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The Sky is the Limit: Assessing Aircraft Market Diffusion with Agent-Based Modeling

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This paper presents an adapted agent-based model for the diffusion of new aircraft model series. Expanding on the classical economic decision framework, where investment decision-making is entirely based on profitability, our holistic modeling approach takes into account profitability, flexibility, as well as the environmental impact of new aircraft model series in the adoption decision process. Technical parameters such as the range and maximum take-off weight of an aircraft model series, various emissions of the aircraft engine, as well as daily operational data, are used to calibrate the model. In validation, our model produces results that are comparable to data on the market diffusion of an existing aircraft model series, the Boeing 737-500. This result shows the applicability of our model, which can also subsequently be used on aircraft with new generations of technologies. Our simulation shows that a price reduction or a decrease in emissions could lead to more adoption and faster diffusion. Furthermore, our modeling approach demonstrates that a holistic framework to include not only profitability but also flexibility and environmental impact can be helpful when modeling the investment decision-making process.

Transportation economics; Technological diffusion; Agent-based modeling; Aircraft

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1 Introduction

From the year 1990 until 2014, global scheduled flights increased by 80%, with an expected further 45% growth from 2014 to 2035. Meanwhile, this growth is being accompanied by an equally strong growth of greenhouse gases and other air pollutant emissions (EASA, 2016). As such, a more sustainable growth in the aviation sector is the common goal for many players in the field, including policy makers, passengers, manufacturers, and airliners. To this end, the ‘Flightpath 2050’ (European Commission, 2011) was released in order to exactly define and quantify these challenging goals that are to be reached by the year 2050 for the European aviation sector. Among others, the goals include ambitious carbon dioxide, nitrogen oxides (NO\textsubscript{x}), and perceived noise reduction targets. Such targets are unlikely to be met by the optimization of the existing systems, and new technologies and other innovations need to be developed and implemented. While many research and development projects are underway to develop new technologies, such as hybrid-electric propulsion or hybrid laminar flow control, the diffusion of such technologies into the future fleet is equally important for estimating and ensuring emission reduction and the successful realization of the Flightpath 2050 targets. Without widespread market diffusion, the impact of innovative technologies cannot be realized. As such, the study of innovation diffusion is paramount. It could help in many ways, such as in choosing the most promising technologies for large-scale commercialization, or to inform producers and distributors regarding the potential scale of adoption and needs for adaptation. This paper thus aims to develop a technology diffusion model that is tailored to the aviation sector, and more specifically, the adoption of new aircraft model series. We aim to incorporate various aspects and players in the diffusion process, including the financial institutions that provide the funds for adoption, regulatory bodies that set the standards, and airliners that aim to earn profit, reduce regulatory and fuel prices risk, and increase fleet flexibility. The calibration is also done in such a way to best reflect the industry landscape.

In this paper, we propose an agent-based model (ABM) to simulate the diffusion process of an aircraft model series. ABM is widely used in the modeling of diffusion processes, and specifically in the field of aviation, ABM has also been applied in various studies. For instance, ABM is used to model European air traffic and German passenger demand (Grether and Nagel, 2013), and to model departure and seat availability in order to help optimizing passenger-trip assignment (Grether et al., 2013). However, few studies have been done regarding the diffusion of new innovative aircraft model series and to examine the economics and the decision-making process behind such adoption behavior.
It is thus our goal to fill the gap with the current study on the aircraft diffusion process using ABM.

The remainder of this paper is divided into four sections. Section 2 reviews past studies and relevant literature. Second 3 establishes our methodology, namely the model setup, the calibration of the setup, as well as the calibration of the model. Second 4 presents the simulation results of one aircraft model series in order to show how our model can be applied. Analysis of the simulation results and discussions of the limitations of our model are also presented here. Second 5 concludes and points out future avenues of further research.

2 Literature Review

The forecast of market adoption of new products has long been a determining and essential question for companies, investors, developers, and policy makers alike. The road from new technologies in the lab and testbed to mass market commercial success is not always guaranteed. But once successful, the new product may not only bring economic gains for firms and investors, but could also (positively or negatively) influence our environment and society significantly. As such, the quest for more advanced theories and models regarding technology diffusion forecasting has been persistent. In the literature, aggregate epidemic models, such as the Bass Model (Bass, 1969) and the agent-based modeling (ABM) approach, have been used to study the diffusion process of product innovations. The aggregate models have a long history, starting with the pioneering work such as that by Fourt and Woodlock (1960), Mansfield (1961), and Bass (1969) (see Geroski (2000) for a detailed overview and analysis of various aggregate diffusion models). These parameterized models aim at formulating differential equations that describe the diffusion process. They classify consumers into general broad groups – e.g. innovators, imitators, early adopters, later adopters – and they use certain parameter values to quantify the rate of their adoption speed, or the influence of exogenous factors on the rate of adoption. Historical sales data are often used to estimate the rate of adoption. In the case that such data are not available, the estimation of parameters can also be done via survey estimation or the analogy principle. Such aggregate models have certain limitations, for instance in terms of the overgeneralization of the micro-structure and the process of individual consumer decision. Since the early days of model-based technological diffusion research, the vast increase in computational power allows to tackle such problems by employing the ABM approach. In simulating the aggregate diffusion pattern, an ABM allows the incorporation of the consumers’ (or in other words, agents’) individual
adoption decision process as well as their idiosyncratic parameters. Relevant market conditions can also be included as parameters. The model thus becomes more complex but also much richer. The study of technological innovation diffusion phenomena using ABM is relatively established as well. For instance, ABM has been used to study the diffusion of residential photovoltaic systems in Italy (Palmer et al., 2015), electricity generation in biogas plants in Germany (Sorda et al., 2013), as well as alternative fuel vehicles (Zhang et al., 2011). Similarly, technology diffusion in transportation is also studied extensively, for instance Costa and Fernandes (2012) examined the rate of adoption of new urban public transport technology in Europe, Higgins et al. (2012) studied the adoption of electric vehicles, and Liu and Madlener (2019) explored the diffusion of aircrafts with a two-stage model, combining an epidemic diffusion model and a regression analysis. However, a diffusion simulation model for transportation, and specifically aircrafts with specific sector know-how has not yet been established. Our study combines the insights taken from previous ABM innovation diffusion modeling and aviation-industry-specific knowledge in order to build a model that is flexible, relevant, and capable of forecasting aircraft innovation diffusion.

