of this study. Co-creation process was iterative and included several steps of collecting data. Data for building and training the model was collected through price experiments. The purpose of the experiments was to gather data about customers' willingness to pay. Data collection was done through controlled experiments, i.e. systematically varying prices and analysing customers' response.

The co-created proposal, a machine learning model for pricing ancillaries, was presented to the case company's representatives to collect feedback. The implementation of the final proposal was planned to be done in three stages between Q1 and Q3 2020. The first implementation happened as planned during Q1 but due to the outbreak of COVID-19 pandemic early 2020, implementation was put on hold. Due to this, the validation of the model through collecting data on its performance is not included in this thesis.

Keywords	Airlines, Ancillary, Pricing, Dynamic Pricing, Machine learning

Contents

1 Introduction

1.1 Business Context

Aviation is one of the most competitive industries. It is also cyclical, highly capital intensive and generates low profit margins. On average profit margins in the airline industry are between 1 to 2% (Amadeus, 2019). Traditional revenue stream coming from flight ticket has been under pressure for decades. Increased competition resulting from deregulation of air transportation since the late 70s and emerging business models of low cost carriers (LCC) have forced traditional full service airlines to re-think their strategies. At the same time customers' expectations and behaviour have changed dramatically. In the fight for the customers' share of wallet airlines must be able to look beyond selling solely air tickets. Palmer (2019) defines share of wallet as "the dollar amount an average customer regularly devotes to a particular brand rather than to competing brands in the same product category". Airlines are not only competing with other airlines but also other transportation methods and for example, alternative methods of spending free time that can substitute flying.

Ancillary services are products and services that can be purchased on top of the flight ticket to customise the journey. Traditionally many of these products and services have been included in the price of the airline ticket such as seat reservation and baggage but are now unbundled and can be purchased against a fee. Ancillaries are a significant contributor to the profitability of airlines. Ancillaries can generate up to 30 percent of the total revenue of an airline and their contribution to EBIT is often also significant (Sabre, n.d.). For example, Ryanair's average ticket fee in 2019 was 37 euros which is less than their cost per passenger seat but on Q2 2019 they grew their ancillary revenues by 27% achieving over 850 million euros in ancillary revenues. This boost in ancillary revenues was significant factor in keeping their operations profitable (Asquith, 2020).

The importance of ancillaries is unquestionable but mastering the sales of ancillaries is not always straightforward. Airlines are considered as forerunners in the area of revenue management and pricing of flight tickets. The challenge lies in learning how to manage merchandising of these new products and services in combination of the sales of the flight tickets, i.e. to be able to offer the right products to the right customer in the right sales channel at the right time and on the right price.

The case company is a medium sized network airline that operates over 100 routes from its hub. The case company is known for being advanced in the area of ancillary business. Compared to its peers the offering of ancillary services is comprehensive. Ancillaries are considered an essential part of the company's future and are integrated into the company's strategy. There are ambitious targets for growing ancillary revenue during the upcoming years which requires new innovative ways to develop ancillary business in the case company. The focus of this thesis is on improving pricing of ancillary services and specifically studying how machine learning can be harnessed to better target the customers with the right price hence contributing to revenue generation and positive profit margin development.

1.2 Business Challenge, Objective and Outcome of the Thesis

The current pricing of ancillary services is not optimal in the case company. Pricing decisions are based on educated guesses and business experience rather than effective utilisation of collected data. This leads to relatively static prices that do not reflect customers' willingness to pay (WTP) hence resulting in missed revenue opportunities. The objective of this study is to find a solution to this problem by co-creating a machine learning-based model for ancillary pricing. Therefore, the outcome of the study is an ancillary pricing model that utilises machine learning.

1.3 Key Terms and Concepts

Ancillary revenue and services

According to IdeaWorksCompany (2019) "ancillary revenue is generated by activities and services that yield cashflow for airlines beyond the simple transportation of customers from A to B. This wide range of activities includes commissions gained from hotel bookings, the sale of frequent flyer miles to partners, and the provision of a la carte services − providing more options for consumers and more profit for airlines." A la carte services can for example be advance seat reservations, luggage or lounge access purchased on top of the flight ticket.

Take up or pick up rate

Take up or pick up rate is a key performance indicator (hereinafter also referred as KPI) often used to measure ancillary service sales. It is a ratio between passengers who bought ancillary service versus all passengers.

Long haul flight

Long haul flight according to CAPA (n.d.) is "a long distance international flight. Typically inter-continental and of at least six hours in duration".

Short haul flight

Short haul flight according to CAPA (n.d.) is "a short flight usually domestic or regional on nature, typically lasting less than six hours in duration.".

Passenger Name Record (PNR)

Passenger Name Record (hereinafter also referred as PNR) is an airline industry term for a reservation file that is formed when a passenger purchases a flight ticket and a booking for the ticket is created. It is more commonly known as booking reference.

Electronic Miscellaneous Document (EMD)

Electronic Miscellaneous Document (hereinafter also referred as EMD) is an airline industry term for a document that is formed when a passenger purchases an ancillary product. EMD can be either EMD-A meaning it is associated to a flight ticket, i.e. passenger must be in possession of a flight ticket to be able to purchase the ancillary e.g. advance seat reservation for a flight, or EMD-S, standalone, meaning it can be purchased and used independently of a flight ticket, e.g. parking at the airport.

Dynamic pricing

Dynamic pricing is a pricing method in which the price of a product or service changes over time as opposed to the method of fixed pricing. In fixed pricing, price points - once established - are maintained for an extended period of time. In the context of this thesis dynamic pricing refers to algorithm-based pricing models unless otherwise stated.

1.4 Thesis Outline

In the first section of the thesis the design of the research is presented. This section includes detailed description of the data collection methods as well as evaluation of the validity and reliability of the study. The second part introduces the current state analysis in which the extent of the business problem is examined. This was done by conducting interviews with selected employees of the case company and reviewing existing ancillary pricing documentation. This section is followed by a review of the existing knowledge and literature around the main topics related to the business problem: ancillary pricing and utilising machine learning in pricing. Based on the current state analysis and existing knowledge a proposal for ancillary pricing model is co-created. This process is presented in section five of the thesis. The proposal is validated by testing the model and collecting feedback from key stakeholders. The validation process is described in section six. Finally, the findings or the final proposal of the model and the entire research process are summarised and discussed in the last section of the thesis.

2 Research Method and Design

In this section the research methods and design are explained. Data collection and analysis methods used in the study are introduced. Additionally, validity and reliability of the study are discussed. The basis for selecting methods used in the study were the business problem and the objective of the study. As previously mentioned, the objective was to co-create an ancillary pricing model that utilises machine learning. In order to be able to meet this objective, appropriate methods needed to be selected and used.

2.1 Research Approach

This study was an applied research project that aimed to solve a specific problem at the case company. The study was conducted over a time period of approximately one year as a part of a project conducted in the case company between 2019 and 2020. The objective of the study was to co-create an ancillary pricing model that utilises machine learning.

2.2 Research Design

The research design was derived from the business problem and the objective of co-creating an ancillary pricing model that utilises machine learning. The research started with a current state analysis that identified the strengths and weaknesses of the existing ancillary pricing processes. This was followed by familiarisation with the existing knowledge and literature based on which a conceptual framework for the study was created. Based on the findings from the current state analysis and conceptual framework an initial proposal was co-created. The final stage was validation of the proposal through internal review with stakeholders as well as technical validation to ensure the pricing model performed in desired manner. Research design of this study is visualised in Figure 1.

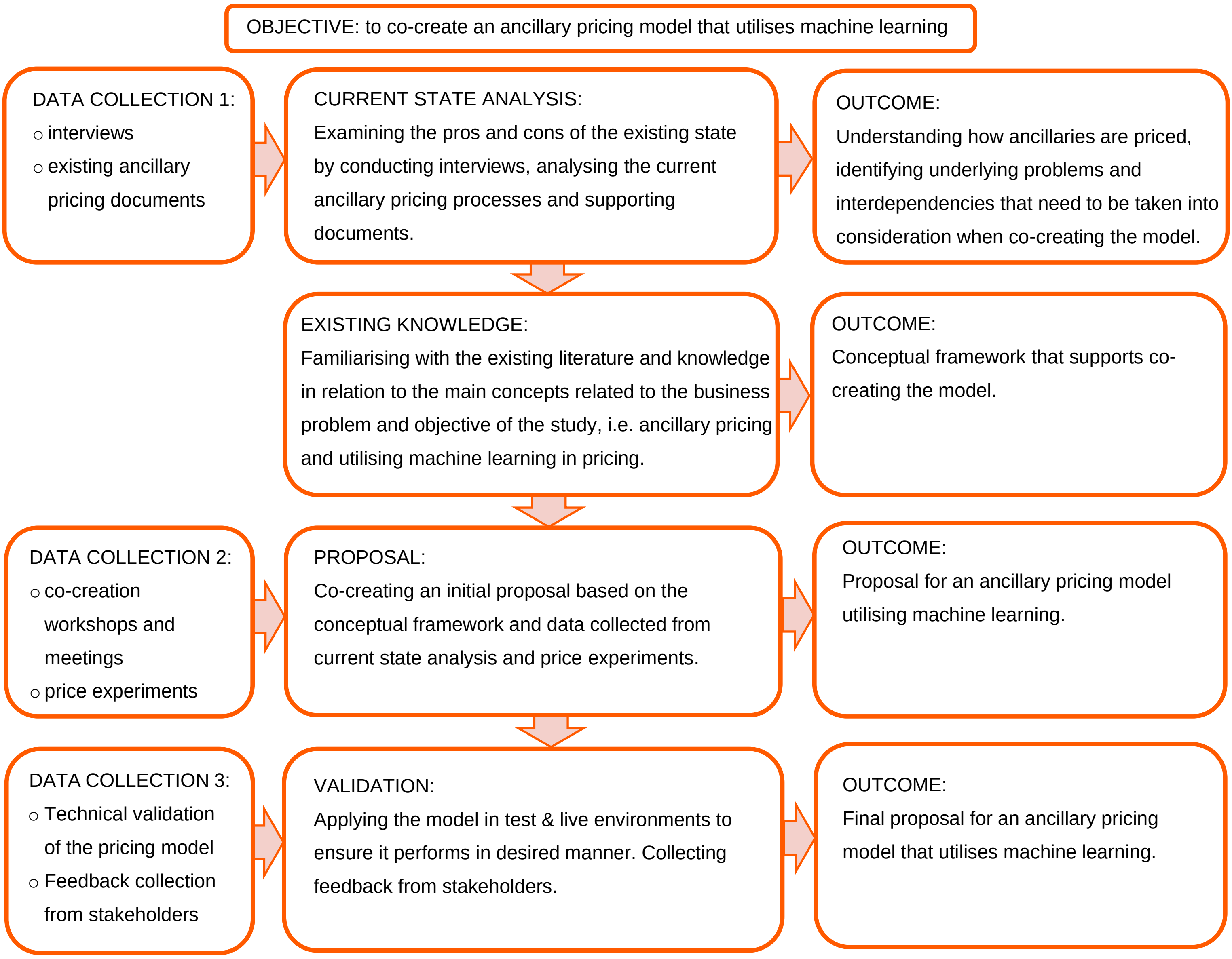

Figure 1. Visualisation of the Research Design

2.3 Data Collection and Analysis

The data for this research was collected in three stages. In the preliminary stage (data collection 1) data was collected through interviews and analysis of existing company internal ancillary pricing documents. When co-creating the proposal data was collected in co-creation workshop and meetings (data collection 2) through observation and collecting field notes. In addition, data about customers' willingness to pay was collected through price experiments. The data collected was used to build and train the machine learning model. Co-creation process was iterative and included several steps of collecting data, training the model and gathering feedback hence data collection stages 2 and 3 happened simultaneously. This can be seen in summary of data collection process (Table 1) where timelines are presented more in detail. The proposal was also validated through testing the model in both a closed testing environment and live environment. Table 1 illustrates the three data collection stages, type of data collected and the source, data collection date, approach and outcome as well as the purpose of the data collected.

Table 1. Summary of Data Collection Process

Data Round	Data Collection Method	Approach	Data Source	Timing	Outcome	Purpose
Data 1 Current State Analysis	Case Company Internal Documents	Retrieving documents	Ancillary pricing process	Jan 2019	Process description	To gain a better understanding of the current state of ancillary pricing
	Interview	Face-to-face 45 mins	Person formerly responsible for ancillary pricing	Feb 12, 2019	Transcribed	
		Face-to-face 45 mins	Head of Pricing Strategy and Ancillaries	Feb 14, 2019		

Data 2 Co-creation of the Proposal	Price experiments	Quantitative data analysis	Data collected through experiments	Test 1: May 6 – June 9, 2019 Test 2: Aug 21 – Oct 2, 2019 Test 3: Jan 8 – Feb 18, 2020	Quantitative data	Testing with different price points to understand customers' willingness to pay
	Workshop	Face-to-face	Project team	Mar 25-26, 2019	Transcribed	Project kick off, creation of a project plan
	Meeting	Virtual via Webex	Project team	Apr 26, 2019	Transcribed	Planning first price experiment to collect data
	Meeting	Virtual via Webex	Project team	Jun 19, 2019	Transcribed	Reviewing learnings from the first price experiment, first model co-created
	Meeting	Virtual via Webex	Project team	Aug 2, 2019	Transcribed	Planning price experiment 2
	Meeting	Virtual via Webex	Project team	Sep 13, 2019	Transcribed	Planning model testing in a closed testing environment to ensure model and tools perform as expected
	Meeting	Virtual via Webex	Project team	Oct 18, 2019	Transcribed	Reviewing learnings from second price experiment, training the model with the new data
	Meeting	Virtual via Webex	Project team	Dec 3, 2019	Transcribed	Reviewing technical testing results from closed testing environment and agreeing sign-off to live environment
	Meeting	Virtual via Webex	Project team	Jan 31, 2020	Transcribed	Reviewing technical testing results in live environment

Data 2 Co-creation of the Proposal	Meeting	Virtual via Webex	Project team	Feb 20, 2020	Transcribed	Reviewing learnings from third price experiment, updating the model with the new data and agreeing on the implementation schedule
Data 3 Validation of the Proposal	Meeting	Face-to-face	Customer service team heads, key ancillary stakeholders	Jul 2, 2019	Transcribed	Presenting pricing model and first process draft of model-based pricing, collecting early feedback
	Meeting	Face-to-face	Ancillary pricing analysts & IT system specialist	Oct 28, 2019	Transcribed	Technical validation of the model in a closed testing environment to ensure model & tools perform as expected
	Meeting	Face-to-face	Customer service team heads & ancillary stakeholders	Jan 8, 2020	Transcribed	Presenting model and new model-based pricing process, collecting feedback
	Meeting	Face-to-face	Revenue Management and Pricing team	Jan 29, 2020	Transcribed	Presenting model and new model-based pricing process, collecting feedback
	Meeting	Face-to-face	Ancillary pricing analysts & IT system specialist	Jan 30, 2020	Transcribed	Technical validation of the model in live environment to ensure model & tools perform as expected
	Meeting	Face-to-face	Project team members, representative of case company legal department	Feb 19, 2020	Transcribed	Presenting model-based pricing, understanding the possible regulatory and legal limitations to the usage of machine learning-based models

During *Data collection 1* key personnel involved in the ancillary processes were interviewed to gain a better understanding of the current ancillary pricing process. The interviews were conducted in the following manner: permission for being interviewed were collected from both participants and face-to-face meetings were organised. There was no interview structure set in the form of list of questions, the interview was conducted as an open discussion i.e. informal conversational interview. The discussion was based on high level themes:

- Current ancillary pricing process & roles
- What is working well in the current process?
- What should be improved in the current process?

