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Forecast of Aircraft Retirement Probabilities using Neural Networks

Clemens Schlesinger[a]* , Wolfgang Grimme[a]

[a]*German Aerospace Center (DLR) – Institute of Air Transport and Airport Research, Linder Höhe, 51145 Cologne, Germany*

Abstract

In this paper, we present a novel approach for the prediction of retirement curves, which summarize the survival / retirement probabilities of aircraft. Retirement curves are used to predict the future aircraft fleet composition, as an element of air traffic and emissions forecasts. Furthermore, retirement curves are a tool for aircraft manufacturers and leasing companies to estimate the need for replacement aircraft as part of global aircraft demand. We have applied a methodology involving neural networks, previously being used in the area of predictive maintenance. Transferring this method of data analysis to a new research field goes beyond previously applied methodologies, as neural networks are known for finding connections in data that cannot be explicated with other methodologies. In the context of retirement curves, neural networks can help to explain the influence of economic factors or general market development on aircraft retirement.

We implement a neural network to calculate survival probabilities of aircraft and estimate the impact of economic framework data on survival probabilities. The neural network uses the global passenger aircraft fleet as training data base and predicts survival probabilities which then are arranged into retirement curves. We then compare the results to other retirement curve prediction methods. Finally, we take an outlook on possible enhancements of this method and amplification options to improve the quality of the forecast.

Keywords: Aircraft; Aircraft Retirement; Neural Network; Artificial Intelligence; Air Transport Forecasting

1. Introduction

The lifespan of aircraft has evolved constantly over the last decades. Innovation cycles by aircraft manufacturers have been prolongated in recent decades, compared to the situation in the 1960s and 1970s, where new aircraft types have entered into service at shorter intervals. High aviation growth rates in the past decade in combination with relatively low fuel prices have motivated airlines to keep aircraft in service for a longer time span. This is for instance reflected by the extended service goal for A320 aircraft, introduced by Airbus in 2008, allowing for an operation of up to 120,000 flight hours for each individual airframe (Airbus, 2008). In the current situation, regarding

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COVID-19, this trend has somehow reverted, as cost saving measures seem to be more important than ever before. Aircraft considered by operators as relatively inefficient are retired at comparably young age, in order to reduce operational costs in an environment with considerably lowered demand levels. Boeing estimates that in a typical year about 2-3% of the global fleet are retired, but during previous crises (9/11 in 2001, SARS in 2003 and the global financial crisis 2007-2009), the annual retirement rate has increased to 4%-5% of the global fleet. It is expected that due to the gravity of the COVID-19 pandemic, these values will be surpassed. The trend of retirements of four-engined widebody aircraft like the Boeing 747-400, Airbus A340 and Airbus A380 is an indicator for the surge in retirements in the current situation.

In this paper, we analyze the influence of economic framework data such as oil prices, gross domestic product (GDP) per capita and the number of annual passengers on aircraft retirement, using a neural network. The paper is structured as follows: First, a literature review shows existing work in modelling retirement curves and the application of artificial intelligence, followed by a section on empirical findings on aircraft retirement. We then estimate the survival probability of different aircraft types with a neural network we created for this purpose, utilizing data on the global passenger aircraft fleet as training data. The paper concludes with a discussion on the retirement forecasts' impacts on future aircraft fleet planning and airline business models.

2. Literature Review

The modelling of retirement of commercial aircraft is incorporated in various air transport forecasts. For instance, both the Airbus Global Market Forecast (Airbus, 2019) and the Boeing Commercial Market Outlook (Boeing, 2020) contain sections on the number of retired aircraft in a 20-year forecasting horizon, as these determine together with the number of aircraft required to accommodate aviation growth, the number of new aircraft deliveries. Boeing estimates that between 2020 and 2039 48% of all newly delivered aircraft will be used to replace retired aircraft (Boeing, 2020). In its latest publication, Airbus estimates 12,730 passenger and 1,480 freighter aircraft to be retired between 2019 and 2038 (Airbus, 2019).

Forecasting the retirement of aircraft is also of commercial relevance e.g. to leasing companies, in order to estimate market trends, the residual values of used aircraft and the business planning of ordering new aircraft (Forsberg, 2015). Also, for the forecast of long-term environmental impacts of aviation, the modelling of aircraft retirements is important, as the composition of the global aircraft fleet determines its environmental efficiency. Shorter aircraft life-spans lead to a higher replacement rate with more fuel-efficient types and hence a more environmentally friendly aviation system. Studies in this area include Schaefer (2012), who forecasted emissions for worldwide air traffic until the year 2030 and Dray (2013), who discusses the impact of variations in aircraft retirement on global emissions. While the aforementioned literature is macroscopic, a more microscopic view on the topic is taken by airlines. Based on various factors such as cash flow, maintenance and operational costs they determine the economic life of an aircraft or aircraft fleet. Models in this regard can be found in the literature for instance at Ogunsina et al. (2017).