In this study, we chose to implement the agent-based approach for the following three reasons. Firstly, ABM provides stronger explanatory power compared to the traditional aggregate models (Kiesling et al., 2012). In the traditional model, although the coefficients of innovation and diffusion (Bass, 1969) offer a fast and generalized understanding of the diffusion processes, it is hard to explore further the underlying mechanisms that are responsible for such parameters. In contrast, ABM allows the implementation of diverse decision-making processes and interactions among various agents, which could be used to reflect and explore the underlying adoption behaviors and thus the aggregate diffusion process. Furthermore, as mentioned above, ABM considers a heterogeneous population of adopters. Although in the aggregate model, adopters are also categorized into various groups (e.g. Rogers, 2003) divided the adopters into five categories based on their propensity to adopt), such a categorization does not look into individual heterogeneity and is not as flexible as ABM. Lastly, ABM offers prescriptive guidelines that are implementable in order to influence the diffusion process. Generally, the aggregate model offers a description and explanation of the diffusion process based on different propensities to adopt. However, not much is said about how these diffusion rate parameters are formed and what can be done to alter them. There have been some attempts in the literature, such as the inclusion of price variables (Robinson and Lakhani, 1975), supply and distribution constraints (Jones and Ritz, 1991), and marketing and advertising (Dodson and Muller, 1978). Nonetheless, it
is hard to combine these standalone studies into one model, and the framework in these studies is relatively less flexible for adding new parameters. In contrast, diffusion in ABM is derived from individual decisions which are computed from a myriad of factors that can be flexibly added and altered. The effect of a change in certain parameters, e.g. a price reduction, can then be derived from diffusion process simulations generated through alteration of these parameters. This process will then aid in the formulation of prescriptive guidelines.

3 Methodology and Model Setup

3.1 Adoption Decision

Based on a particular set of decision-making conditions for an airline, i.e. agent $j$ and a specific aircraft model series $a$, the overall benefit, $B(a, j)$, is calculated as the weighted sum of economic, environmental, and flexibility benefits: $b_{econ}(a, j)$, $b_{env}(a)$ and $b_{flex}(a)$, respectively. The weights: $w_{econ}(j)$, $w_{env}(j)$ and $w_{flex}(j)$ are calibrated based on the individual characteristics of agent $j$ and the condition for the adoption decision:

$$B(a, j) = w_{econ}(j) \cdot b_{econ}(a, j) + w_{env}(j) \cdot b_{env}(a) + w_{flex}(j) \cdot b_{flex}(a),$$  \hspace{1cm} (1)

where:

$$\sum_k w_k(j) = 1 \quad \text{for } k \in K : \{ econ, env, flex \}$$

and $w_k(j), B(a, j) \in [0, 1]$.

The adoption occurs when the overall benefit $B(a, j)$ exceeds a certain threshold $B^*$:

$$B(a, j) > B^*,$$

where $B^*$ is obtained by calibrating the model in respect to historical data. This set-up essentially follows Palmer et al. (2015)
3.2 Calculations of Benefits

3.2.1 Economic Benefit

The economic benefit of operating an aircraft is specified as:

\[ b_{econ} = \frac{\max_{pp}(a) - pp(a,j)}{\max_{pp}(a) - \min_{pp}(a)} = \frac{21 - pp(a,j)}{20}, \]  

(2)

where \( \max_{pp}(a) \) and \( \min_{pp}(a) \) are the maximum and minimum possible payback periods of aircraft \( a \), respectively. Given that the accounting life of an aircraft is 20 years i.e. the payback period is calculated over 20 years, and the minimum payback period is one year, \( \max_{pp}(a) \) and \( \min_{pp}(a) \) are calibrated to be 21 and 1 respectively. \( pp(a,j) \) is the payback period of aircraft \( a \) for agent \( j \), and it is calculated as the year when the net present value (NPV) of the investment and the resulting positive cash flow \( R(t) \):

\[ NPV = -I_0 + \sum_{t=1}^{20} \frac{R(t)}{(1+r)^t}, \]  