During the interviews written notes were taken to document the discussions. Thematic analysis methods were utilised in transcribing the interview notes into a comprehensive summary of the main points discussed. The purpose of this is to recognise the main themes surfacing from the discussions. Although high level themes for the discussion were set, interviewees had the possibility to openly express their opinions, i.e. the discussion was not controlled. The summarised interview notes were sent to the interviewees for checking and comments to ensure that the findings collected were a truthful representation of their experiences and opinions.

Data collected through interviewing key people was supported by analysing the existing ancillary pricing documentation to better understanding of the current process and its strengths and weaknesses. When starting to review the existing documentation it became obvious that little had been documented in detail. There was one process description found. The findings from the interviews and reviewing the existing documentation is discussed more in detail in the current state analysis section of this thesis.

In *Data collection 2* data was collected to build the pricing model. This data collection happened through three price experiments which were conducted to collect data about customers’ willingness to pay. The experiments were conducted during the course of Q3 2019 and Q1 2020. Each experiment period was six weeks long and during that period multiple price points were tested for specific ancillary products to learn how the price affected customers’ willingness to pay. The quantitative data collected through experiments was analysed and used to build and train the machine learning model. A project team was formed to co-create the pricing model. The team consisted of data scientists and project experts from both case company and a system provider whose pricing tool was used to implement the model. Co-creation of the model took place over a long period of time and included many iteration rounds in numerous workshops and meetings. The process and timeline of the co-creation meetings and workshops is presented in Table 1 Summary of data collection process. The process of price experiments as well as co-creation of the model is described more in detail in section five of this thesis.

In *Data collection 3* the proposal is validated. Data collection stages 2 and 3 happened simultaneously. As mentioned earlier the co-creation process was iterative and included several steps of collecting data and training the model, simultaneously gathering feedback in iterative cycles. Through early validations it was ensured that stakeholders not participating in the project work were involved and could provide feedback, at the same time staying up to date on the progress of the model and its possible impacts on their daily work. Feedback was collected in meetings where project team findings were presented. Technical validation was also performed to ensure that model as well as the tools performed as expected both in test and live environments. A detailed description of this can be found in section six of this thesis, validation of the proposal.

2.4 Validity and Reliability

In this section of the thesis validity and reliability of the research are discussed. The evaluation is done based on Shenton's (2004) criteria of trustworthy qualitative research. The criteria are credibility, transferability, dependability and confirmability. According to Shenton (2004) creditability describes how well the research findings represent the reality, i.e. how consistent the findings and outcomes are with reality that was studied. Transferability refers to the replicability of the research, i.e. whether the findings can be applied to other situations. Dependability describes the research process and whether the process and methods used are explicitly presented in the study and whether the findings can be repeated. Confirmability refers to the objectivity of both the methods used and the researcher. The evaluation of credibility, transferability, dependability and confirmability of the thesis is presented in Table 2.

Table 2. Evaluation of Credibility, Transferability, Dependability and Confirmability of the Thesis

Evaluation Criteria	Requirements	Evaluation
Credibility	Adoption of research methods is well established and correct operational measures are applied in reference to the concept(s) being studied	The research methods used in this thesis were qualitative utilising un-structured interviews, meetings and workshops. Also, analysis of existing company documents and quantitative method in the form of price experiments as a data collection method were used. The data collected through qualitative methods was complimented with existing knowledge which created a conceptual framework to support the co-creation of the proposal. Similar approach of combining qualitative and quantitative methods have been utilised in previous research examining similar concepts.
	The development of an early familiarity with the culture of participating organisations	The participants of the project team were from the case company and system provider. Majority of the members of the project team had worked in co-operation projects before so were familiar with the company cultures and ways of working of both organisations.
	Random sampling in collecting the interviewees	Purposive sampling was used to interview the people with the knowledge about the subject studied. Additionally, the participants of the project team were selected purposefully to collect the people with necessary skills and knowhow to co-create the proposal.
	Triangulation i.e. use of different data collection methods	Initial data for current state analysis was collected from the few case company employees with the knowledge about the subject studied. The collected data was supported by analysis of company internal documentation. Data collection took place in face-to-face interviews, workshop and virtual meetings where some of the project team members participated remotely.
	Tactics to help ensure honesty of interviewees	Interview participants were provided the possibility not to participate to ensure they were willingly providing information. Participants were informed that discussions and notes taken during the interviews were confidential and could not be tracked back to the interviewees.
	Iterative questioning, e.g. rephrasing questions to ensure same answers are collected when asked again later	Face-to-face interviews were conducted only once with the selected interviewees. The interviews were conducted in an unstructured manner allowing free discussion around defined topics concerning the studied subject. During the lengthy discussions both interviewees were consistent with the way they described the studied subject.

Credibility	Negative case analysis e.g. refining a hypothesis until it addresses all cases within the data collected	Not applicable for the thesis as the thesis was conducted as an applied research project that concentrated on solving a specific business problem at the case company.
	Frequent debriefing sessions	Debriefing sessions were monthly between the project team members. Additionally, the researcher, in the role of ancillary pricing analyst, had monthly meetings with their superior to discuss daily work related matters. The project was also followed up in these meetings.
	Peer scrutiny of the project	Stakeholders from the case company were involved early to provide insights and suggestions. Meetings were conducted to present the project, research methods and estimated timelines, feedback was collected.
	Researcher's reflective commentary	Available in section 7 of this thesis, Discussion and Conclusion
	Background, qualifications and experience of the researcher	Not applicable for this thesis
	Member checks	Interviewees were provided with the possibility to read transcripts of their interviews to ensure that the notes taken were a truthful expression of their expressed inputs and opinions. Proposal was validated and inputs collected.
	Thick description of the phenomenon under scrutiny	The current state analysis section (section 3 of this thesis) explains the business problem and the context surrounding it, research steps and data collection methods are documented in an explicit manner. A full description of all contextual factors however is not provided in this thesis as the study is reported anonymously without revealing the case company.
	Examination of previous studies	Thorough review of existing knowledge and previous studies was conducted, this is introduced in section 4 of this thesis.
Transferability	The number of organisations taking part in the study and where they are based	Employees from two organisations were involved in the study, from case company and system provider. Companies are based in two different countries. No detailed location, e.g. countries where the organisations are based, can be enclosed as the study is reported anonymously without revealing the case company

Transferability	Any restrictions in the type of people who provide data	Data was provided from very limited number of people all in relatively homogeneous positions in their organisations. To avoid any bias, stakeholders from other parts of the case company organisation were involved from the early stages of the project. Project team was international consisting of six different nationalities. Common language was English but none of the project team members was a native speaker hence risk of misunderstanding was higher than if all participants would have shared same native language.
	Number of participants involved in the fieldwork	Core project team consisted of six employees from the case company and five employees from the system provider. Additionally, three case company employees from different positions participated in consulting role. Validation was done in several meetings, some which were open for anyone to access, so the exact number of participants is not known.
	Data collection methods	The data collection methods used in this thesis were qualitative utilising unstructured interviews, meetings and workshops. Also, analysis of existing company documents and quantitative method in the form of price experiments as a data collection method were used. More detailed description available in section 2.3 of the thesis.
	Number and length of the data collection sessions	2 interviews of 45 minutes (data set 1) 1 workshop of 2 working days, approx. 10 hours (data set 2) 9 project team meetings appr. 1 hour each (data set 2) 6 validation meetings appr. 1 hour each (data set 3)
	Time period over which the data was collected	January 2019 – January 2020
Dependability	Research design and its implementation	Research design and implementation steps are explicitly described (section 2 of the thesis).
	Operational detail of data gathering	The steps taken to gather the data in all three data collection phases are described in detail (section 2 of the thesis).
	Reflective appraisal of the project	The project and effectiveness of the methods used are evaluated in section 7 of the thesis.
Confirmability	Researcher’s possible bias and subjectivity and the importance of triangulation	The researcher is an employee of the case company working in the role of ancillary price analyst. Therefore, the point made by Shenton (2004) regarding the concept of prolonged engagement of the researcher should be considered. This refers to researcher becoming so immersed to the culture of the organisation that their judgement is compromised.

		Data was collected utilising different methods: through face-to-face interviews as well as in virtual meetings and workshops. Interviews were unstructured where themes relevant to the subject studied were used to guide the discussion. Interviewees were allowed to express their opinions and openly talk about the key themes without interruptions. Clarifying questions by repeating the words of the interviewee were made to ensure that the interviewer had correctly understood and noted what was said. The collected data was supported by analysis of company internal documentation. Additionally, comprehensive research plan is presented in Table 1 to support audit trail evaluation.

3 Current State Analysis

In this section of the thesis the current state of ancillary pricing in the case company is presented and analysed. Focus is especially on the decision making process to find out how ancillaries are priced and what are the strengths and weaknesses in the current process.

3.1 Overview of the Current Ancillary Process

As mentioned in section 2 explaining the data collection methods used in this thesis, both interviews as well as existing company internal material were used to collect data about the current state of the ancillary pricing process. Through analysis of the collected data a better understanding of the decision-making process behind ancillary pricing was gained. The existing process documentation gave a clear picture of the existing ancillary pricing process. The high level process is visualised in Figure 2.

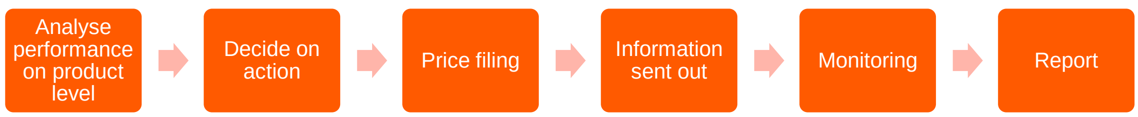

Figure 2. Current Ancillary Pricing Process

All the steps described in the process are conducted by one individual: the ancillary pricing analyst. The pricing process is divided into six steps out of which the first two steps, analysis and deciding action, include determining a price for a certain ancillary product. Third step, price filing, refers to the process of implementing the fees. The latter steps of the process are not included in the analysis as the interest in the current state analysis is to understand how the price decisions are currently done, and how the prices are implemented. The pricing process starts by ancillary pricing analyst analysing the performance of the ancillary services on product level by looking at certain key measures. These key measures consist of the following:

- Past sales – revenues and volumes sold
- Pick up rate – percentage share of passengers who buy ancillary product from the total number of passengers
- Revenue per passenger – ratio between ancillary revenue and total number of passengers
- Benchmarking – following competitors' prices and actions
- Other criteria such as travel time, passenger type, e.g. leisure or business, travel destination, travel origin etc. that may define the optimal price for a specific product

Based on this analysis a new price is decided (step two in the process). Price changes are approved by the analyst's manager and/ or the ancillary category manager, i.e. the person responsible for the overall development of the ancillary product.

The current prices are static, meaning there is very little variation in the price levels. Depending on the ancillary product, pricing might have been differentiated based on flight distance, e.g. short haul versus long haul flights or geographical zones traffic areas e.g. Europe and Asia. In the past prices have been reviewed annually or bi-annually depending on the product. Some price discount campaigns have been conducted but the scope has often been relatively narrow, e.g. discount only for specific sales country or flight route. Additionally, campaign periods have been short. In addition to these limitations, the number of campaigns has been limited so no far-reaching conclusions about correct price levels can be drawn based on the campaign results that have been collected.

Ancillary prices are stored in Airline Tariff Publishing Company's database. Airline Tariff Publishing Company, hereinafter referred as ATPCO, is an organisation owned by several airlines serving the airline industry by filing and publishing flight ticket tariffs and ancillary fees. Through ATPCO database airline's content is distributed to all sales touchpoints, e.g. airlines webpages, global distribution systems etc. Case company ancillary fees are also filed and distributed through the ATPCO database. The process how the filed fees flow from the ATPCO database to the customer touchpoint is visualised in Figure 3 using airline's own webpage booking flow as an example.