The summarized representation of survival probabilities of individual airframes is shown in survival curves, also commonly referred to as "retirement curves". These curves represent the summarized individual decisions of aircraft operators in relation to the economic and technical life span of aircraft and also include the effects of involuntary aircraft retirement due to accidents and damages beyond repair. Typical methodologies for the estimation of retirement curves include logistic regression and Cox models. The mathematical techniques for the calculation of aircraft survival and retirement do not fundamentally differ from those frequently applied for the analysis of mortality of populations, e.g. in medical statistics or in the insurance business.

With the propagation and further development of artificial intelligence, a new methodological approach for the estimation of retirement curves has emerged. The methodology applied in this paper for the estimation of retirement curves has its origins in the area of predictive maintenance. While older theses like Hashemian (2010), Wetzer (2004) and Grall et al (2002) often use manually approaches to determine the predictive maintenance, there are already some attempts using artificial intelligence. Susto et al. (2014) use Machine Learning for Predictive Maintenance. The authors train multiple classification models to provide different performance tradeoffs thus minimizing the downtime and associated costs regarding maintenance of machines. Heng et al. (2009) present a novel approach for the forecast of machine failure. The authors train a feed-forward neural network to estimate the future survival probabilities of assets to create survival curves, achieving a prediction more accurate than using manual approaches. Langone et al. (2013) present a novel approach using the unsupervised Machine Learning technique of Kernel Spectral Clustering on the sensor data to distinguish between normal and abnormal data, thereby detecting faults early and showing the need of maintenance in analyzed machines.

3. Empirical Trends in Aircraft Retirement

Aircraft retirement is strongly dependent on many factors. The availability of more efficient aircraft are a key driver, although in times of high demand, also technologically less efficient aircraft can be operated profitably. Also fuel price can be considered a main driver of the airlines' retirement strategy, as this highly influences profitability of the operation of aircraft with different fuel efficiencies.

Figure 1 a) shows the number of aircraft retirements per year during the last three decades. It can be seen, that since the 90s the number of annually retired aircraft is rising, coinciding with the increase in global fleet numbers and the replacement of existing aircraft. Most likely this is caused by the entry into service of new aircraft models with higher fuel efficiency, more range and a higher payload capacity. But around the year 2013 the number of annual retirements started to fall. This timeframe coincides with strong demand growth in the aftermath of the global financial crisis encountered in the timeframe from 2008 to 2012 and relatively moderate fuel prices. Hence, it is very likely that airlines had an incentive to operate their aircraft longer in order to participate in market growth.

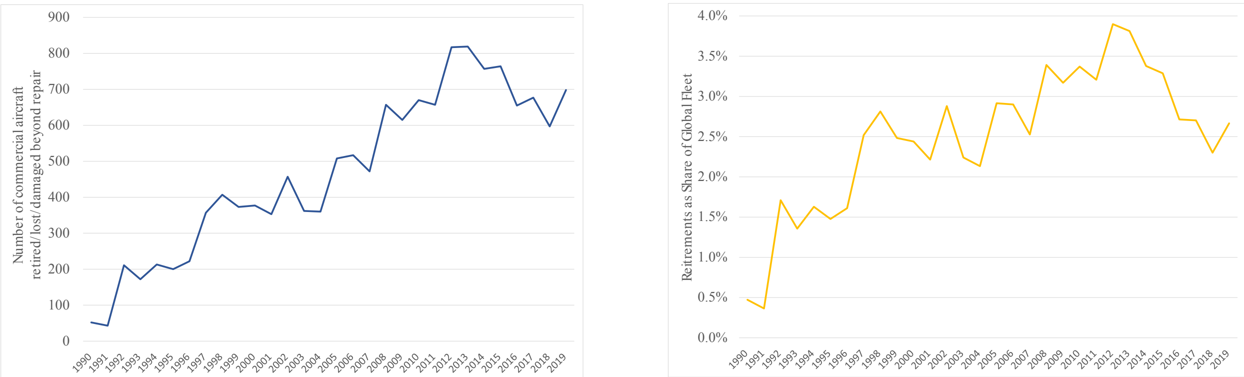

Fig. 1. (a) Retirements and Total Losses of Commercial Aircraft >19 Seats between 1990 and 2019; (b) Retirements of Commercial Aircraft as Share of Global Fleet (Source: Cirium Fleets Analyzer)