(3)

where:

\[ I_0 = \text{ListPrice} \cdot \text{Discounts} \]  

(4)

\[ R(t) = \text{ASM}(a) \cdot (\pi(j) + c_{own}(j)) \cdot k(a,\text{sales}) \cdot 365. \]  

(5)

turns from negative to positive. \( I_0 \) is the initial investment cost, or ownership cost, of an aircraft and \( R(t) \) is the cash flow from operation (revenues minus operating costs) per period. In our analysis, the list price of an aircraft is taken from the manufacturer’s official website, whereas the purchase cost discount is assumed to be 40\% based on observed industrial practices (Michael, 2012). \( \text{ASM}(a) \) is the average daily available seat miles (ASM) of aircraft \( a \), \( \pi(j) \) is the average operating profit per ASM of agent \( j \), and \( c_{own} \) is the average cost of owning or renting an aircraft for agent \( j \) per ASM. The sum of \( \pi(j) \) and \( c_{own} \) is thus the operating profit before investment cost per ASM. In accounting and reporting, \( \pi(j) \) is usually calculated as revenue minus various costs, including ownership costs, \( c_{own} \). However, since ownership cost is already represented by \( I_0 \), \( c_{own} \) is added back here to avoid double
counting. The values for \( \pi(j) \) and \( c_{own} \) are simulated in the model based on observed profitability in the industry and will be elaborated in the subsection 3.4 Calibration of the Model. \( k(sales) \) is a scale factor that captures the learning-by-doing effect and economies of scale effect. Organizational learning, as shown by Attewell (1992), is very relevant for the diffusion of technology innovations. It adjusts the operating profit based on the total number of sales. \( k(sales) \) is thus a function of total adoption, i.e. sales of aircraft \( a \) by all agents, and is updated every period of the simulation as the number of sales progresses. ASM and \( k(sales) \) are estimated in the following way:

\[
ASM(a) = S_a \cdot D_a \cdot L_a 
\]

\[
k(sales) = 1 + \frac{sales}{M},
\]

where \( S_a, D_a, \) and \( L_a \) are the number of seats available on aircraft \( a \), the average number of daily departures, and the average stage length per departure for aircraft \( a \). These differ for each aircraft model series and by airline, as airlines often use the same aircraft model series differently. Hence, an estimated industrial average is used here for estimation. Airplanes also undergo routine checks and maintenance; however, the number of daily departures is calculated as the daily average, and thus has already taken this into account.

The yearly cash flow \( R(t) \) generated by the investment in an aircraft is calculated as the product of the daily ASM, operating profit per ASM adjusting for \( c_{own} \), i.e. \( (\pi(j) + c_{own}(j)) \), the total number of days in a year, and the scale factor \( k(sales) \). The discount rate \( r \) is assumed to be 7.5% based on industry historical weighted average cost of capital values from IATA (2018). Notice that this set-up is a modification of the economic utility calculation from Palmer et al. (2015). We follow the approach of Palmer et al. (2015) in the calculation of \( b_{econ} \) based on payback period, whereas the exact calculation of \( I_0 \) and \( R(t) \) are tailored to fit the aviation industry.

### 3.2.2 Environmental Benefit

The environmental benefit \( b_{env} \) considers the engine emission of unburned hydrocarbon (UHC), carbon monoxide (CO), smoke (particulate matters), nitrogen oxides (\( NO_x \)), as well as noise. It is estimated as the overall improvement relative to regulatory standards including those set by the Committee on Aviation Environmental Protection (CAEP), a technical committee of the International Civil
According to the ICAO website:

_Aircraft are required to meet the environmental certification standards adopted by the Council of ICAO. These are contained in Annex 16 (Environmental Protection) to the Convention on International Civil Aviation. This Annex at present consists of two volumes, viz., Volume I: Aircraft Noise and Volume II: Aircraft Engine Emissions. These certification Standards have been designed and are kept up to date in order to respond to concerns regarding environmental impact of aviation on communities in the vicinity of airports as well as society at large._

(ibid)

Accordingly, the environmental benefit is calculated in the following way:

\[ b_{env}(a) = \sum_m w_m \cdot (1 - E_m), \]  
(8)

where:

\[ \sum_m w_m = 1 \quad \text{for } m \in M : \{UHC, CO, Smoke, NO_x, Noise\} \]  
(9)

\[ E_m \in [0, 0.1]. \]  
(10)

\(E_m\) is the emission by the engine of aircraft \(a\) expressed as a percentage of the regulatory limit set by CAEP. Noise emission specifically is measured as the cumulative noise of take-off, flyover, and approach. New and more stringent emission standards could lead to the emission of older out-of-production models to exceed 1. However, as adoption is considered not retrospectively but contemporarily, the emission is estimated based on the standards used at the time. \(E_m\) is thus always between 0 and 1, since emission must satisfy the regulatory standards.

\(w_m\) is the weight assigned to each emission product as well as noise. This is because the impact on climate, local air quality, and environment differs for each type of emission. Husemann et al. (2018) did a survey study on the weights that airlines place on various performance and product criteria when selecting aircraft model series. A 1 to 5 scale is used in the survey with 1 meaning the most important. We assume that each point is equidistant, and therefore noise is considered to be twice as important as \(NO_x\). Moreover, smoke and \(NO_x\) contribute relatively more to local air quality concerns than UHC.
and CO do (Dickson, 2014). As such, the weight is calibrated to be 0.1, 0.1, 0.2, 0.2, 0.4 for UHC, CO, Smoke, NO\textsubscript{x}, and Noise respectively, assuming transitivity.