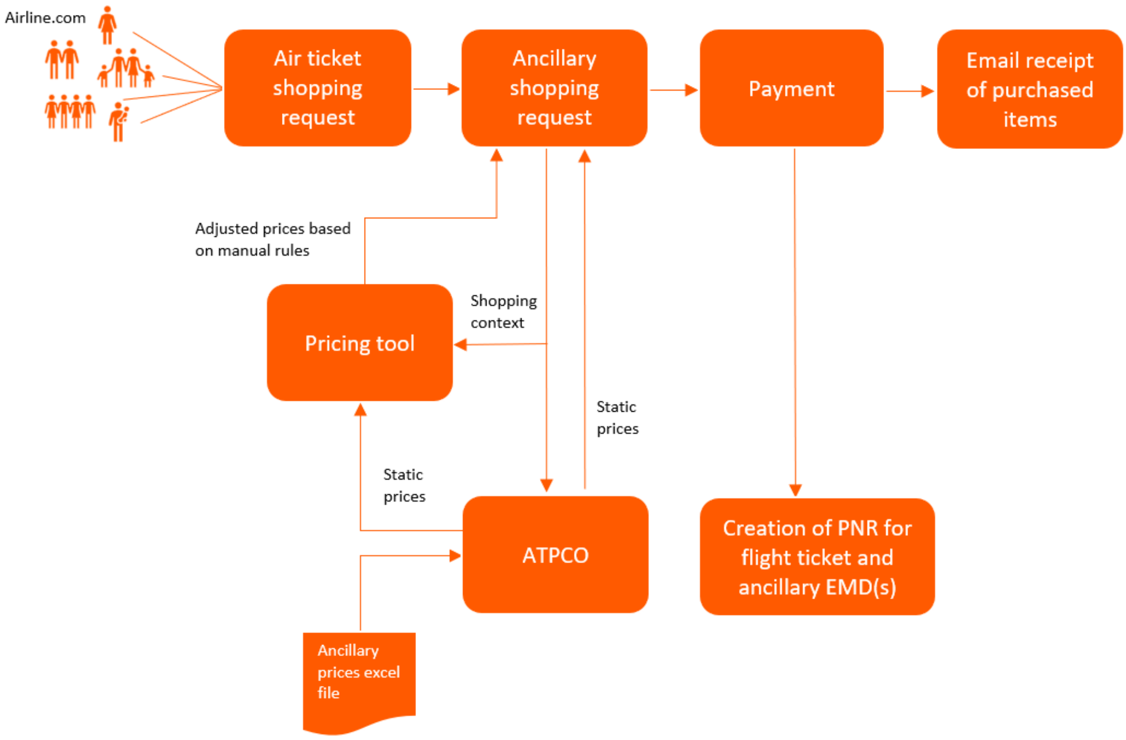

Figure 3. Ancillary Prices Flow into the Passenger Booking Process – Current State

After a decision of ancillary prices has been done (step 2 in the pricing process), the new fees need to be filed into the ATPCO database (step 3). Ancillary pricing analyst fills an excel request sheet including the new ancillary fees based on business requirements. The request sheet is validated by the fare filing manager to ensure that business needs are correctly translated into a filing request on the excel sheet and no inconsistencies are found. For instance, it is important that the fees are filed in the right order as the ATPCO system reads the stored information from top to down and always applies the first fee that matches the shopping context of the passenger. For example, frequent flier who is eligible for lounge discount based on their membership status buys a flight from Europe to North America and wants to purchase lounge access. If in the

ATPCO system lounge price of 50 euros for passengers travelling from Europe to North America is filed before the member level fee 25 euros, the system returns 50 euros lounge fee to the frequent flier.

After the request sheet has been validated it is sent to a fare filing team where the content is manually inserted into the ATPCO database. The case company also utilises a pricing tool that can be used to quickly create rules for pricing ancillaries, e.g. price campaigns. The pricing tool utilises the filed prices in the ATPCO database and applies price adjustments based on the manual rules created by the ancillary analyst. A rule can, for example, be applying 20% discount on the price of lounge access for flights that depart between 20:00-24:00.

When an ancillary shopping request is made, the shopping context, e.g. flight origin and destination, frequent flier status, time to departure etc., is mirrored to the ATPCO filing and the first static ancillary fee that matches the context is shown to the customer. If there are pricing rules in the pricing tool, those will overwrite the ATPCO system price and the adjusted price is shown to the customer. When the customer makes the payment a PNR is created for the flight reservation which includes ancillary EMD(s) for the purchased ancillary/ ancillaries.

3.2 Analysis of the Current Ancillary Pricing Process

During *Data collection 1* key personnel involved in the ancillary processes were interviewed to gain a better understanding of the current ancillary pricing process and roles related to it as well as its strengths and weaknesses. There were not many people in the organisation familiar with the current pricing process. There was one dedicated person responsible for the pricing of the ancillaries. This person, however, was not only responsible for ancillary pricing, hence time was divided between different tasks. Only recently ancillary pricing responsibility had been moved to the revenue management and pricing department and a new position dedicated solely for ancillary pricing had been established. Interviews were conducted with the former ancillary pricing responsible as well as the head of the new team in which the new position of ancillary pricing analyst was established. In both interviews the dominant theme that stood up in the discussion was the issue with static ancillary pricing which does not reflect customers’ willingness to pay and hence results in missed revenue opportunities either through selling products on a lower price than passenger would have been willing to pay or charging too much and losing the sales completely. Another issue in the current process, that came up in both interviews, was the slowness of the pricing process and complexity of the operating environment. One person is not able to manually analyse and implement new prices on a such a granular level that would be required to better capture WTP, while at the same time maintaining and monitoring all pricing rules for several different ancillaries in an effective manner.

The simplicity of the process description and the fact that there is little documented reflects the reality, in its current form the pricing of ancillaries is very static and manual process. During interview with the former ancillary pricing responsible a point was made that a static pricing structure might not only be perceived as a negative thing. Some stakeholders considered static pricing that rarely changes helpful. A simple pricing structure was perceived as easy to communicate and easy to understand. Additionally, employees who are in direct customer contact and actively sell ancillary products may perceive static pricing easier as they may quote products from their memory without having to check the price while talking with the customer.

Researcher's own early experiences in the role of ancillary pricing analysts was that the organisation is very flat and there are no heavy reporting structures. Decision making power is given to the pricing analyst which enables reacting quickly to changes in the market by adjusting the prices. There are no detailed processes or guidelines therefore giving the analyst freedom to decide the appropriate approach. A suggested pricing approach is presented to the team head who approves or suggests improvements. This often takes place in a quick face-to-face meeting. Furthermore, ancillary product responsible person(s) are consulted when making pricing decisions. This is also often done via a quick instant message or face-to-face discussion where high level approach is agreed. Process is perceived as flexible and quick.

The biggest limiting factor in the current pricing decision making process is that it is fully based on human analysing large quantities of complex data. It relies on the analyst's ability to analyse all the different data and based on that make accurate pricing decisions. Current analysis tools do not fully support the process as all the necessary data is not readily available. To support decision making, the analyst is expected to analyse and combine multiple data sources, some of which are not easily and quickly available, nor easily combinable.

Table 3. Key Findings Regarding the Existing Ancillary Pricing Process

STRENGHTS	WEAKNESSES
Very flat organisation – analyst is empowered to make the decisions → speed to the market	Relies on multiple data sources to be used for the base of the pricing decisions (some of which are not easily and quickly available), current analysis tools do not fully support the process.
Flexible process with very few steps and no strict guidelines → freedom for analyst to implement adjustments based on own judgement	Dependent solely on analyst's ability to decipher and combine reported data and make accurate decisions based on that
Simple pricing structure that is easy to understand and communicate.	No clear guidelines on how price should be adjusted within given circumstances
Static price points simplify sales in direct customer contact points.	Missed revenue opportunities if customers' willingness to pay is higher than what they paid and missed sales opportunity if price is too high and customer does not purchase the ancillary → revenue dilution over time.

Table 3 summarises the key findings of the current state analysis. The key findings are that the current ancillary pricing does not reflect customers' willingness to pay hence resulting in missed revenue opportunities. In addition, the analyst is responsible for collecting and analysing large amounts of data from different sources, some of which are not readily available, and based on the analysis implement pricing actions. The analyst is at the same time very empowered to make independent decisions regarding the pricing but also expected to make accurate assumptions based on the data without any clear guidelines.

4 Existing Knowledge

This section of the thesis presents existing knowledge in the areas of airline ancillary products, ancillary pricing and machine learning and its usage in pricing. The existing knowledge was summarised into a conceptual framework that supported co-creation of the ancillary pricing model that utilises machine learning.

4.1 General

Despite the importance of ancillary products to airlines there is relatively little research conducted in this area of aviation industry. Leon and Uddin (2017) state in their ancillary study that although there have been relatively many choice and behavioural studies conducted related to air transportation, very little research has been done amongst the topic of ancillaries. Similar findings have been made by Ødegaard and Wilson (2015) who refer to ancillary services as an "undeveloped research area" as well as (Mumbower, Garrow and Newman, 2015) who state that despite their importance there have been few studies looking into the different factors leading to ancillary purchases and affecting customers' willingness to pay for these services.

4.2 Ancillaries in the Airline Industry

According to IdeaWorksCompany (2019) "ancillary revenue is generated by activities and services that yield cashflow for airlines beyond the simple transportation of customers from A to B. This wide range of activities includes commissions gained from hotel bookings, the sale of frequent flyer miles to partners, and the provision of a la carte services − providing more options for consumers and more profit for airlines." A la carte services can for example be advance seat reservations, luggage or lounge access purchased on top of the flight ticket. What is typical to the ancillary products, especially to the a la carte services, is that traditionally these products and services have been included in the price of the flight ticket or were offered only to passengers travelling in premium cabins. In addition to a la carte services, punitive charges, e.g. flight ticket cancellation fee and credit card charges collected by the airline, are considered as ancillary revenue. Many airlines also offer third party services such as car rentals through their own web pages. Additionally, advertising revenues as well as sales conducted through frequent flyer programs are considered as ancillary revenue. The classification of ancillaries into a la carte and third party as well examples of different ancillary products is visible in Figure 4.

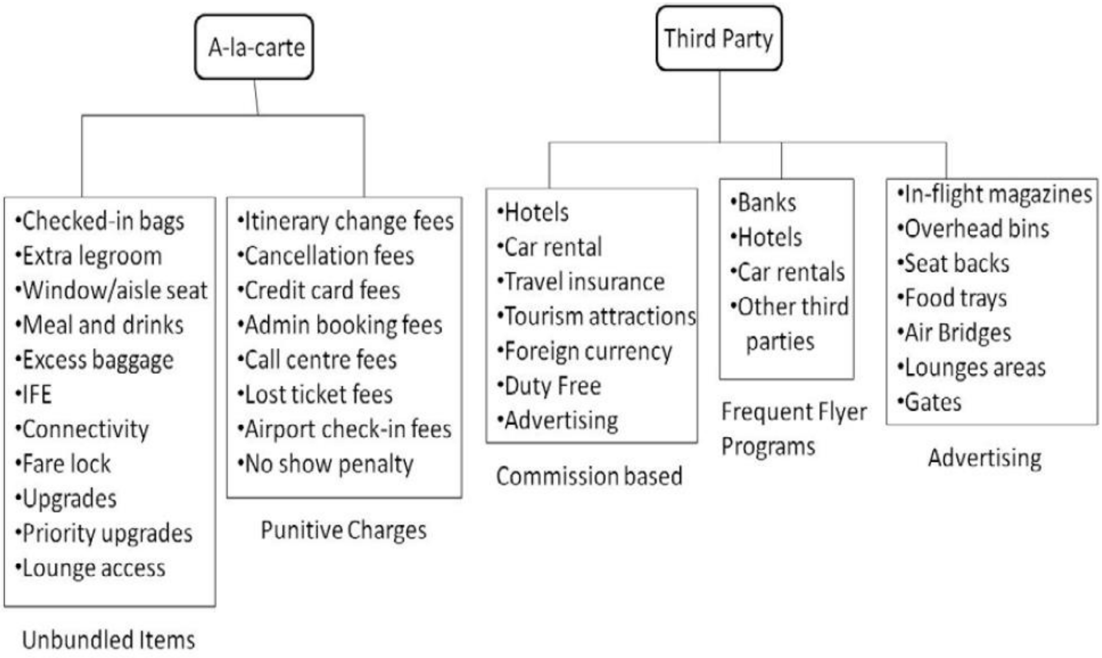

Figure 4. A-la-carte and Third Party Ancillary Classifications (Warnock-Smith & O'Connell, 2015)

The importance of ancillary revenues to the airline industry continues to grow. IdeaWorksCompany (2019) estimated that in 2019 worldwide airline ancillary revenue will be 109.5 billion US dollars which means almost fivefold increase compared to the 2010 figure of 22.6 billion. As previously mentioned, ancillary revenues are an important contribution to the profitability of airlines. Although flying is more popular than ever and the number of passengers carried grows year after year, airlines are struggling to make flying a profitable business. Average profit margins in the airline industry are between 1 to 2% (Amadeus, 2019). Ancillary profit margins are often much higher than those of airline tickets. Warnock-Smith, O'Connell & Maleki (2015) found out that there is a positive correlation between a high share of ancillary revenue from the airline's total revenue and strong profit margins.

When done right, ancillaries are not just a boost for the profitability, they are also a way for an airline to differentiate themselves from the competitors and an enabler to offer elevated customer experience. Airlines have become better in merchandising and selling other products and services than mere flight tickets. At the same time consumers have also learned to appreciate the new offers provided by the airlines (IdeaWorksCompany, 2018). Initially offering ancillaries was considered standard for the low cost carriers but full service carriers followed relatively quickly. Despite the initial retaliatory response, passengers have learned to appreciate the flexibility of purchase they get through having the power to decide the level of products and services they want to include in their travel experience (Shukla, Kolbeinsson, Otwell, Lavanya & Yellepeddi, 2019).

On airline level the share of ancillary revenue from the total revenue depends largely on the strategy and business model of the airline. Traditionally low costs carriers have more ancillary revenue as they sell flight tickets that include very few benefits whereas ticket from a full-service airline has often included many products and services, e.g. luggage and meal. Nowadays this clear line between no-frills and full-service carriers has blurred and it is common that carriers offer different types of tickets that include different levels of additional products and services. IdeaWorksCompany (2018), based on their research of leading airline industry ancillary sellers, categorise carriers into four groups based on their ancillary strategy and the structure and share of their ancillary sales (Figure 5).