The impacts of global events on the retirement rate (measured by the proportion of retired aircraft in the total active fleet) can be seen in Figure 1 b). Often with a short time lag, events like the Asian financial crisis (1997/98), September 11 (2001) and SARS (2003) have temporarily increased the retirement rate close to 3%, with the global financial crisis after 2007 leading to a temporary increase in the retirement rate up to 4%. Since 2013 the retirement rate has shown a falling trend, reaching a low of 2.3% in 2018.

Consequently, we hypothesize that the retirement/survival probability of aircraft is highly dependent on economic factors. The factors analyzed in this paper are the following:

- Gross domestic product per capita (global average) (GDP/capita)
- Global volume of air passengers

- Oil price

4. Input Data & Modelling Approach

For the preparation of training data, we combine two data sources: the global fleet of passenger aircraft between 1955 and 2017 in order to provide tagged training data for the neural network and economic data for the years 1960 to 2019 to enrich the aircraft data with the economic factors. The source of the fleet data is Cirium's Fleet Analyzer (Reed Business Information Ltd., 2019) and we use the crude oil prices for West Texas Intermediate (WTI), obtainable e.g. from the US Energy Information Administration (EIA, 2020), GDP per capita data from the World Bank (World Bank, 2020) and global passenger volumes from ICAO (ICAO, 2020).

In order to avoid problems of non-stationarity of time series data for oil price, passenger volumes and GDP per capita, we use the percentage rate of change in comparison to the previous year.

Another challenge in the process of data preparation was to enrich the aircraft data with the economic data. The economic data in the build year of an aircraft is not relevant for the determination of the survival probability. It is exactly the opposite: the retirement of an aircraft depends on the economic situation in its last year of use and its age. Therefore, we should use the economic data of the last year of use to determine the retirement probabilities. This is not a problem for older aircraft, that already retired. But we do not know the last year of use of new aircraft, which are still in use. To bypass this problem, we use the economic data in the build year, which is known, as well as the economic data each 10, 20 and 30 years after the build year of the aircraft. These values can be calculated, using the build year and data sheets on the economic data.

As it is the aim of this paper forecasting future retirement curves depending on economic framework developments, future scenarios on the developments of GDP/capita, oil price and passenger volumes for the next 30 years have been set up. Through the usage of two different growth rates for each of the three economic factors under consideration, 8 scenarios have been generated. Table 1 shows the combination of economic factors for the 8 scenarios. The data on specific growth rates for GDP/capita, oil price and passenger traffic have been oriented at the IEA World Energy Model (2019), Vaillancourt et al. (2014) and Olsthoorn (2001).

Table 1. Combination of different forecasts

Number of scenario	GDP growth	Oil price growth	Passenger growth
1	2.1 % (low)	2.5 % (low)	3.4% (low)
2	2.1 % (low)	2.5 % (low)	3.9% (high)
3	2.1 % (low)	3.5 % (high)	3.4% (low)
4	2.1 % (low)	3.5 % (high)	3.9% (high)
5	3.1 % (high)	2.5 % (low)	3.4% (low)
6	3.1 % (high)	2.5 % (low)	3.9% (high)
7	3.1 % (high)	3.5 % (high)	3.4% (low)
8	3.1 % (high)	3.5 % (high)	3.9% (high)

These scenarios each will lead to a different forecast of the neural network. The neural network used to predict the survival probability of the aircraft is trained with the described training data. Tests with several different network shapes have shown, that a rather small network with fewer layers and neurons leads to a better result, that a larger network with more layers and neurons. Through short training periods, overfitting is avoided. In the end, a three-layered neural network was used, where the input layer receives the data, passes it to a hidden layer with 20 neurons and a ReLU activation function and the prediction of the survival probability is provided by the output layer with a softmax activation function. This is an important feature to translate the classified input data, whose data tuples are tagged with 1 or 0 (1 for active, 0 for retired) into a steady survival probability. The softmax activation function outputs the affiliation probability for each class. This way, the affiliation probability of the class "active" can be used as survival probability of the aircraft. The neural network was trained in 20 epochs and the resulting forecast of survival probabilities was validated using the Kolmogorov-Smirnov test (K-S test). Furthermore, the created retirement curves were compared with existing retirement curves. The result of each the K-S test and the comparison with existing retirement curves led to an acceptance of the neural network's forecast.