### 3.2.3 Flexibility Benefit

According to Husemann et al. (2018), flexibility, especially in terms of range, capacity (here we consider the number of passengers, i.e. pax, to be the capacity) and commonality, is considered by airlines to be a vital feature and almost equally important as direct operating costs. This could be the reason behind the purchase of oversize aircraft despite higher fuel costs, and suggests that airlines do prefer aircraft with a range that more than covers the intended operational range. In our simulation, commonality is not considered, as it would require the configuration of the existing fleet of each airline. This could, however, be explored in future studies. In order to capture the benefit of flexibility, \( b_{flex} \) is estimated as the weighted sum of benefit from range, \( b_{range} \), and the benefit from the number of passengers or capacity i.e. pax, \( b_{pax} \), in the following way:

\[
 b_{flex}(a) = w_{range} \cdot b_{range}(a) + w_{pax} \cdot b_{pax}(a). \tag{11}
\]

In order to calculate \( b_{range} \) and \( b_{pax} \), it is important to first classify the aircraft model series \( a \) into either short-haul (SH), medium-haul (MH), or long-haul (LH). This is because for each category, airliners have a different set of optimal range and capacity parameters. The classification is done in the following way: If the range of aircraft \( a \) is smaller than the minimum range required by airlines for medium-haul flights, then aircraft \( a \) is classified as a short-haul aircraft, and if the range is longer than the minimum required for long-haul flights, it is classified as a long-haul aircraft. The benefits are then calculated as:

\[
 b_{pax}(a) = \begin{cases} 
 1 - \beta \cdot (pax_a - l\text{pax}_{sh,mh,lh})^2, & \text{if } pax_a \leq l\text{pax}_{sh,mh,lh} \\
 1, & \text{if } l\text{pax}_{sh,mh,lh} \leq pax_a \leq u\text{pax}_{sh,mh,lh} \\
 1 - \gamma \cdot (pax_a - u\text{pax}_{sh,mh,lh})^2 & \text{otherwise}; 
\end{cases} \tag{12}
\]
\[ b_{\text{range}}(a) = \begin{cases} 
1, & \text{if } \text{range}_a \geq \text{optrange}_{\text{sh, mh, lh}} \\
\frac{\text{range}_a}{\text{optrange}_{\text{sh, mh, lh}}}, & \text{otherwise.}
\end{cases} \tag{13} \]

The quadratic function is used for capacity here to represent the risk-averse nature of investor behavior. The \( b_{\text{pax}} \) here essentially captures the idea that the benefit is at 1 when the capacity of aircraft \( a \), i.e. \( \text{pax}_a \) is within the upper and lower optimal capacity bound (\( l \text{pax} \) and \( u \text{pax} \)) deemed optimal by airlines, and when there is under- or over-capacity, the marginal decreases in the benefit increases with the deviation from the optimal capacity bound, as it becomes increasingly difficult or operationally expensive to fill the seats. \( \beta \) and \( \gamma \) are calculated such that \( b_{\text{pax}} \) lies between 0 and 1.

The benefit for range, \( b_{\text{range}} \), is not quadratic, since additional range does not necessarily lead to higher costs in operations. Therefore, \( b_{\text{range}} \) is 1 as long as the range of aircraft \( a \), i.e. \( \text{range}_a \), fulfills the optimal range \( \text{optrange} \), and it decreases as \( \text{range}_a \) falls from \( \text{optrange} \). Note that the respective lower bound of optimal passenger capacity for SH, MH and LH aircrafts \( l \text{pax}_{\text{sh}}, l \text{pax}_{\text{mh}}, \) and \( l \text{pax}_{\text{lh}} \) applies depending on the classification of aircraft \( a \). This is the same with other parameters as well.

### 3.3 Calibration of Weights for each Benefit

The weights \( w_{\text{econ}}(j), w_{\text{env}}(j) \) and \( w_{\text{flex}}(j) \) need to be calibrated in order to calculate the overall benefit, \( B(a, j) \). In some other literature, calibration is conducted by fitting simulation results with historical data (Palmer et al., 2015). In this model, this is achieved in a systematic way based on airline characteristics as follows:

\[
\begin{align*}
w_{\text{econ}}(j) &= 1; \tag{14} \\
w_{\text{env}}(j) &= \frac{\text{region} \cdot \text{size}}{k}; \tag{15} \\
w_{\text{flex}}(j) &= \begin{cases} 
0.8, & \text{if the airline is a low-cost carrier (LCC)} \\
0.67, & \text{otherwise.}
\end{cases} \tag{16}
\end{align*}
\]

\( w_{\text{econ}}(j), w_{\text{env}}(j) \) and \( w_{\text{flex}}(j) \) are then adjusted proportionally so that the sum of all weights is 1.