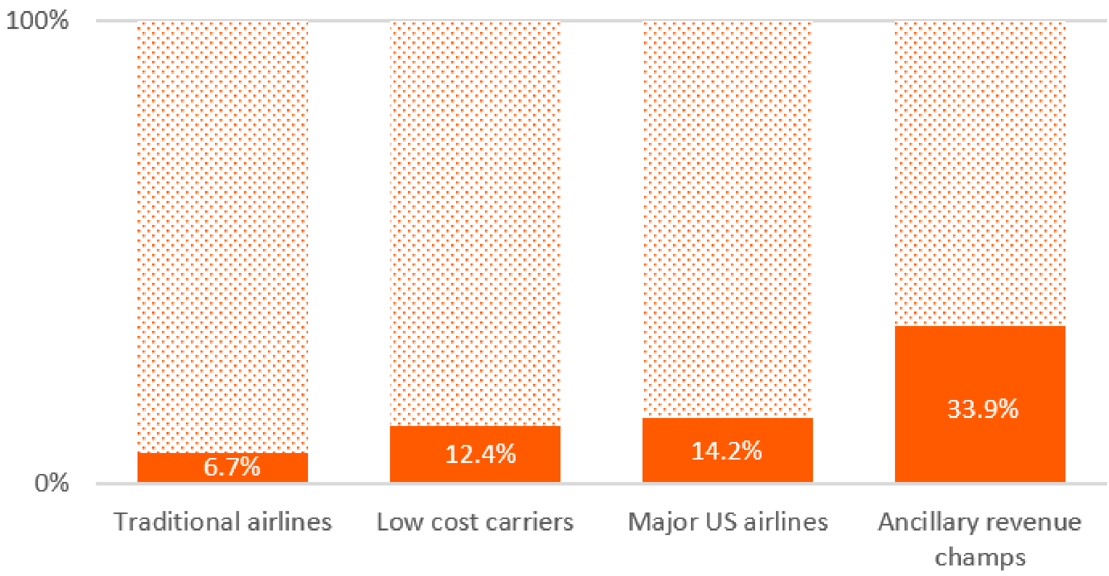

Figure 5. 2018 Leading Airline Industry Ancillary Sellers' Ancillary Revenue Share from Total Revenue (IdeaWorksCompany, 2018)

Traditional airlines' ancillary revenue is often formed of different kind of bag fees such as excess and heavy bags, extra leg room seating and frequent flyer programs. Among this group the share of ancillary revenue from the total revenue was 6.7% in 2018. Low cost carriers examined in the study had a 12.4% ancillary share from their total revenue. Major US airlines are traditionally more advanced in their merchandising actions therefore generating strong revenue. Ancillary share for this group was 14.2 % in 2018. For them it is also common that majority of the revenue is generated through popular frequent flyer programs and co-branded credit cards. For example, it was estimated that the frequent flyer programs of American Airlines, United Airlines, Delta and Southwest, generated 73-84% of these airlines' ancillary revenue in 2019. This is significantly more compared to their European competitors, e.g. Lufthansa 32% and KLM-Air France 21% (IdeaWorksCompany, 2019). So called ancillary revenue champs are carriers that are leaders in ancillary sales and innovation, collecting ancillary revenues from a wide scale of services and products. Ancillary revenue share in this group was 33.9% in 2018. (IdeaWorksCompany, 2018)

4.2.1 Traditional Ancillary Pricing

PROS (2019) describes traditional pricing journey as a five-step process. First step is hiring pricing analysts, second analysts gathering data and analysing it manually using spreadsheets and rather generic business intelligence (BI) tools. Pricing changes are manually processed when issues are noticed (step 3) and process is slowly improved based on feedback and monitored performance (step 4). Eventually as step five technology might be implemented to automate some of the former process steps. According to PROS (2019) this evolution is a slow process that might take years but the reason why it is so common is that it is intuitive and at the same time for long it has been the sole option available for many organisations and pricing teams. This is because utilising advanced data, predictive algorithms and/ or machine learning has required noticeable investments into improving the underlying pricing and revenue management systems.

According to Sabre (2017) many airlines manage prices through monitoring of competitors and by conducting analyses. There are often manual processes involved which are prone to human errors. In addition, this kind of ad hoc analysis does not provide all the necessary data to make informed pricing decisions. Very often this kind of pricing methods do not support customer segmentation and willingness to pay. Understanding how to accurately price ancillaries is a new challenge of airlines. How the price of an ancillary is perceived varies greatly and it can also affect the overall perception of the total price paid, i.e. combination of flight ticket(s) and additional service(s). Hamilton, Srivastava and Abraham (2010) argue that although standard economic theories state that customer should be as willing to purchase a product e.g. television for 100 euros plus a delivery fee of 20 euros, as they are to purchase the same television with free delivery for 120 euros, several research shows that dividing the price into components affects customers' perception of the price, willingness to pay as well as likelihood to repeat the purchase. They state that whether a company should keep their pricing straightforward and not do price portioning depends on several different factors. Companies should consider whether customers compare competitive offers, how sensitive they are to the price of the different components (e.g. delivery or installation), how the price of one components reflects to the price of the others (e.g. small or large price difference) and which are the components that best meet the customers' needs i.e. are most desired. One benefit found to support price portioning is that customers usually remember the base price correctly and tend to forget about the components. Especially when the base price is higher it may make components seem minor in comparison. This means that the customers' perception of the paid price might actually be less than what they actually paid for (Hamilton, Srivastava and Abraham, 2010).

Mumbower et al. (2015) had similar findings. They found out that the purchases of a specific seat product with more legroom space are influenced by several different factors such as "the minimum price that must have been paid for the flight, departure day of week and time of day, and market effects". They state that customers with higher fare flight ticket were more likely to purchase a seat. They also found out that two and three people travelling together are more likely to buy a seat than individuals or larger groups. A group of four or more were least likely to buy seats which they state may indicate the price sensitive of bigger families for whom buying relatively expensive leg room seat products could end up paying 60-260 US dollars extra for their trip.

In their study about airline advance seat reservation pricing Shao, Kauermann & Smith (2020) suggested an alternative way of pricing the ancillary relative to the air ticket price. They found out that the price sensitiveness towards advance seat reservation was lower if seat was purchased after the ticket purchase. They argue that the effect of the flight ticket price declines over time and hence passengers are less sensitive to the seat price later on. The ticket price in the context is a so called reference price to which the seat price is compared. In addition to this, they also found out that higher ticket prices are more associated with higher probabilities of purchasing a seat.

Some ancillaries might be priced based on the costs incurred from providing the service or producing the product. According to Hamilton, Srivastava and Abraham (2010) cost-based pricing has been popular as it is considered as fair by customers. They state that research shows that customers approve companies charging little extra to maintain reasonable profit margins and that price increases done due to cost increases are better accepted than “opportunistic” increases where sole purpose is to increase margins. Hamilton, Srivastava and Abraham (2010) however argue that in the long run cost-based pricing is not beneficial to the company profits nor does it maximise customer satisfaction. They found out that price sensitivity increases with components that customers perceive less valuable relative to the high-benefit components, e.g. paying for television installation might be perceived less valuable by those who feel they are able to do the installation work themselves. This underscores the importance of companies to be able to offer relevant solutions to customers and at the same time be able to find the correct price that the specific customer is willing to pay for the product or service.

4.2.2 Advanced Ancillary Pricing

According to McKinsey (2017) airlines have been forerunners for cutting-edge revenue management technologies for decades. They have been among the first to use dynamic inventory pricing and forecasting models. As the importance of ancillaries is becoming more obvious, new ways of managing and optimising total revenue, i.e. combination of flight tickets and additional services, are required. Bundling tactics, product suggestions and dynamic pricing are some of the new methods that could provide significant advantage. These methods as such are nothing new and many industries have been using them already some time but as in airline industry the focus has so long been solely on flight tickets these new methods require fundamental changes in the way revenue management is perceived. (McKinsey, 2017)

According to McKinsey (2017) biggest barriers for applying extensive revenue management methods efficiently on both flight tickets and ancillaries are that revenue management department that traditionally is responsible for ticket revenues, often is siloed from other departments that possess important data and understanding of customer behaviour when it comes to ancillaries. Additionally, the lack of experienced data scientists is hindering airlines from creating predictive revenue-optimisation models. According to McKinsey (2017) finding as solution to these issues and being able to harness advance data into models could result in 5-10% revenue increase. Shukla et al. (2019) argue that ancillary pricing strategies of airlines are often not fully developed because ancillaries are relatively new area of business. Airlines do not possess the understanding of how to price these new products that are fundamentally very different from the air tickets. Air tickets are often a necessity, at least to a certain level, whereas ancillaries are optional. Willingness to pay for something that is optional is inherently different as price expectations, sensitivity and customer's motivations to buy differ. Today revenue management system only looks at the possible revenue gained from selling the flight ticket. For example, a customer who is willing to pay 90 euros for their flight ticket but not buy an ancillary at is preferred over a customer who is willing to pay 80 euros for their ticket and buy 20 euros ancillary on top of it (Shao, 2019).

Furthermore, airlines have very little knowledge of the relationship between primary products customer choose to buy, i.e. different ticket types, and ancillary products they buy in combination. The challenge according to Shukla et al. (2019) is that these additional products are fully optional and hence the purchase is differently dependent on individuals' personal preferences and the purpose of their travel. Understanding this relationship and the underlying motivations of the passengers to purchase are keys to price the products correctly. In addition, many ancillary products compete between each other for the customer's share of the wallet but also for the space and visibility in the different sales channels of the airline. This ancillaries-in-relation-to-other-ancillaries is something that needs to be taken into consideration when deciding on pricing (Shukla et al., 2019).

In a survey conducted by Diggintravel (2019) 45 airlines were asked questions regarding their ancillary strategy and digital sales practices. As illustrated in Figure 6, in 25% cases ancillary pricing is static. Majority of the respondents (41%) said that their ancillaries are priced based on some kind of segmentation e.g. per route whereas only 7% said that ancillaries are priced dynamically. According to the study, one of the reasons why dynamic pricing of ancillaries is not used more can be that communication of this kind of complex product offering alone is challenging. To some passengers, additional payments for services and products that used to be included in the ticket fee still come as a surprise. A structure of fixed prices is perceived clearer and hence helps in communicating the overall offer. It is also stated that this situation is changing already as passengers are becoming more and more accustomed to variating ancillary prices. Fixed prices have helped airlines to bring the new products to the market but now that many of the products are mature, dynamic pricing can be utilised to maximise revenues. (Diggintravel, 2019)

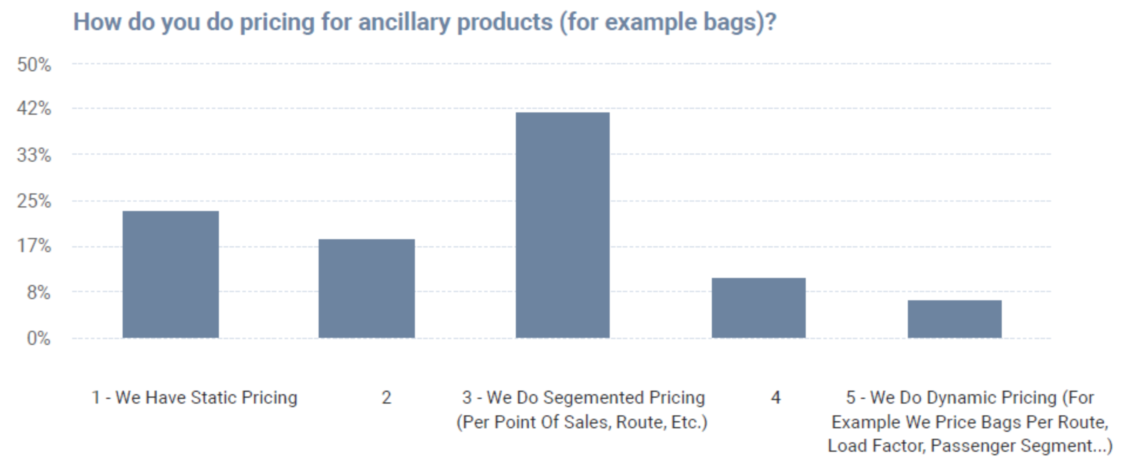

Figure 6. Survey Replies Regarding Current Ancillary Pricing Methods of 45 Studied Airlines (Diggintravel, 2019)

According to Leon & Uddin (2015) traditionally airlines have not been very successful in capturing the individual preferences of their customers. Ancillaries are offered either randomly or based on segmentation strategies. They state that many airlines are missing significant revenue opportunities by not understanding and acting based on the individualised preferences. For example, AirAsia has dynamically priced their ancillaries since the end of 2017. During 2018 this resulted in 6.7% improvement in the take up rate (IdeaWorksCompany, 2018). Also, Volaris, a Mexican low cost airline, is dynamically pricing their ancillaries. Volaris has stated that they use models based on multiple variables such as season, route, customer attributes, time before purchase, type of market, time of purchase and type of flight. However according IdeaWorksCompany (2019) dynamic pricing as a term is loosely used in the airline industry and can easily mean different things in different context so the level of sophistication of the Volaris and AirAsia models is left unclear.

Scandinavian Airlines (SAS) partnered with Accenture Amadeus Alliance and Massachusetts Institute of Technology (MIT) to utilise artificial intelligence in ancillary revenue generation. In the study they concentrated on the advance seat reservation pricing on the short haul network of SAS. The goal was to understand how the customer context affected purchasing behaviour. Factors such as duration of the flight, time before departure, day of travel, ticket booking class and ticket price were studied to map the behaviour. AI was used to understand the most important factors driving customer behaviour and based on them draw estimates of purchasing probability. Through machine learning algorithms those probabilities were transferred into price recommendations which were applied in real life context. During the twelve weeks project SAS implemented eleven new pricing policies as a result of the analysis. After a three-month monitoring period there was an increase of 14.5% in the revenue collected from short haul advance seat reservations. (Amadeus, 2018)

4.2.3 Willingness to Pay as a Basis for Effective Pricing

Understanding customers' willingness to pay is a key for developing effective dynamic pricing (Vinod, Ratliff & Jayaram, 2018). There are multiple different methods to study willingness to pay, the most common defined by Breidert, Hahsler and Reutterer (2006) are presented in Figure 7.