5. Results

Table 2 shows the neural network's forecast for narrowbody type aircraft. The survival probability ascends with increasing age. This phenomenon is easy to explain: The older an aircraft, the more likely it is that it will retire. If plotted in a graph, a retirement curve is created as shown in figure 2. The left graph shows the survival probability forecast of the neural network, while the right graph shows retirement curves, which were estimated using a traditional logistic regression approach.

Table 2: Forecast of survival probabilities for narrowbody aircraft

Aircraft Class	Construction Year	Reference Year	GDP	Oil price	Passenger	Survival Probability
Narrowbody	1960	2020	Low	Low	Low	0.0043
Narrowbody	1965	2020	Low	Low	Low	0.0066
Narrowbody	1970	2020	Low	Low	Low	0.0102
Narrowbody	1975	2020	Low	Low	Low	0.0180
Narrowbody	1980	2020	Low	Low	Low	0.0455
Narrowbody	1985	2020	Low	Low	Low	0.1374
Narrowbody	1990	2020	Low	Low	Low	0.3822
Narrowbody	1995	2020	Low	Low	Low	0.7421
Narrowbody	2000	2020	Low	Low	Low	0.9305
Narrowbody	2005	2020	Low	Low	Low	0.9842
Narrowbody	2010	2020	Low	Low	Low	0.9966
Narrowbody	2015	2020	Low	Low	Low	0.9992
Narrowbody	2020	2020	Low	Low	Low	0.9998

The main difference between these two curves is the fact, that the neural network forecast has a little edge at around 20 years. This is most likely caused by the use of economic data, which is processed by the neural network. Neural networks are known for finding contexts in data, that are invisible for the human eye. Another main difference is the first few years of the "Turboprop" retirement curve. In the DLR forecast ((b), green), its survival probability drops to about 90% after 5 years, while the survival probability stays close to 100% for the first 15 years in the prediction of the neural network ((a), red).

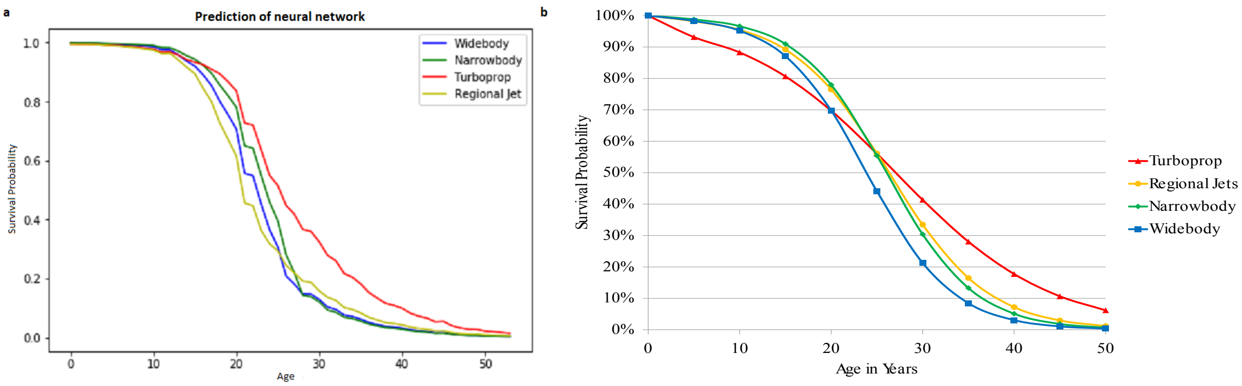

Figure 2: (a) Neural network forecast (b) DLR forecast

Taking a closer look at the training data, figure 3 shows, that the world passenger aircraft fleet, if plotted, shows little edges too. The graph shows all aircraft in the training data set sorted by age and every age groups percentage of non-retired aircraft. During the training epochs of the neural network, the algorithm has sorted out characteristics and generalized to achieve the best possible prediction.