The calculation of \( w_{\text{env}} \) requires the three parameters \( \text{region} \), \( \text{size} \), and \( k \). \( \text{region} \) is calibrated in the model to be from 1 to 4, corresponding to Africa, Asia Middle East and Oceania, Americas,
and Europe. Size is calibrated as 1 and 2 for large and small airlines, respectively. The rule-of-thumb formulation for $w_{env}$ captures the idea that (1) larger airlines tend to care more about emissions and noise, and (2) regions such as Africa and Asia have relatively less stringent pollutant emission reinforcement. $k$ is then adjusted to fit historical data.

The calculation of $w_{econ}(j)$ and $w_{flex}(j)$ is derived on survey results and differs based on whether the airline is LCC or not. The values are adapted from Husemann (2015)\textsuperscript{1}.

The entire decision process is summarized in Figure 1. The agent-based model features airlines, financial institutions such as banks, passengers, and regulatory bodies as different types of agents. Airlines would be the agents that make the adoption decisions actively. Banks and other financial institutions determine the financing cost, i.e. the discount rate that enters into the agent-based model during the calculation of the economic benefit, $b_{econ}(a, j)$. Passenger behavior influences what the airlines consider as optimal passenger number, and this is used in the calculation of the flexibility benefit, $b_{flex}(a)$. Lastly, regulatory bodies set the emission limit, which is then used in the calculation of environmental benefit, $b_{env}(a)$. These agents’ behavior and preferences determine the agents’ parameters, which are fed into the model to set up the calculation of $b_{econ}(a, j)$, $b_{flex}(a)$, and $b_{env}(a)$. In addition, aircraft model series information would also be fed into the model during this step.

Once the agents parameters and aircraft parameters are set up, economic benefits $b_{econ}(a, j)$, flexibility benefits $b_{flex}(a)$, and environmental benefits $b_{env}(a)$, respectively, are calculated based on individual agent’s parameters and aircraft parameters. The weights: $w_{econ}(j)$, $w_{flex}(j)$ and $w_{env}(j)$ for $b_{econ}(a, j)$, $b_{flex}(a)$, and $b_{env}(a)$ respectively are calculated at the same time, again based on agent’s individual parameters. Combining the weights for each agent as well as $b_{econ}(a, j)$, $b_{flex}(a)$, and $b_{env}(a)$ for each agent, we can obtain the overall benefit $B(a, j)$ for each agent. This overall weight is then compared to the threshold $B^*$ (which is the same for all agents) in order to arrive at the final adoption decision.

\textsuperscript{1}In Husemann (2015), surveys are sent out to various airlines regarding their preferences when purchasing airplanes. The airlines could choose on a scale from 1 to 5 regarding how important they consider various parameters including costs and flexibility. In their scale, 1 is considered most important and 5 least important, and the percentage of airlines choosing each number on the scale is given. In this study, we therefore converted the scale based on the following rules: the scale 1 to 5 is converted to 1, 0.8, 0.6, 0.4, and 0.2 respectively, with 5 converted to 0.2. These values are then multiplied with the corresponding percentage of airlines choosing them. For instance, for national airlines (non low cost airlines), in terms of flexibility, 5% ranked it at scale 1, 65% at 2, 10% at 3, and 20% at 5. Hence the weighted average is $0.05*1 + 0.65*0.8 + 0.1*0.6 + 0.2*0.2 = 0.67$, and this is assigned as $w_{flex}(j)$ for non low cost airlines. Meanwhile, for the same airline group, 100% ranked costs at 1, hence $w_{econ}(j)$ is 1 here.
3.4 Calibration of the Model

To simulate the model, a number of assumptions are made regarding the parameters as introduced above. An overview of the values used, with the source of the values, is listed in Tables 1 and 2.

Based on data presented in Table 2, \( \pi(j) \) excluding \( c_{own} \) per ASM is simulated as a discrete random number drawn from a uniform distribution between operating profit per available seat miles (upper bound and lower bound, i.e. 0.036 USD and 0.013 USD, 1USD \( \approx 0.9\text{euro} \)).

The model is set up in the following way: 1000 decision slots, i.e. the market potential to be made regarding adoption is assigned to airlines. Airline characteristics and other conditions for decision making are then simulated and attached to each decision, including LCC (low cost carrier) or traditional, region, airline size, and \( \pi(j) \) excluding \( c_{own} \). 1000 decision slots are assigned to airlines, rather than 1000 agent airlines being generated, because in reality, one aircraft model series is usu-
ally adopted by only a few airlines but in bulk rather than each airline making a binary decision on adoption or no adoption.

After setting up, the model is run 20 times, representing 20 years in reality. In each run, the following calculation is made:

1. Decision slots where the decision in the last period is ‘not adopting’ are selected;
2. Adoption decisions are made based on the benefits calculated;
3. The total number of adoption for the current run is computed, i.e. sales;
4. The sales number of aircraft $a$ is updated in the model for calculation in the next run.

$B^*$ is calibrated such that the total number of sales in each period best corresponds to historical data. Projection for future adoption or adoption of other aircraft model series can then be performed.