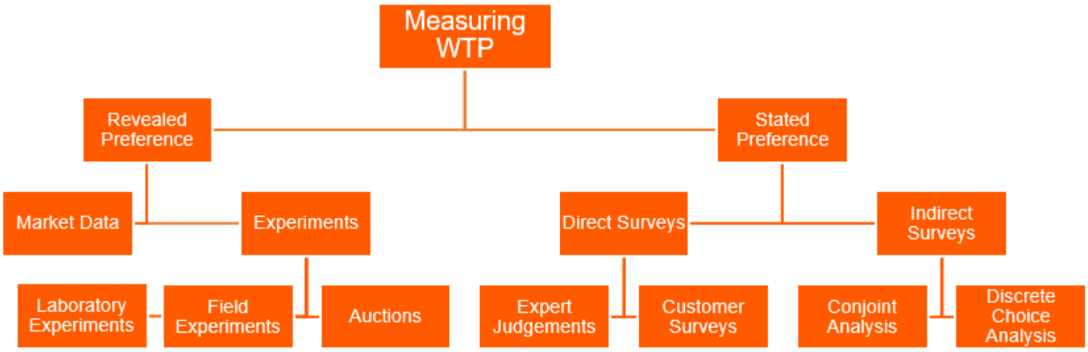

Figure 7. Methods for Measuring Willingness to Pay

Breidert, Hahsler and Reutterer (2006) use a three-level classification of the WTP measuring methods. On the highest level the distinction is done based on whether the methods include survey techniques or if the methods are based on actual or simulated price response data. Results from price responses are referred as revealed preference. Market data refers to the usage and analysis of sales data in estimating willingness to pay and purchase behaviour. It is considered as a cost and time effective way to collect data, especially in cases where historical data is readily available. Since data reflects actual demand, results are generally reliable. However, Breidert, Hahsler and Reutterer (2006) state that utilising historical data is problematic in case it does not cover wide enough spectrum of the WTP of the customers and add that some researchers have classified estimating WTP based on market data infeasible. Laboratory experiments refer to set ups in which subjects are given a certain amount of money to spend on specific goods while systematically varying prices and the goods offered. A limitation to this approach according to Breidert, Hahsler and Reutterer (2006) is that simulating natural purchase behaviour in a laboratory setting is difficult as subjects may tend to be more rational in their decisions when they know they are being observed. Also, the fact that the money the subjects are using is not their own might lead to completely different kind of purchase decisions than under normal circumstances. Field experiments refer to systematically varying prices in test markets and analysing customers' response. Main drawback to this method, compared to e.g. laboratory experiments, is higher costs and relatively long time span of collecting data. Auctions can be carried out in both laboratory and field setting. In auction method good is sold to the highest bidder. This method is considered useful especially for collecting knowledge about customers' valuation of goods however it has been criticised for overestimating WTP. According to Breidert, Hahsler and Reutterer (2006) this is because people tend to start overbid above their truthful WTP to increase their change of winning.

Contrary to revealed preference methods such as market data analysis and different experimentations, data collected through surveys is referred as stated preferences. Survey methods are often used when there is no historical market data or when it is not possible to test price response experimentally, e.g. when a new or differentiated product is created. Surveys are often also beneficial when there are financial or time constraints for collecting data. Expert judgement refers to utilising the market expertise of people working closely in the field with the customers. This method is stated to have many risks for example bias of the people providing information and is most reliable in environments where customer base is very small, and customers are known well enough to estimate their WTP. Customer surveys refer to the practise of directly asking from customers about the price they see would be fitting for a product, e.g. what is the maximum you are willing to pay for product X and at below what price would you hesitate buying product X because the low price reflects poorer quality. This approach has been criticised for overemphasising price over the other product attributes. In addition, customers have no real incentive to express their truthful WTP and most importantly even if they do, this might not reflect their real purchasing behaviour. (Breidert, Hahsler and Reutterer, 2006)

From survey participant perspective indirect surveys are considered easier as in this method participants are not required to assign specific price for a given product, but to evaluate pre-defined prices. Breidert, Hahsler and Reutterer (2006) state that conjoint and discrete choice analysis are the most important survey methods. In conjoint analysis individuals' preferences are measured via systematically varying product attributes that bring value or utility to the consumer. Participants are confronted with different products (or set of attributes) from which they are either asked to select the preferred combination, or to rank the combinations. As a method it can also be used to study how consumers' valuation of a product changes when certain attributes are replaced e.g. flight ticket including a meal, seat reservation and luggage vs flight ticket including a meal, seat reservation and lounge access. When conjoint analysis is used in pricing studies, price is inserted into the study as an additional attribute. The benefit of conjoint analysis is that it can take into consideration the different product attributes in relation to the price as well as all potential products that can serve as an alternative.

As all methods, conjoint analysis has limitations. Theoretical problem refers to the concept of price and whether it can be considered to have utility in the sense of something that brings direct value to the consumer. By definition, price is the exchange rate for different utility sets but not something that generates utility on its own. Practical problem refers to a situation in which, when price is assigned as one of the attributes and different attributes are randomly assigned, in some cases the set of attributes combined may result in an extremely good deal, e.g. low price combined with more attractive product attributes, or a poor deal in which high price is combined with less attractive product attributes. This leads to inconsistent ranking and ratings of the specific cases where the practical problem occurs (as opposed to cases where the different attributes are more reasonably assigned). An additional limitation to conjoint analysis is estimation problem that refers to conjoint analysis not including choice behaviour, e.g. respondent is not able to indicate that they would not accept a certain product on the price level shown. Discrete choice analysis is another indirect survey method. Discrete choice method is also referred as choice-based conjoint analysis, which is fitting as, similarly as in conjoint analysis, respondents are presented with different alternatives from which they choose the preferred one. Often an option to express refusal is also provided. (Breidert, Hahsler and Reutterer, 2006)

Vinod, Ratliff & Jayaram (2018) suggest using discrete choice analysis and conjoint analysis for studying WTP and how customers value and rate the quality of service e.g. comfort, quality of food and reliability. They also suggest, opposite to the findings of Shukla et al. (2019), that an alternative research method could be assuming that ancillaries have similar price elasticity as flight tickets and utilising the historical ticket sales data. They add that this is a reasonable alternative especially in situation in which no or little historical data about ancillary sales is available. According to Vinod et al. (2018) controlled experimentation as a research method that is becoming more common way to study the willingness to pay. For example, Google, Amazon, Facebook and Airbnb are mentioned as examples of utilising direct experimentation. In direct experimentation, controlled sets of experiments e.g. a new price or product are tested in real life business setting. For example, randomly allocating different price points across different products based on for example markets, departure dates or sessions. Through this kind of testing businesses can find answers to questions such as at which price is the revenue maximised and which algorithm or business approach generates best results. Vinod et al. (2018) emphasise that allocating the experiments e.g. different price points randomly is important to ensure that the data collected is not biased. For example, there might a temptation to impact how different price points are allocated and hence displayed to customers taking into consideration for example high and low peak sales or departure weekdays. This kind of interference would result in biased data and would not give a reliable interpretation of the willingness to pay.

When concentrating on improving pricing and for example testing different price points it is vital to keep the customer in focus. In the SAS price experiment conducted with Amadeus and MIT, customer feedback was closely monitored during the project to ensure there was no negative impact or customer resentment towards the differentiated seat pricing (Amadeus, 2018). It is important to set KPIs for measuring both revenues and customer satisfaction. Common revenue measures are ancillary product revenue per passenger, shopping basket size and conversion rate. Customer satisfaction can be measured through monitoring net promoter scores, utilising different awareness, attitudes, usage (AAU) metrics that are used to measure changes in customer perceptions and behaviour, and analysing possible changes in customer price sensitivity. Customer satisfaction metrics can be complemented by digital measures such as session length, retention rates, numbers of active users and product load times. (Amadeus, 2019)

4.3 Artificial Intelligence & Machine Learning

According to a definition by Gartner (2018) artificial intelligence is “technology that emulates human performance, typically by learning from it. AI can augment humans, as it has the ability to classify information and make predictions faster and at higher volumes than humans can accomplish on their own". The problem with AI is that there is no universally agreed definition to it. AI is evolving and hence also the definitions are changing. In PROS (2019) definition AI is divided into four categorised based on the business context:

- Perceptual AI e.g. chat bots and different kind of digital assistants such as Siri and Amazon Alexa
- Internet AI recommendation-based systems such as Amazon, Spotify and Netflix
- Business AI decision making support through algorithms and business process development such as fraud detection and automation
- Autonomous AI e.g. robotics and self-driving vehicles

AI and machine learning are often incorrectly considered as synonyms. According to Gartner (2020) AI is an umbrella term that includes both machine learning techniques, and non-learning techniques, e.g. other type of statistics or linear programming. In AI software is taught to perform certain tasks. Machine learning learns from the data, it can use collected data and e.g. recognise patterns. According to PROS (2019) machine learning can be described as the process of taking data and turning it into a model. The model learns from the data with the aim that it also provides useful outputs that can be turned into business actions, e.g. estimates about willingness to pay. What differentiates machine learning and AI systems is the way in which the model is being updated based on new data and whether the updating is happening automatically or not; this is what PROS (2019) refer as the learning loop. An example of this is how Netflix algorithms learn from customer behaviour and utilise that data in an automated way to become better in suggesting movies and tv-series to the user. In machine learning system is learning by itself whereas in traditional AI system performs tasks based on pre-programmed rules. (PROS, 2019)

There are traditional machine learning techniques such as linear regression that deciphers the relationship between two or more variables, and classification in which data is classified into categories and then matching new observations into the existing classifications. An example of more advanced techniques is deep neural networks, i.e. sets of algorithms that loosely mimic the human brain in the way they interact (PROS, 2019). According to Gartner (2020) it is extremely important to distinguish between the classification of AI and machine learning but also the different techniques. The approach and technique chosen determines the type and amount of data needed to build and train a model and also, how much data preparation is required in the process.

4.3.1 Utilising Machine Learning in Business Context

The business use cases for machine learning are numerous. The system learning from user behaviour and becoming increasingly better in suggesting new products to users, e.g. Amazon or Spotify, improves both revenues and customer experience. Utilising AI and/or machine learning in pricing helps to maximise revenues and profit margins. Additionally, savings can be made in improving process efficiency for example through automating repetitive tasks leading to more productivity as employees can concentrate on more cerebral tasks that require human inputs. (PROS, 2019)

Traditionally airlines have been perceived as early adopters and advanced in many technologies and systems partly resulting from the complexity of the industry. To be able to organise the complex processes systems needed to be advanced. For example, aviation industry passenger service systems (PSS) and global distribution systems (GDS) were long considered most efficient of any industry, however the complexity has become a burden. Other industries capable of taking advance of the emerging technologies in an agile manner have bypassed aviation (Accenture Amadeus Alliance, 2016).

According to Amadeus (2018) advance analytics methods are being used in travel industry in numerous ways. Most traditional use case has been in predicting demand for airline tickets. In addition, chatbots and operational applications have become more common as the technologies develop. Through algorithm-based dynamic pricing models and other more advanced merchandising techniques, airlines can better meet the needs and preferences of their customers and increase conversion. Advance analytics-based solutions do not only benefit the airlines' bottom lines, customers also benefit from better catered offers that capture their needs and willingness to pay. What makes algorithm-based prediction models superior compared to traditional mathematical or human based predictions and estimations, is that customers are predictably irrational. Amadeus (2018) quotes 2017 Nobel prize winner Richard Thaler who has studied the concept of irrational predictability which he describes as people making decisions based on psychological, emotional and social factors overriding rational consideration and creating their own subjective social reality. For example, a traveller may choose to visit a destination seen as more rewarding in terms of social capital although the destination in question would not in reality be their first choice.

Data amounts and computing capabilities have long been barriers for utilising advanced analytics. For example, according to Simchi-Levi (2017) for many organisations for a long time it was possible to optimise pricing of only few products at the same time. The complexity of analysing huge amount of data and limited computing capabilities prevented usage of more advanced analytics. New data management and computing capabilities have opened machine learning-based price optimisation to many businesses. Nowadays it is possible to optimise prices in real time for hundreds if not thousands of products. Benefits are clear, in his research, Simchi-Levi (2017) studied utilisation of machine learning in the pricing activities of three online retailers. After implementing machine learning methods, he saw a double digit growth of revenues, market shares as well as profitability.

In a study conducted by McKinsey Global Institute (2018) it was discovered that the greatest potential for AI and machine learning type of solutions is with use cases in which more advanced analytical techniques such as regression and classification techniques are already used, one example being pricing. In the study it was estimated that these kinds of techniques could potentially worldwide create annual value between $3.5 and $5.8 trillion. Depending on industry this means one to nine percent of the total 2016 revenue. According to PROS (2019) in 2021 artificial intelligence-based systems will create almost 3 trillion USD in business value while at the same time recovering more than 6 billion hours of worker productivity. The obvious potential is huge but at the same time it is noted that there are several technical limitations hindering the adoption of these techniques. In order to benefit from advanced analytics solutions there is a need for large volume of data which should be labelled and organised so that it could be used for training algorithms. More challenging is the readiness and organisation's capability to build, manage and develop these algorithms. Additionally, regulation for example related to the use of personal data should be considered. (McKinsey Global Institute, 2018)

4.3.2 Utilising Machine Learning in Pricing

Dynamic pricing as a concept is nothing new. Typically, it is based on either willingness to pay or value of resource. Both of these factors are calculated based on numerous parameters and variables that affect the demand (Friedli & Hadwick, 2019). As stated in a study by IdeaWorksCompany (2019) the level of sophistication of dynamic pricing solutions differs greatly and there is no unanimous definition what is considered as dynamic in the airline industry. According to Friedli and Hadwick (2019) dynamic pricing is the action of setting and modifying prices automatically based on multiple factors. Airlines use some level of dynamic pricing in the pricing of airline tickets when automatically defining which inventory buckets they open and close based on multiple factors. There is a lot of automation that goes into the process of forecasting the demand and optimising the pricing of each bucket. There are different kind of business need-based fare rules that segment customers to for example business and leisure passengers. Also, certain type of minimum stay at the destination -rules for example are determined based on estimation of the willingness to pay. (Friedli & Hadwick, 2019)

According to PROS (2019) potential use cases for using advanced analytics, AI and machine learning are generating more personalised price points which are optimised based on customers' sensitiveness to price, operational constraints as well as business needs and objectives. These prices should be delivered in all point of sales in real time or at least close to real time. The potential is vast as there are no human capacity limitations in handling large amounts of data. This leads to faster response to the market and larger cumulative returns. Allowing the technology to do the heavy lifting will free human personnel to focus on e.g. more strategic task. Overtime customer satisfaction will improve if the perceived value for money is more accurate through the personalised pricing (PROS, 2019). Shao (2019) points out that personalised pricing as a term is also used relatively widely considering that the practise of actually offering truly differentiated price points to each individual customer is not a common practise. He adds that for airlines collecting individual data is often not even possible as one flight booking often involves multiple individuals, e.g. a family or group of colleagues travelling together or in a case of a bigger group 30 passengers so capturing an individual's preferences from the data is not possible.

Shukla et al. (2019) tested the effects of dynamic pricing models on ancillary revenues. They found out that machine learning techniques outperformed human based methods. When utilising machine learning methods conversion improved by 36% and revenue generated per offer increased by 10%. They implemented and tested two algorithms to find an optimal price for ancillary based on customer demand function and a set of attributes that influence the customers' willingness to buy an ancillary at a given price. The attributes found to be most significant to the demand function were time, origin destination pair, items already added to the shopping cart and length of stay. Two types of time-related attributes were found to influence willingness to pay: number of days to departure and departure date and time. Shukla et al. (2019) found out that customers who buy their tickets well in advance are more price sensitive than customers who purchase tickets last minute. There was also a strong seasonality found, customers departing on specific days and/or times were more likely to buy ancillaries, e.g. during holiday peaks. It was also found that certain origin destination pairs have higher ancillary demand, impacted by for example, the fraction of business travellers versus leisure passengers. The number of days planned to be spent in the destination also affects ancillary demand. For example, it was found that demand for additional baggage increased when length of stay was medium which according to Shukla et al. (2019) could be because on medium length trips people might require additional storage space at the destination. On shorter stays demand for additional baggage was lower assumedly due to the fact on short stays there is lesser need for belongings. Shukla et al. (2019) considered over several features when building the ancillary purchase probability model, examples of these are presented in Figure 8.