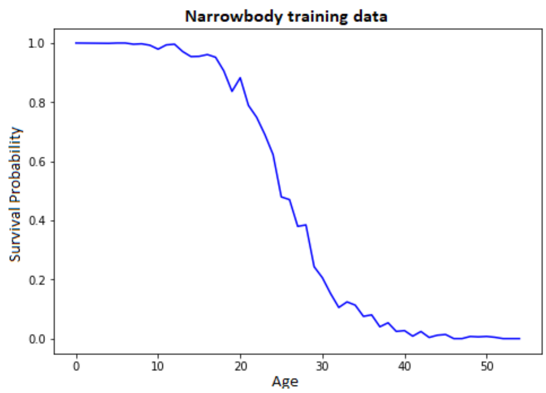

Figure 3: Visualization of training data

Another interesting comparison is looking at forecast for different economic scenarios. Table 3 shows three scenarios with different growth of GDP, oil price and passenger numbers. The first scenario assumes low growth for each GDP, oil price and passenger numbers, while the last scenario assumes high growth rates for all three economic factors. The second scenario assumes a low GDP growth rate, leading to a low passenger number growth rate.

Table 3: Three scenarios with different economic data

Color	GDP growth	Oil price growth	Passenger numbers growth
Blue	Low	Low	Low
Green	Low	High	Low
Red	High	High	High

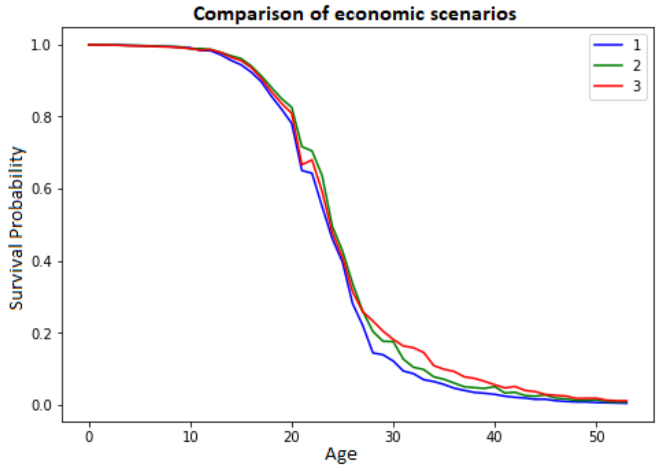

Figure 4: Impact of different economic scenarios on narrowbody survival probability

Figure 4 shows three forecasts for different economic scenarios, as described in Table 3. The difference between the scenarios comes on the one hand side from different economic data for each scenario, on the other hand side it is a deviation caused by separated training of the neural networks.

6. Impact on airline business models and research

The predicted retirement curves described in the preceding section concentrate on the identification of the survival probability of aircraft depending on the age and type of the aircraft including economic data. These can be used in multiple ways.

Retirement curves depict in a summarized way the individual decisions of airlines with regards to their fleets. Hence, they can be valuable indicators helping to explain the mechanisms in the aviation industry, with a particular emphasis on external effects like economic, demand and oil price development. Understanding the impacts of different economic factors on the retirement of aircraft can help increasing the precision of forecasts, so that economic data which is typically reflected in traffic forecasts are also considered in the retirement curves. Here, the approach using neural networks in the prediction of retirement curves can be valuable addition for air transport modelling.

7. Conclusions

As a conclusion, we can say, that using economic data in a neural network to predict retirement curves of aircraft was a successful new approach. This is confirmed by the fact, that clear differences can be seen between the two predictions in figure 3. Using economic data in the neural network, lead to an edge in the retirement curve, which was not predicted using the manual methods without economic data. To what extent this is an improvement has to be determined yet.

Another advantage of the neural networks forecast is the fact that it is a scalable approach. The result of the prediction can be influenced by adding, removing or changing the form of economic data into the training data. For example, the addition of the cohort year of the aircraft already showed an improvement in the estimation of survival probabilities in traditional approaches using a logistic regression. Adding such data is an interesting approach to improve the prediction quality of the neural network. Using the global passenger fleet as training data, the training data base is guaranteed to grow over the years, because the global passenger fleet will grow over the years, creating more and more training data.

Other ideas for optimizing the neural networks forecast are for example the change of the neural networks shape or the usage of different activation functions and dropout layers in the network. There are almost no limits when it comes to adjust neural networks. It might be helpful to separate the neural network into multiple, smaller networks, each processing only one aircraft type. This dimension reduction could improve the networks performance and might be the next step to enhance the prediction of retirement curves. All in all, our method is a good starting point for the new approach, but many improvements and optimizations can be implemented in future. Among these are the usage of more refined training data, reflecting the issue that censored data (i.e. the aspect that aircraft which have not yet been retired) are contained in the training data set and the usage of multiple model definitions in order to minimize the variance of each individual forecast.

In the end we can say, that the prediction of retirement curves using neural networks is like every artificial intelligence approach: the more training data the better the prediction will be. While achieving already good results, the performance of the neural networks forecast will increase over the years due to a consistently growing training data base.

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