Furthermore, we chose the Boeing 737-500 model for our simulation. It is part of the Boeing 737 Classic narrow-bodied jet airliner comprising of Boeing 737-300, -400, and -500 series. The Boeing 737 Classic jetliners improved upon the previous generation of 737-100/-200 model series whose production started back in 1966. Newer series based on the 737 Classic include 737 Next Generation and 737 Max. The production of the Boeing 737-500 ran from 1990 to 1999, which means that the diffusion process has stopped, thus allowing the comparison of simulation results with a complete actual diffusion process. This model is also very much relevant to modern aviation because of the relatively recent production period and the new generation of Boeing 737 models. Lastly, because the Boeing 737-500 is a classic and widely used model, parameter data especially operational data for this model can be gathered more easily than for newer types of aircraft model series. More specifically, we chose the 737-500 series instead of the other two variants mainly due to data availability issues.
Table 1: Overview of model parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model Setup Parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percentage of flights by low cost carrier vs traditional airlines</td>
<td>20%, 80%</td>
<td>EASA (2016)</td>
</tr>
<tr>
<td>Market share of large airlines vs small airlines</td>
<td>46%, 54%</td>
<td>ICAO (2016)</td>
</tr>
<tr>
<td>Current fleet region breakdown: Africa, Asia Middle East and Oceania, Americas, Europe</td>
<td>5%, 40%, 35%, 20%</td>
<td>Boeing (2018)</td>
</tr>
<tr>
<td>Discount rate</td>
<td>7.5%</td>
<td>IATA (2018)</td>
</tr>
<tr>
<td>Operating profit per ASM upper bound (excluding ownership cost)</td>
<td>0.036 USD</td>
<td>refer to Table 1</td>
</tr>
<tr>
<td>Operating profit per ASM lower bound (excluding ownership cost)</td>
<td>0.013 USD</td>
<td>refer to Table 1</td>
</tr>
<tr>
<td>Expected life of an aircraft</td>
<td>20a</td>
<td>Industry Accounting Working Group (2016)</td>
</tr>
<tr>
<td><strong>Decision Parameters</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( w_m ) for ( m \in M ): {UHC, CO, Smoke, NOx, Noise} in calculating ( b_{env} )</td>
<td>1, 1, 2, 2, 4</td>
<td>calculated from Husemann et al. (2018); Dickson (2014)</td>
</tr>
<tr>
<td>( w_{range} ) and ( w_{pax} ) in calculating ( b_{flex} )</td>
<td>9.2, 8.6</td>
<td>calculated from Husemann et al. (2018)</td>
</tr>
<tr>
<td><strong>Aircraft Parameters for Boeing 737-500</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>List Price</td>
<td>34.5 million USD</td>
<td>archived manufacturer website in 1999</td>
</tr>
<tr>
<td>Available Seats ((S_a)), Daily Departure ((D_a)), Stage Length ((L_a)) for calculating ASM</td>
<td>112, 5.4, 561 miles</td>
<td>average calculated from Economic Development (2017)</td>
</tr>
<tr>
<td>range</td>
<td>2733 miles</td>
<td>Startup (2007), converted from nautical miles</td>
</tr>
<tr>
<td>Emission, ( E_m ) for ( m \in M ): {UHC, CO, Smoke, NOx}</td>
<td>36.7%, 75.8%, 21.1%, 96.7%</td>
<td>ICAO (2018)</td>
</tr>
<tr>
<td>Emission for Noise, ( E_{noise} )</td>
<td>97%</td>
<td>FAA (2012)</td>
</tr>
</tbody>
</table>

1 Average from 2000 to 2018 of industry weighted average cost of capital (WACC)  
2 Accounting life  
3 Apart from the 737-800 model, one single aircraft model series is sold mostly around 1000 times  
4 Noise is twice as important as NOx and other emissions if using straight line method to calculate survey result  
5 Smoke and NOx are highly important to air quality, UHC and CO to a lesser extent  
6 http://www1.boeing.com/commercial/prices/index.html, archived page in year 1999  
7 Emission data taken for the corresponding engine used on Boeing 737-500  
8 Noise data taken directly for Boeing 737-500, due to various regulatory standards, 100 is chosen here as an arbitrary standard. This does not affect the simulations since it is only a conversion parameter.
### Table 2: Calculations for operating profit per ASM upper and lower bounds

<table>
<thead>
<tr>
<th>Parameter (USD per ASM)</th>
<th>Value for Upper Bound</th>
<th>Value for Lower Bound</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average total revenue</td>
<td>0.101</td>
<td>0.101</td>
<td>average from Global Airline Industry Program (2019)</td>
</tr>
<tr>
<td>EBIT margin</td>
<td>30%</td>
<td>5%</td>
<td>Pearce (2016)</td>
</tr>
<tr>
<td>EBIT</td>
<td>0.0303</td>
<td>0.00505</td>
<td>Own calculation</td>
</tr>
<tr>
<td>Operating expenses and depreciation</td>
<td>0.0707</td>
<td>0.09595</td>
<td>Own calculation</td>
</tr>
<tr>
<td>Aircraft ownership cost as percentage of total cost</td>
<td>7.8%</td>
<td>7.8%</td>
<td>Stalnaker et al. (2016)</td>
</tr>
<tr>
<td>Aircraft ownership cost</td>
<td>0.0055</td>
<td>0.0075</td>
<td>Own calculation (1)</td>
</tr>
<tr>
<td>EBIT before deducting aircraft ownership cost</td>
<td>0.036</td>
<td>0.013</td>
<td>Own calculation</td>
</tr>
</tbody>
</table>

1 This calculation is done by multiplying operating expenses and depreciation with the aircraft ownership cost as a percentage of total cost. Note that here we are looking at the industry overall aircraft ownership cost in order to find the general EBIT before deducting aircraft ownership cost, and we are not calculating the ownership cost of a specific aircraft model series. The cost of a specific aircraft model series would be done in our agent-based model during the adoption decision process when we look at the NPV of purchasing a specific aircraft model series.