Temporal features
- Lenght of stay
- Seasonality (time of day, month etc.)
- Time of departure
- Time of purchase
- Time to departure

Market specific features
- Arrival and destination airport
- Arrival and destination city
- Ancillary popularIty on the route

Price comparison scores
- Scores based on alternative/ same flights across/ within the booking class

Journey specific features
- Group size
- Booking class
- Fare group
- Number of stops

Figure 8. Features Used in Building Ancillary Purchase Probability Model (Shukla et al., 2019)

Amazon is often mentioned as a textbook example of utilising advanced analytics in pricing. Amazon's real-time customised pricing are based on automated algorithms. These complex machine learning-based algorithms are able to consider, for example overall supply and demand, customer's purchasing history, competitors' pricing actions as well as strategic initiatives (McKinsey, 2017).

4.3.3 Building Machine Learning Models

According to McKinsey Global Institute (2018) data volume is the key for a machine learning model to perform on an accurate level. To receive a decent level of performance in classifying tasks a deep learning model needs thousands of data records, in some cases millions to be able just to perform on a level of humans. According to one estimate a supervised deep learning algorithm needs five thousand data records per category it is supposed to be classifying to achieve an acceptable performance level. Matching or exceeding human level requires 10 million labelled examples. Advance analytics methods such as machine learning are especially useful in cases where data volumes are big: millions or billions of rows of data. In cases where data volume does not reach the needed level, these methods may not bring any additional value to the traditional analytics methods. Also, collecting and storing granular data requires more IT resources which needs to be taken into consideration when starting to utilise advanced analytics. The complexity of the model and data required needs to be considered. Often a more aggregated level of data is more easily and economically available and most importantly, is sufficient for building models (Shao, 2019).

It is not sufficient only to collect data for creating the model, data also needs to be cleaned for model training and supporting systems developed. According to McKinsey Global Institute (2018) in one out of three cases they studied, data refreshing was needed at least monthly, sometimes even daily. This requires skilled workforce from the organisation or resources to outsource the maintenance of the model(s). Another important factor to ensure the model performance is on a desired level is agility; model training must happen frequently enough for it to be able to adjust to changing conditions in the operating environment. There must be business processes in place to support this kind of maintenance work.

Measuring the model performance is key to ensure it is performing in a desired manner. Shukla et al. (2019) developed a model which provides dynamic pricing recommendations customised to each customer interaction while aiming to optimise revenue per customer. In their study they tested different price points by offering discounts from the existing price. Their aim was to improve take up rate in a controlled way so that revenue per offer did not decline. They note that there is a risk of the revenue per session declining and highlight the importance of monitoring the experiment through carefully selected metrics. Two key metrics were set to measure the performance of their model: conversion rate and revenue per session. Revenue per session is mentioned as the most essential as it quantifies the actual performance by measuring the revenue effect of the model while taking into consideration total sessions.

According to McKinsey Global Institute (2018) the limitations in utilising advance analytics-based systems are the need of large amounts of data, difficulty in keeping decision making transparent and possible bias in data and resulting algorithms. In addition to the need of large amount of data, there is also a lot of manual work that goes into the creation of the model. Data used to train the model often needs to be labelled and in supervised learning the model is taught by providing new data and fitting it into the model, this is done manually so the system does not automatically learn in the process. This takes time and requires resources. Another consideration is keeping the transparency in decision making. This can become an issue when part of the decision making happens in a “black box”, especially in industries where regulation is high and certain processes, rules and choices need to be explainable. According to Gartner (2020) different advance analytics techniques have different level of explainability, i.e. there are more simple techniques that utilise more interpretable models and more advanced techniques where the complex computation happens in a black box. The accuracy of the complex models is higher compared to the simple models. From business perspective a decision needs to be made which is the most important and choosing the technique accordingly. The decision how much explainability is required comes from the business context and should always be clarified with the stakeholders in the organisation before starting to develop advance analytics solutions. With the existing methods, 100% explainability is not possible, but it is suggested to involve stakeholders from early on to determine the required level of explainability and give them visibility into the data used in training to get a better understanding of what information the model is based on. This builds trust internally in the organisation as it helps to understand the decisions made based on the model outputs.

Another limitation to advance analytics techniques according to McKinsey Global Institute (2018) is the fact that the models often cannot be transferred from one task to another, the learning usually cannot be generalised. In most cases systems are not able to apply learnings to a new set of circumstances, it always requires collecting new data and using it to train the model. Also, the risk of bias in the data and algorithms is a possible issue when utilising advance analytics. This can happen e.g. when the data used to train the model does not accurately represent the population to which the model is applied. Gartner (2020) suggests using diverse sets of data for training the models to minimise this risk.

According to both McKinsey Global Institute (2018) and Gartner (2020) the biggest challenge from business perspective however, after investing noticeable resources in developing advance analytics capabilities, is ensuring that the insights and suggestions provided by the model are actually integrated into the business activities and utilised in decision making. According to Gartner (2020) there are ways to ensure the models are implemented and meet the business needs. Too often models are built from data collection perspective, in order to ensure the model is operationalised and meets the business needs, the starting point for utilising advance analytics methods should be a business problem. Business problem will define what kind of advance analytics methods are applicable and hence also the data collection method used. Another roadblock for implementing the models can be organisational culture. Often the results of the models are overlooked assuming the experience of decision makers results in better decisions. Additionally, insufficient data infrastructure can become an issue. Infrastructure must support utilising advance analytics, i.e. sufficient hardware and software solutions as well as experienced and skilled data scientists. (Gartner, 2020)

4.3.4 Considerations for Utilising Machine Learning

Utilising data-based advanced analytics methods such as machine learning models poses a new issue to businesses: digital ethics. This means that businesses must ensure that all autonomous decision making is happening in an ethical and fair manner. Biased algorithms may not only lead to bad business decisions but also result in negative response from the public (Gartner, 2019). An example of this is Uber and their algorithm-based pricing. Uber’s surge pricing reacts to sudden demand peaks by increasing prices. In 2016 there was emergency situation in New York as people tried to get safe after an explosion in the city centre. Algorithm reacted to the sudden demand peak by doubling, even tripling, prices. Although company was quick to react and switched off the surge pricing algorithm approximately ten minutes after the incident, damage had already been done. It resulted in public outcry and the case became a long-time issue for the company. There are risks associated with algorithm based pricing models and leaving models unsupervised can lead to unemotional and unreasonable pricing decisions (Gartner, 2019).

In an article by Sabre (2017) it is pointed out that although algorithm-based pricing and forecasting models are superior compared to any other known methods the importance of human touch cannot be overlooked. Explainable artificial intelligence (AI) is one of the top trends Gartner (2019) is suggesting for the year 2020. It means that any business that has AI or machine learning based decision making models should be able to transparently show how the algorithm works to be able to prove that no biased decision making is taking place. This is potentially a massive issue as many of the autonomous decision making happens in a “black box”. The definition for explainable AI by Gartner (2019) is that it should be able to describe how the model works and its strengths and weaknesses but also predict possible behaviour and identify any bias in it. Friedli & Hadwick (2019) add that whenever segmentation is done at the basis of any kind of pricing it is important to ensure that the segmentation is done based on behaviour in a specific context and actual supply and demand rather than segmenting based factors that are ethically and even legally questionable e.g. nationality or gender. Shao (2019) adds that organisations looking to implement advance analytics need to take into consideration different consumer protection regulations and laws in their operating environment. These regulations also set boundaries on the type of data that can be collected. Also, requirements to the storage and usage of the collected data are often included. (Shao, 2019)

Simchi-Levi (2017) highlights that a machine learning project is not solely a technology development project. For example, change management is required to ensure that any possible internal resistance within the organisation is overcome. He states that the key message that should be conveyed across the organisation is that the technology will not replace the existing roles, it will complement by adding a very efficient tool and at the same time allow specialists to concentrate on more strategic tasks.

4.4 Summary of the Conceptual Framework

The starting point for collecting existing knowledge was to build a basis for co-creating a machine learning model for ancillary pricing. Examination of existing knowledge concentrated on three main topics: ancillaries, ancillary pricing and machine learning usage in pricing. The focus of the conceptual framework summary is on the latter, i.e.

machine learning usage in pricing to support the process of building and implementing a machine learning model to price ancillary products. The key points are summarised in Figure 9.

Strategy for applying machine learning in ancillary pricing

(IdeaWorks, 2018)
(PROS, 2019)
(Sabre 2017)
(Simchi-Levi, 2017)
(McKinsey Global Institute, 2018)
(Amadeus, 2018)

- Airline ancillary strategy
- Current state vs aspiration
- Benefit to both airline & customer
- Which part(s) of the pricing process can be enhanced with advanced analytics?

Building & implementing machine learning model(s)

(IdeaWorks, 2018)
(McKinsey Global Institute, 2018)
(Hamilton, Srivastava & Abraham, 2010)
(Mumbower et al., 2015)
(Vinod, Ratliff & Jayaram, 2918)
(Shukla et al., 2019)
(Shao, 2019)

- Resources available
- Importance of understanding customers' willingness to pay
- Importance of data collection & ability to collect & store sufficient amount of data
- Training & developing the model(s)
- Measuring model effectiveness

Considerations for implementing pricing models

(Amadeus 2018, 2019)
(Simchi-Levi, 2017)
(McKinsey Global Institute, 2018)
(Gartner, 2019)
(Shao, 2019)
(Friedli & Hadwick, 2019)

- Customer focus
- Change management
- Regulations and laws related to data usage & storage
- Ensuring model insights & suggestions are integrated into decision making
- Transparency of decision making
- Digital ethics

Figure 9. Conceptual Framework

When starting to plan utilising machine learning or other types of advanced analytics methods in ancillary pricing one should understand what the overall strategy of the airline is and how it is reflected in the ancillary pricing strategy i.e. what the current state of the ancillary pricing is and what is the aspiration level, e.g. aiming to move from the level of traditional airline to ancillary champ as presented in the study by IdeaWorksCompany (2018). It needs to be clarified which parts of the existing process could be enhanced through implementing machine learning (PROS, 2019). The benefits are undeniable. Advance analytics-based solutions do not only benefit the

airlines, customers also benefit from the improved offering that better matches their willingness to pay (PROS, 2019, Simchi-Levi, 2017, McKinsey Global Institute, 2018, Amadeus, 2018).
Although the benefits are clear, there are several factors to consider when starting to build machine learning models. The organisation needs to ensure there are sufficient resourcing for such a project. Vast amount of data needs to be collected, labelled and stored which requires time, skilled workforce and IT-capabilities (McKinsey Global Institute, 2018). In some case data might already exist in the organisation but is not easily available due to organisational silos (McKinsey, 2017). The importance of the data collected cannot be emphasised too much, as Vinod et al. (2018) state: the performance of the model is as good as the underlying inputs and data used to build the model. Models are built and trained based on historical data and hence need validation and refining in business context (Vinod et al., 2018).

Resources are not only required for building and training the model, additional data needs to be collected frequently to further train and develop the model to ensure the model performance remains on a desired level (McKinsey Global Institute, 2018). Model performance also needs to be monitored. Two key metrics used by Shukla et al. (2019) in their ancillary pricing model research were conversion rate and revenue per session.

Understanding WTP is the basis for building a machine learning model for pricing (Hamilton, Srivastava & Abraham, 2010, Mumbower et al., 2015, Vinod, Ratliff & Jayaram, 2018, Shukla et al., 2019). Factors found to affect the willingness to pay for ancillaries, i.e. possible inputs to consider when starting to build a pricing model, were:

- Departure day of week and time of day, and market effects, number of passengers travelling together (Mumbower et al., 2015)
- Season, route, customer attributes, time before purchase, type of market, time of purchase and type of flight (IdeaWorksCompany, 2019)
- Duration of the flight, time before departure, day of travel, ticket booking class and ticket price (Amadeus 2018)
- Number of days to departure and departure date and time (Shukla et al., 2019)
- Are customers comparing competitive offers? (Hamilton, Srivastava & Abraham, 2010)

- How the price of ancillaries compares to the ticket price, i.e. small or large price difference (Hamilton, Srivastava & Abraham, 2010, Mumbower et al., 2015, Shukla et al., 2019, Amadeus, 2018, Shao, Kauermann & Smith, 2020)
- Understanding customer needs and offering relevant ancillary products (Hamilton, Srivastava & Abraham, 2010)

There are several ways to measure WTP. Breidert, Hahsler and Reutterer (2006) categorise the WTP measuring methods into revealed preference methods, i.e. analysis of market data and different types of experiments, and stated preference methods, i.e. direct survey methods and indirect survey methods such as conjoint and discrete choice analysis. In their study they state that each method has its strengths and weaknesses and that choosing the suitable method depends on the business case, e.g. level of data need, time and budget available.

There are several factors that need to be taken into consideration when planning to start implementing machine learning or any type of advance analytics methods. Although the focus is much of the development of the technology and collection of the data, customer should not be forgotten. Especially when collecting data and conducting experimentation, e.g. with prices, it is important to monitor customer feedback and behaviour (Amadeus, 2018 & 2019). Simchi-Levi (2017) also states that machine learning projects are not solely technology development projects, e.g. change management needed to overcome possible internal resistance (Simchi-Levi, 2017). It is also important to keep decision making transparent, i.e. should be able to transparently show how the algorithm works to be able to prove that no biased decision making is taking place (McKinsey Global Institute, 2018). It also needs to be ensured that autonomous decision making is happening in an ethical and fair manner and that biased models or data is not used (Gartner, 2019). Friedli & Hadwick (2019) add that whenever segmentation is done at the basis of any kind of pricing, it is important to ensure that the segmentation is done based on behaviour in a specific context and actual supply and demand rather than segmenting based factors that are ethically and even legally questionable e.g. nationality or gender. Organisations also need to take into consideration regulations and laws for example related to the collection, usage and storage of personal data (McKinsey Global Institute, 2018 & Shao, 2019).

5 Co-Creation of the Proposal

In this section of the thesis the process co-creating the proposal, i.e. ancillary pricing model that utilises machine learning, is described. The basis for the co-creation process were the current state analysis and the conceptual framework presented in previous sections of the thesis.

5.1 Overview of the Co-Creation Process

For building the initial proposal a project team was formed. The project team consisted of employees of the case company as well as employees of a system provider whose tool was used to implement the pricing model that utilises machine learning. Project team participants from case company were data scientists with knowledge of building algorithm-based models, revenue management system experts with data science knowledge and ancillary pricing analyst who was in charge of coordinating the project and also participated as the super user of the pricing tool that was used to implement the model based pricing. The employees of the system provider had previous experience of utilising machine learning models in ancillary pricing. The pricing tool utilised in the case company for ancillary pricing actions, e.g. campaigns, is supplied by the system provider. There was a strong aspiration from their side to develop the tool to support advance analytics models. At the same time case company was looking into developing ancillary pricing so the project was seen mutually beneficial. Co-creation process was iterative and included several steps of collecting data, creating model proposals and gathering early feedback.

5.2 Project Team Workshop – Starting the Co-Creation Process

The starting point for the co-creation process was a two-day workshop held in the premises of the case company. As earlier mentioned, the system provider company is located in a different country. In the kick-off workshop a comprehensive project plan was formulated. There had been years of cooperation on numerous projects between the case company and system provider so on both sides there was a good level of understanding on the ways of working and company cultures. It was important that all project participants were able to meet to face-to-face as majority of the project participants did not know each other and it was known already at this point that the project would run for approximately a year and most of the communication would take place virtually.

The first step in creation of the project plan was defining a starting point. The purpose of this was to ensure that all participants had a similar level of understanding of the current state of the case company, its ancillary sales and current ancillary pricing. At the same time the system provider employees shared their experience of similar projects previously done as well as their plans of developing the pricing tool and how it could be enriched through machine learning methods. A target state was defined together to serve as a goal for the project, i.e. a machine learning model for a selected ancillary product is implemented through the system provider’s pricing tool. An initial timeline was agreed to support major deliverables such as first version of the model and testing of the pricing tool user interface. Business objectives for the project were also defined. There was discussion whether the focus is on increasing take up rate, i.e. volumes of ancillary products sold in reference to the total passenger numbers, or if focus is on maximising the revenue of each ancillary sold. This definition is important for being able to set the correct KPIs used to measure whether the model is performing as intended. The focus in this project was on maximising the revenue of each ancillary sold. The fundamental idea of this was that by capturing the WTP and offering the ancillary product at the right price will naturally results in an increase in take up rate and volumes sold.

For scoping the project work and model creation, a decision of which ancillary product(s) and categories, e.g. baggage, seats, meals or lounge, would be in the scope of this project. Also, it needed to be defined whether one selected product or all the products in the category, e.g. a selected meal or all meals offered, would be in the focus. The decision was based on the perceived revenue potential of the product as well as the experience of the system provider side with building models for the specific product category. The decision was also made keeping in mind that on the case company side, there was strong strategical intent to expand model based dynamic pricing across multiple ancillary categories in the near future, hence at no point was the intention to narrow the development but rather keep it applicable to any ancillary product. It also needed to be decided whether the project scope would be on selected traffic areas or flights, or whether the entire network was targeted. For this project the entire network was selected to ensure quick implementation with large coverage and hence bigger revenue impact.

For the machine learning model building different data collection methods were discussed. Controlled experiment, i.e. systematically varying prices in test markets and analysing customers’ response, was chosen as a method as it is commonly used in this type of studies (Breidert, Hahsler and Reutterer, 2006 & Vinod et al., 2018). The main drawbacks to this method presented by Breidert, Hahsler and Reutterer (2006), i.e. higher costs and relatively long time span of collecting data, were also discussed. No high cost from the data collection was expected as test prices could be implemented through the existing pricing tool from where price points were distributed across different sales touchpoints. The second issue with data collection through experiments was relatively long time of collecting data. This was also acknowledged and taken into consideration when planning the project timelines, however it was not considered an issue. Selection of the machine learning method for building the model was also discussed. The methods discussed were all applicable for solving a pricing problem. For example, decision trees, clustering, regression models, neural networks and random forest model -methods were discussed. Conclusively, neural networks were chosen as the method it was the method case company data scientists had the most experience with. The benefit of the method is high accuracy, but it is relatively complex to build and train (Gartner, 2020).

5.3 Follow-up Meetings to Support Co-Creation

In the kick-off workshop a follow up schedule was agreed. Monthly virtual calls were organised amongst the project team to discuss the progress of the project and any possibility issues that could cause delays or problems. To support the building and implementing of the model a five-step process was created. The first step of defining business objectives was done during the kick-off meeting described in the previous section of this thesis. The first step to start the model building was data collection through controlled experiments. Based on the collected data a machine learning model was built and trained. Model was them implemented, first in a test environment to ensure all technical tools were working and integration between the model and the pricing tool was working as intended, i.e. the price returned into the reservation system were according to the model outputs. After technical system validation was concluded, testing was performed in real life setting by applying model-based pricing in customer interface again ensuring that the prices shown were according to the model outputs. The initial project plan stated that after the implementation performance of the model is monitored and improvements done, i.e. development through re-training to ensure high level performance. These steps are discussed more in detail in the next chapters.

5.3.1 Data Collection

The basis for building the machine learning model was collecting data through price experiments. The purpose of the experiments was to gather data about customers' willingness to pay. Data collection was done through controlled experiments, i.e. systematically varying prices and analysing customers' response. Different prices were implemented through the system provider's pricing tool already used by the case company by applying manual rules to discount and mark-up on the prices filed in the ATPCO system in a controlled manner.

Three price experiments were conducted to collect data. The first price experiment was conducted on a smaller market area to mitigate any possible customer retaliation. During the assessment period of six weeks five different price points were applied for the selected ancillary products. This was done by applying discounts and mark ups to the price filed in the ATPCO database. A fictious example of the price experiment logic is presented in Figure 10.

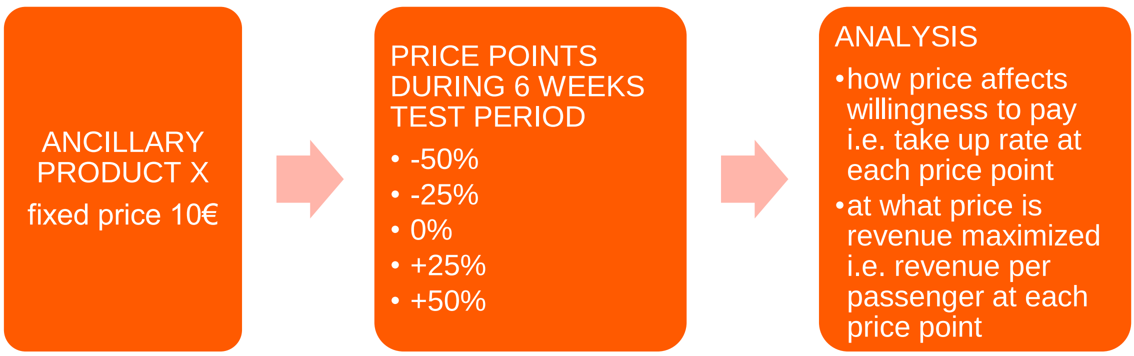

Figure 10. Fictious Example of the Price Experiments Conducted in Data Collection 2

Each price point was applied for specific departure dates. E.g. for flights departing on May 7th the price of ancillary product X was five euros, -50% from the ATPCO price of ten euros, but for flights departing on the next day price was 15 euros (+50%). Assigning the price points on certain flight dates facilitated data collection and made it easier to track what price was offered to which customer. By combining the information of ancillary purchase date and flight departure date it was possible to track which ancillary price point the customer was exposed to. The price points were randomly assigned to each flight departure date. Vinod et al. (2018) emphasise that allocating the experiments e.g. different price points randomly, is important in order to ensure that the data collected is not biased. For example, there might a temptation to impact how different price points are allocated, and hence displayed to customers, taking into consideration e.g. high and low peak sales or departure weekdays. This kind of interference would result in biased data and would not give a reliable interpretation of the WTP.

The data collected through the price experiments was cleaned by removing e.g. those ancillary EMDs that were sold before the experiment. After the data cleaning, analysis of the collected data was performed. As the business objective was to maximise the revenue of the ancillary product, the question the project team set out to answer through the collected data was: at what price is the revenue maximised? This is illustrated in Figure 11.

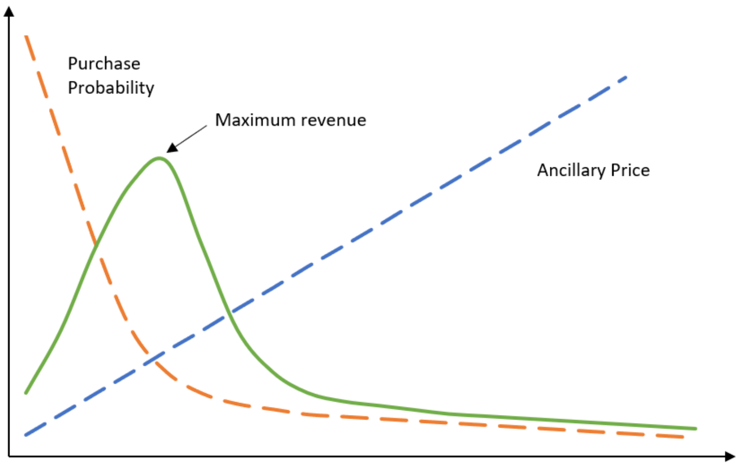

Figure 11. Graph Displaying the Relationship between Ancillary Price and Purchase Probability to Maximise Revenue

As per classical price-demand theories when the price increases the demand or purchase probability drops. The purpose of the price experiment was through testing different price points to get closer to the price were both price and purchase probability are optimised resulting in maximum revenue.

The findings of the first price experiment were reviewed in a project team meeting. The revenue per passenger returned from each of the five price points was calculated to find out at what price revenue per passenger was maximised. This is visualised in Figure 12 where price point 3 represents the current price. As can be seen from the graph, both of the higher price points (4 & 5) generated higher revenue per pax than the existing price (price point 3) hence indicating that the WTP was higher. Based on these findings the price of the studied ancillary was increased before the second price experiment.

Figure 12. Revenue per Passenger on Each of the Price Points Used in Price Experiment 1

Additional findings were that price experimentation was a fitting method to collect data. However, the price points tested during the first experiment did not capture the maximum price at which demand curve would start noticeably decreases indicating that WTP was much higher than anticipated. It was decided that for the second price experiment the scope will be widened to cover the entire network but also that the test prices will be increased with the intention to capture the maximum range at which the demand for the product starts to decrease to a level where the maximum revenue also drops. Both the second and third price experiments were conducted in a similar manner as the first one described above. The findings of these experiments were discussed in the project team meetings and the data collected was used for building and training the machine learning model. As suggested by Amadeus (2018 & 2019) customer feedback was actively monitored throughout all three price experiments. There was no customer resentment or negative impact caused by the varying prices. Additionally, no negative impact on the sales, volumes and revenues, of the ancillary was observed during the experiments.

5.3.2 Building the Model

The data collected through the first price experiment was used to build and train first version of the model. As previously discussed, the project team decision was to use neural network as the method to build and train the pricing model. The basis for the model building was identifying relevant model inputs, i.e. attributes that correlate indicating to have effect on WTP. As presented in the existing knowledge section there are numerous factors that have been identified to have effect on WTP. Multiple factors were discussed in a project team meeting and tested based on the collected data. For example, flight route, flight duration, booking time, number in party, travel purpose and time of departure were considered. A set of attributes found to form the best combination to affect WTP was selected to train the machine learning model. Machine learning methods were used to estimate purchase probability based on the selected attributes and to output price suggestions. The data collected through second and third price experiments was used to train the model to ensure optimal performance across the entire network of the case company.

5.3.3 Implementing the Model

The model was implemented through the existing pricing tool. In the pricing tool ancillary pricing analyst defines price adjustments rules based on business requirements. For example, on flights between Europe and North America static ancillary price filed in the ATPCO database is twenty euros. However, we can see that with the given attributes used to train the model, the suggested optimal prices are in fact between ten and thirty euros depending on the shopping context e.g. origin and destination city, departure weekday, flight duration, departure date, duration of stay etc. Ancillary pricing analyst defines rules in the pricing tool stating that when optimal price suggested by the model is e.g. fifteen euros a five-euro discount is applied to the base price. Similarly, when optimal price according to the model is twenty-five euros, a mark-up of 5 euros is applied etc. When a customer purchasing a flight from Europe to North America is purchasing an ancillary, their shopping request and context is mirrored to the manual rules set by the pricing analyst. For those travelling from Europe to North America model-based pricing is applied and based on the booking context the matching output is applied and an adjusted price based on model output is returned to the customer. If the shopping context does not match the rules defined, e.g. passenger is booking a flight within Europe, the 20 euros price filed in the ATPCO database is returned. This process is visualised in Figure 13.