The model calibration and application process is summarized in Figure 2.

![Model Initialization and Calibration Diagram](image)  

**Model Initialization and Calibration**
- Initialization
  - Generation of agents
  - Characterization of agent type, region, size
- Simulation Step 1
  - Adoption decision
- Simulation Step 2
  - Adoption decision
- Last Simulation Step N
  - Adoption decision
- Model Calibration
  - Threshold calibration with historical data

**Product Parameters**
- Parameters of aircraft to be diffused

**Potential Model Applications**
- New Product Parameters
  - Parameters of aircraft to be diffused
- Diffusion projection of new product
- Longer Time Horizon
  - Increase number of steps in the simulation
- Future diffusion pattern of existing product based on historical data

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Figure 2: Illustration of the model initialization, calibration and application process
4 Results and Analysis

4.1 Simulation and Calibration Results

Because certain parameters for agents are randomly drawn from a distribution, we ran the simulation 50 times in order to have an overview of possible simulation outcomes. In contrast to the traditional approach, where only one or several simulation results are reported, our method presents a more general and unbiased picture of possible outcomes. Figure 3 (left) shows the diffusion curve for 50 simulations, each with 10 periods of simulation steps. The reason for a 10-period simulation is that this aircraft model series considered (Boeing 737-500) was only delivered for 10 years from 1990 to 1999 based on historical delivery data from the official Boeing website (Boeing, 2019). We have calibrated the model based on the actual historical data, and set $B^*$ to 0.79, and $k$ to 25. We observe that the diffusion curves at the early stage of adoption are less scattered than at the later stage, which reflects well the reality that a longer time horizon brings larger uncertainty in a simulation. Moreover, with 50 simulations, no result that is extremely unlikely in the actual market is produced, which shows the stability of our model-based projections.

To compare our simulation with actual historical data, we first need one representative simulated diffusion curve. To achieve this, for each step of the simulation we take the average across 50 simulations and compute the average diffusion curve. The comparison with actual data is plotted in Figure 3 (right). The historical data of deliveries is again taken from the official Boeing website (Boeing, 2019) for the model Boeing 737-500. It is worth noting that although the results with 50 simulations show a broad band of potential outcomes, the averaged curve performs extremely well when compared with actual data. Both the predicted overall number of adoption as well as the diffusion process fit well with the actual data.
4.2 Application of the Simulation Results

In this section, we show the applications of the simulated and calibrated model. Our model could be applied in several ways to generate a meaningful diffusion projection or to construct alternative scenarios. For instance, parameters of an aircraft model series with new technologies could be fed into our model in order to predict the diffusion of this enhanced aircraft model series. In addition, we could also generate different scenarios by changing different parameters. For instance, the parameter for the list price of Boeing 737-500 is set to 34.5 million USD for baseline simulation. The exact change to sales with a price reduction to, say, 33 million USD can be simulated, the results of which are shown in Figure 4. This estimate could aid manufacturers considerably in their production and pricing decisions.

Figure 3: Diffusion curves from 50 simulations (left) and actual historical sales vs mean of simulation results (right) for the Boeing 737-500, $B^* = 0.79$
Another scenario with respect to environmental impact could also be constructed. Figure 5 shows the diffusion process if the NO\textsubscript{x} emissions are reduced from the actual 96.7% of the regulatory limit to a hypothetical 70%. This shows that, to a certain extent, emission reduction technologies are not only relevant for our environment, but such technologies could also be translated to improved commercial adoption of greener products.

Additionally, the calibrated model could be applied to the forecast of new product diffusion process, shown as the part encircled by the bold dotted line in Figure 6. This means, we keep the decision threshold $B^*$ calibrated to be 0.79, and weights scale $k$ calibrated to be 25 during the simulation process here as well, and run the simulation again with these calibrated values.
Here we have chosen the Boeing 787-8, a relatively new model with readily available data. The Boeing 787-8 is part of the Boeing 787 Dreamliner, a long-haul, mid-sized, wide-body, twin-engine jet airliner. As a relatively new series, it incorporates many advanced technologies such as composite material in the construction of the airframe, electrical flight system, and raked wingtip. The design of the 787-8 was intended to replace the older model of the Boeing 767. We only use aircraft specific parameters shown in Table 3. Instead of using $S_a$, $D_a$, and $L_a$ (the number of seats available on aircraft $a$, the average number of daily departures, and the average stage length per departure) to calculate daily available seat miles (ASM), we use ASM directly taken from the source provided.
Table 3: Input Parameters for Boeing 787-8

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Sources</th>
</tr>
</thead>
<tbody>
<tr>
<td>List price</td>
<td>152.75 million USD</td>
<td>Archived manufacturer website (1)</td>
</tr>
<tr>
<td>ASM</td>
<td>1,350,000</td>
<td>Average taken from US DOT Form 41 data</td>
</tr>
<tr>
<td>Range</td>
<td>8406 miles</td>
<td>Boeing Official Website (2)</td>
</tr>
<tr>
<td>Pollutant emissions, $E_m$ for $m \in M$:</td>
<td>8.2%, 27.1%, 26.1%, 46.1%</td>
<td>ICAO (2018)</td>
</tr>
<tr>
<td>Noise emissions, $E_{noise}$</td>
<td>98%</td>
<td>FAA (2012)</td>
</tr>
</tbody>
</table>

1 Average price from archived Boeing website in 2010 http://boeing.com/commercial/prices/index.html
2 https://www.boeing.com/commercial/787/, converted from nautical miles to miles

Using an existing aircraft here rather than a completely new aircraft not yet in service gives certain advantages. Firstly, with an existing model, product-specific information is readily available. Secondly, we could still run the model only with information that is available before the diffusion (i.e. product level information and ABM calibration results from before). In this way, our simulation would be as if the product is being newly launched. Lastly, we could compare the simulation results with actual sales data in order to gauge the forecasting performance of our ABM. Figure 7 shows the simulation results from 50 runs and the comparison between actual sales and the average of all simulations. We see that the simulation results are relatively close to actual sales.

Figure 7: Diffusion curves from 50 simulations (left), and actual historical sales vs mean of simulation results (right) for the Boeing 787-8

The second application of this model would be to increase the number of steps i.e. time periods, in order to forecast future sales of an existing model, shown as the part encircled by the bold dotted line in Figure 8.
Building on the simulation of the Boeing 787-8 from above, we ran the model for 20 steps instead of 10 steps. The results are presented in Figure 9. For companies planning production and deliveries of airplanes, for airlines planning their fleet maintenance strategy, as well as for policymakers with interest in the aviation industry, this could be very helpful in knowing the market potential and diffusion patterns shown in Figure 9.
4.3 Discussions and Limitations

In our study, we concentrate on the binary adoption decision for one singular aircraft model series, whereas in some cases, airliners are choosing between several similar competing models. This process of comparison and choice behavior is not implemented in our model, and it could be further explored in future studies. A second limitation of our model is inherent in the random assignment during the setup of the model. As agent characteristics are randomly generated from distributions, the simulation results vary each time, which could lead to difficulties with interpreting the results and using the results to derive actionable plans. However, this may also reflect the uncertainty that is always associated with new product launch and sales forecasting. Furthermore, unexpected rare but extremely impactful events, such as a plane crash resulting from an aircraft’s technical (e.g. mechanical problems), could severely affect the diffusion of that aircraft model series e.g. the case with the Boeing 737 Max. This uncertainty is also not included in our model due to the difficulties associated with the quantification and modeling process. In addition, for the simulation and application, we only used aircraft model series by Boeing due to data availability issues. However, when data are available for Airbus or other aircraft manufacturers, the agent-based model could be adjusted and applied as well since there is no inherent assumption of manufacturers in the model. This is especially the case given that the airplane market is almost a duopoly between Airbus and Boeing, and their orders and
deliveries, as shown by Figure 10 match each other relatively closely. Note that Figure 10 shows the yearly orders and deliveries, not the cumulative orders and deliveries.


Source: Airbus and Boeing Official Website: https://www.airbus.com/aircraft/market/orders-deliveries.html; http://www.boeing.com/commercial/orders-deliveries

Lastly, many other aspects that could influence the diffusion process are not included in the model. First, the competition and strategic behavior of suppliers, adopters, as well as the market structure are not included. These interactions and structures could have a significant effect on the adoption of technological innovations by organization as shown by Gatignon and Robertson (1989). Moreover, trend and change in technology development and consumer taste are also not included here. Lastly, we do not study the general macroeconomic conditions such as the the business cycle or international trade issues which could influence demand for air travel, financing cost, etc., for instance, Irwin and Pavcnik (2004) examined how the trade agreement influences prices and costs for Boeing and Airbus planes under the duopolistic market structure. For a more advanced and holistic model, these aspects should ideally be considered.
5 Conclusion

In this study, we built and calibrated an agent-based model for the prediction of aircraft model series diffusion. Rather than focusing only on the profit-maximizing behavior of airlines in their decisions to adopt, we include additional aspects, i.e. environmental and flexibility concerns, to reflect the complexities facing airline operations today. This does not only reflect more closely the multidimensional decision-making process in the firm, but also allows more flexibility and more information to be generated from construction of alternative scenarios. Our model is calibrated based on historical data and the results are shown in comparison with actual data. Our results are highly consistent with actual data, which suggests good applicability for future aircraft model series. Our constructed scenarios with price reduction and emission reduction also demonstrate how this model could aid the pricing and production decision of manufacturers as well as the design decision to include emission technologies. This model can be applied to the forecasting of similar newer models where no historical data are available. Alternatively, with aircraft model series that have been recently launched, our ABM can be calibrated and then applied in order to forecast expected future diffusion. As with all simulation models, some degree of simplification is inherent in our model as well, and thus leaves ample room for future research.

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References


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