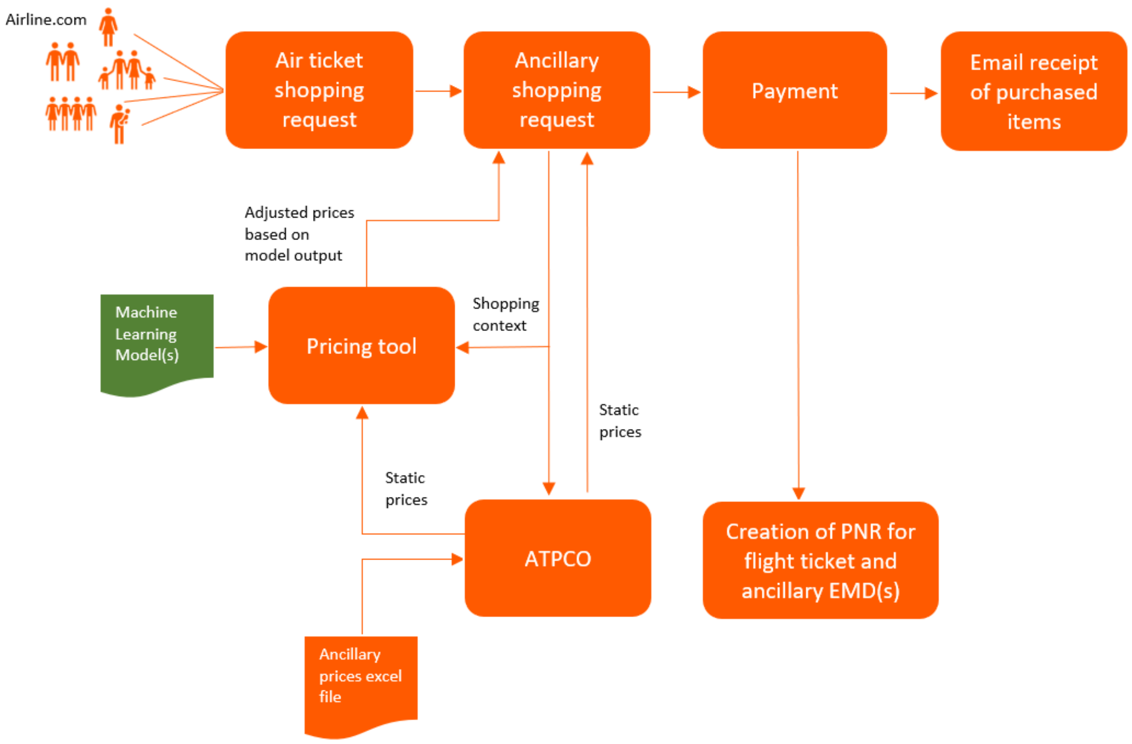

Figure 13. Ancillary Prices Flow into the Passenger Booking Process with Ancillary Pricing Models

There was discussion in the project team meeting regarding automating the procedure so that the suggested prices from the model would flow directly into the sales touchpoints removing the need of creating any manual rules in the pricing tool. However, a decision was made that at the early stages manual intervention is preferred. For example, market impacts can be considered when setting the manual rules, e.g. on certain routes setting lower prices than those suggested by the model due to competitive situation etc. It will also allow the analyst to manually define some minimum and maximum adjustment levels which are applied to the ATPCO filed price. This can be useful if e.g. on a specific route the suggestion of the model is to price the ancillary very high but due to strategic business reasons, e.g. brand image, the price should be kept lower than what the model suggests.

The implementation was planned to be done in three stages. This was decided to ensure the model performance in a smaller market area before expanding to the entire network. The first implementation was done during Q1 2020 with a plan to follow with market area 2 after the impacts of the first go live had been estimated and more data about the model performance collected. This also allowed more time to work on refining the model for areas 2 and 3 which were planned to be launched during Q2-3 2020. This plan, however, was postponed due to the global outbreak of coronavirus early 2020 which brought almost entire global airline industry to a standstill (Ghosh, 2020).

5.3.4 Monitoring & Developing the Model

A natural continuum for implementing the model is monitoring its performance. The KPIs for monitoring were agreed in the kick-off workshop of the project. The focus of the project was on maximising the revenue of each ancillary sold. The KPIs hence were ancillary revenue per passenger and total ancillary revenue. Model was implemented through A/B -testing. Through A/B-testing it was possible to monitor whether the model outperformed the old static pricing.

In addition to monitoring, the model also needs to be developed through training. As previously described in the existing knowledge section of the thesis, it is not sufficient to only train the model once. Model training must happen frequently enough for it to be able to adjust to changing conditions in the operating environment (McKinsey Global Institute, 2018). A training schedule was agreed within the project team for the operating year of 2020. It was also agreed that the data collection for re-training the model happens in the same manner as the initial data collection for model building, i.e. price experiments.

5.4 Summary of the Co-Creation Process

Co-creation process was iterative and included several steps of collecting data, building and training the model proposal and gathering early feedback. The co-creation process can be summarised in a six-step process presented in Figure 14.

Figure 14. Building & Implementing a Machine Learning Model for Ancillary Pricing

The initial step of the co-creation process was definition of business objectives and building a project plan around it. This was done in a two-day face-to-face workshop where all project team members were present. The business objective was to build and implement a machine learning model to price ancillaries. A timeline, more detailed description of the scope, i.e. which ancillary products, data collection methods as well as method used to build the machine learning model were agreed and included in the project plan. In the workshop also follow up schedule, monthly virtual meetings, was agreed to ensure project proceeded as planned and information was shared amongst the project team members. The second phase was data collection which took place through three sets of six weeks price experiments conducted between Q2 2019 and Q1 2020. Based on the data collected a model was built and trained. Model implementation was planned to be done in three stages between Q1 and Q3 2020. The first implementation happened as planned during Q1 but due to the outbreak of COVID-19 pandemic, rest of the implementation plan was put on hold.

6 Validation of the Proposal

In this section of the thesis the validation of the proposal, i.e. ancillary pricing model that utilises machine learning, is described. The proposal was validated by collecting feedback and by conducting technical testing to ensure mode and related system performed as anticipated.

6.1 Validation by Collecting Feedback

As mentioned earlier the co-creation process was iterative and included several steps of collecting data and training the model. Key stakeholders from case company were involved in the process from early stages. Through early validations it was ensured that stakeholders not participating in the project work were involved and could provide feedback, at the same time staying up to date on the progress of the model and its possible impacts on their daily work. Feedback was collected in meetings where project team findings were presented.

There were altogether six validation meetings conducted. After the first price experiment the model and adjusted pricing process were presented to the managers of case company’s customer service teams as well as to key ancillary stakeholders. The purpose of this meeting was to present the machine learning model -based pricing concept and also explain the practical implications it will have on the daily work of the customer facing teams. Feedback collected was more targeted to the supporting processes related to ancillary pricing rather than the actual machine learning model. E.g. need for frequent communications and having sufficient supporting material in place well in advance before implementation was emphasised. A second round of validation with the same group of people was done after the second price experiment had been finalised and results were available. At that point an implementation plan created by the project team was in place and could be shared with the stakeholders. It was noticed that some of the existing wording how the pricing of the ancillaries was presented on the airline's webpages needed to be changed. No proactive external communication was considered necessary as towards the customer the message had always been that the price of ancillary products may change due to different factors, so no price promises were made. There had also been some level of price differentiation in place already, e.g. depending on the sales channel and through campaigns. Additionally, the general feeling was that very few customers compare the ancillary prices frequently enough to notice changes in the price level, especially if the changes are relatively small. This assumption was supported by the fact that during the price experiments conducted no feedback was received from customers concerning ancillary prices. This of course does not mean that customers did not react to the experiments, as very few actually take the time to give feedback.

Validation was also performed with case company revenue management and pricing team members in a meeting by presenting more details about the machine learning model and the implementation plan. Feedback and inputs were also collected from case company legal department. This was done in a face-to-face meeting with a representative from the legal department. As suggested by Shao (2019) local regulations and laws in regard to data collection, storage and utilisation must be considered when applying advance analytics. Points discussed in the meeting were personal data protection and privacy regulations, advertising and marketing regulations in relation to price information, and consumer protection laws. No legal or regulatory restrictions for implementing the model were identified.

6.2 Technical Validation

In addition to collecting feedback from key stakeholders, technical validation was performed to ensure that the model as well as all interfaces performed as expected both in test and live environments. Technical validation was performed by ancillary pricing analyst and IT system expert. Flight bookings were created in reservation system and ancillary was added to the booking to ensure it was correctly priced. First technical validation was performed in a closed test environment where it was possible to replicate the entire booking flow to ensure all steps of the flow worked as planned when model was implemented.

After the model was integrated into the pricing tool for test environment, pricing analyst created several pricing rules utilising the model. In the test environment the model was applied on selected flights to be able to validate both, how model-based pricing worked on those flights, and that the pricing of the ancillary on rest of the flights was not impacted by the model. Several different flight bookings were created to the flights on which model-based pricing was activated. The purpose of this was to test different combinations of booking context and what kind of prices those resulted in. Fictious examples of test bookings could be a single passenger travelling on a selected date from London to Paris for a day, departing on Tuesday morning and returning late in the evening, or a family of three, two adults one child of four years, travelling from London to Paris on a specific date for one week. These two passenger groups most likely have a very different kind of willingness to pay for the ancillary, and therefore should get very different kind of price suggestions for the ancillary from the model. The ancillary prices for the test bookings were documented and checked by the project team's data scientists to ensure that the price shown in the reservation system was according to the model suggestion. No inconsistences in the model-based pricing in the reservation system were found during the validation. A similar validation round was performed in the live environment utilising the same reservation funnel that is used by the passengers. In this test the model-based pricing was restricted only to the office location of the case company, i.e. only for bookings created by specific employees of the case company. This was done to ensure that passengers were not exposed to the model-based pricing at this point. Similar to the tests performed in the testing environment, the prices shown in the reservation system were according to the model suggestions.

6.3 Summary of the Validation

The proposal was validated by collecting feedback from key stakeholders as well as by conducting technical testing to ensure all interfaces were working when the model was implemented through the pricing tool. Due to the outbreak of COVID-19 pandemic during the model implementation, the primary method planned for validation, monitoring and analysing the model’s impact on ancillary revenue, was not possible within the scope of this study.

7 Discussion and Conclusions

In this section the thesis is summarised. An overview of the study, research methods used, co-creation process and the outcome are presented. Additionally, evaluation both from case company’s, as well as author’s perspective is included.

7.1 Summary

This study set out to solve a business problem of the case company. The problem was that the existing pricing of ancillary services was not optimal. Pricing decisions were based on educated guesses and business experience rather than effective utilisation of collected data. This led to relatively static prices that often did not reflect customers’ willingness to pay (WTP) hence resulting in missed revenue opportunities. The objective of this study was to find a solution to this problem by co-creating a machine learning model for pricing ancillaries.

The starting point for solving the business problem was to gain a better understanding of the current state of the case company’s ancillary pricing. Data about the current state was collected through interviews with selected employees of the case company and through reviewing existing process documentation concerning ancillary pricing. Existing knowledge and literature around the main topics related to the business problem, ancillary pricing and utilising machine learning in pricing, was reviewed. The main findings were summarised into a conceptual framework which supported the co-creation of the machine learning model. The co-created proposal was validated by testing the technical functionality of the model and by collecting feedback from key stakeholders in the case company.

7.2 Practical Implications

The importance of ancillaries is undeniable for airlines. When done right, they do not only contribute to the revenues and profits of airlines but also support customer satisfaction and building strong brand. Ancillaries are considered an essential part of the case company's future and are integrated into the company's strategy. There are ambitious targets for growing ancillary revenue during the upcoming years which requires new innovative ways to develop ancillary business in the case company. The outcome of this study, machine learning model for pricing ancillaries, will support the company in reaching these ambitious revenue targets. In the long run, the model-based pricing will also contribute to customer satisfaction as the model will learn to price the ancillaries more accurately. This will be enabled by frequently training the model so that it will become better in estimating the willingness to pay.

The project has also been a learning opportunity for the all the people involved. Within the project team knowledge and expertise was shared. Also, the change from a static pricing and price lists into a dynamic model-based pricing has required a change of perspective from the stakeholders, especially the ones selling the ancillaries in different customer touch points. Change management practices were applied, e.g. early involvement of stakeholders as well as frequent communications and information exchange, to ensure the change was not perceived too sudden or extreme when implementation of the model-based pricing started.

Three price experiments were conducted in this study to collect data about WTP. During the early stages of the project, based on the findings of the first price experiments, changes to the existing static pricing structure were made. These changes had a significant positive revenue impact during 2019. Although the model implementation and validation through collecting data about its performance was not possible in this study due to the outbreak of COVID-19 pandemic early 2020, there is reason to believe that the machine learning model-based pricing will further boost the revenues of the case company once fully implemented.

This study was the first scratch on the surface of understanding the willingness to pay of the case company's customers when purchasing ancillary products. Utilising advanced analytics methods in ancillary pricing poses significant advances. It is of utmost importance that the case company continues to develop the existing pricing model by frequent data collection and re-training of the model while continuing to develop new models and advanced ways to price ancillaries.

7.3 Evaluation

As earlier mentioned, the objective of this study was to find a solution to the business problem of the case company by co-creating a machine learning model for pricing ancillaries. The business problem was that ancillary pricing decisions were based on educated guesses and business experience rather than effective utilisation of collected data which led to static prices that did not reflect customers' willingness to pay and resulted in missed revenue opportunities. The outcome of the study, co-created machine learning model, was a first step towards utilising advance analytics methods for pricing ancillaries. The final proposal is by no means optimal. The model can be developed noticeably to better capture WTP. However, it is a significant improvement to the previous static pricing. In addition to the improved pricing, the project also benefitted the organisation in other ways. Through the learnings gained by creating and implementing the model, there now exist better capabilities, understanding and readiness to continue to develop advance analytics -based solutions for ancillary pricing in the organisation. Additionally, there is an existing process and tools that have been validated to support this work.

7.4 Afterword

This final section of the thesis is author's reflection of the study. In the role of ancillary pricing analyst in the case company, I had a good understanding of the business problem and also had the privilege to coordinate the co-creation project. Machine learning as a thesis subject would not have been my first choice. For this, I am grateful to my manager who suggested the topic and also supported me with both, the thesis and coordination of the project. It was challenging going into this project with very little data science knowledge, but it was an enormous opportunity to learn. For the learning, I have the project team members to thank for. They patiently explained the basics of machine learning to me over and over again, supporting my learning journey throughout the project.

When starting the project, I believed that we were embarking a technology development project. As discussed in the existing knowledge section of this thesis, this is a relatively common misconception about advance analytics projects. What in my mind started as a technology development project, ended up being a 360-degree dive into change management practices, effective communications, airline industry systems, legislative and regulatory aspects, and technical details of ancillaries.

As previously discussed in the thesis, the implementation of the model was interrupted due to the outbreak of COVID pandemic early 2020. No data of the model performance was collected as flight operations started to be shut down quickly right after the first part of the implementation took place. At this point of time, the future of the whole airline industry is very open. These difficult times, however, only emphasise the importance of ancillaries for the healthy and profitable future of airlines.

The co-created machine learning model and the new model-based ancillary pricing are the first steps for the case company to move towards optimised ancillary pricing. The changes done to the old static pricing structure based on the finding of the first price experiment already had a significant positive impact on the ancillary revenues in 2019. Looking at the results of similar studies conducted previously there is reason to believe that when implemented, the model will result in double digit growth of ancillary revenue. In addition to this, the case company now has better readiness to continue the journey of utilising advance analytics in ancillary pricing. This will support the successful way forward after the COVID-19 crisis is over.

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