Study on Traffic Scenarios
Interdependency of Capacity, Environment, and Cost based on Traffic Forecasts

FINAL VERSION

Ibon Galarraga, Itziar Ruiz de Gauna
Metroeconomica, Bilbao

Thomas Standfuss
TU Dresden, Institute of Logistics and Aviation, Chair of Aviation Technology and Logistics

Executive Summary

The performance evaluation of Air Navigation Service Providers ensures safe, punctual, and cost-effective operations. In recent years, the environmental component of air traffic gained more and more attention in benchmarking exercises. With regards to resource planning, the trade-off between costs and capacity leads to the necessity of a precise traffic forecast. Despite it has been demonstrated that air traffic forecasts are mostly imprecise, the consequences regarding delays, emissions, and environmental costs of different traffic scenarios are still unknown. We aim to determine those interdependencies using state-of-the-art methods, most of them already validated in earlier investigations.

The study is based on the STATFOR traffic forecasts from autumn 2021, including three scenarios (here named as high, base, and low). To consider the low forecast quality, we created two additional scenarios (super-high, super low). For each scenario, flights are forecast for 2021-2027 at the ANSP level. For each ANSP, the expected resources and ATCO employment costs are calculated. The range between super-high and super-low scenario reflects the uncertainty regarding resources and costs. Based on 2015-2019 data, the interdependence between demand and delays is estimated using exponential regression formulas. These formulas can then be used to predict delays based on the previously predicted flights. This approach was performed for all ANSPs, FABs, and Europe separately, and addresses both the total delay and the CRSTMP delay.

Based on the total predicted delays, the cost of these delays was estimated. The first attempt to monetize the cost of one minute of ATFM delay was made by the Transport Studies Group from the University of Westminster (2004) with costs of 72 €, on average per minute of delay. Successive revisions were published (in 2011 and 2015). In 2015, the network average cost of ATFM delay, per minute, was 100 €. However, using the average values does not seem to be a good representation of the real costs, as not all flights are subject to the same amount of delay, so it is crucial to determine the distribution of these delays and how they affect the total cost. This can be done by estimating a cost curve (mathematical) function per minute of delays. In this study, we have compared the results of applying an average value of 100 € and a function. Annual data on total delays (not on CRMSTP delays) have been used to estimate the costs of delays with the average, while in the case of the function, the calculation has been made with daily data for ANSPs. In the absence of information, annual data have been used for FABs and Europe.

To establish the link between forecast and environment we use the indicators KEA and KEP, which evaluate the horizontal flight efficiency. In order to forecast the scores, we must first determine the influencing factors. Using multiple regression analyses, we quantify the influence of e.g., weather, route charges, and CO_2 pricing for each unit. The optimal model is then used to forecast future values for KEA and KEP.

As it is essential to analyze the efficiency of flight paths in order to optimize and balance environmental costs, other variables such as CO_2 emissions and their likely increasing cost need to be explored. A CO_2 price forecasting exercise has been carried out. However, climate and environmental costs go beyond CO_2 costs. For example, they include factors such as non- CO_2 emissions that also cause climate change, noise, or habitat damage. Therefore, in the study, we first focused on CO_2 costs and then moved on to a broader definition of climate and environmental costs: the cost of CO_2 emissions accounts for 34% of the total cost of climate change, with the remaining 66% coming from other sources. All in all, climate change (CO_2 + non-CO_2 effects) represents 63.16% of the total environmental cost.

The traffic scenarios reflect that STATFOR forecasts do not meet their own confidence interval in the majority of cases. However, the additional scenarios also imply greater uncertainty: At the European level 4.8 Mill. Flights, respectively 5,596 ATCOs, or about 860 Mill. €. The interdependency between demand and delay can be approximated by a hyperbolic function in the case of saturated airspaces, while the function tends to be linear for unsaturated airspaces. Applying those formulas led to a total delay between 17.9 Mill. and 45.2 Mill. minutes on a European level. Assuming no change in productivity, respectively technology, the pan-European delay target of 0.5 minutes per flight won't be feasible in any of the scenarios for the years 2026 and 2027. The difference in delay costs when using the average versus the function gives values between 0.69 and 0.78, which means that, when the function is applied, the estimates are between 69% (or 78%) of the average values. In other words, the function makes the value 31% (or 22%) lower than the average.

The prediction of the HFE scores yields intuitively plausible results, but an individual consideration of single units is necessary due to the ANSP-specific particularities. We calculated a KEP between 3.61% and 4.84% for Europe in 2027. The KEA will probably be between 1.94 and 3.06%. Based on these two indicators, the CO_2 costs in 2027 will probably amount to approximately 2,981 to 4,564 Mill. €, depending on the scenario and whether KEA or KEP is considered. The range of values for the climate costs will be between 8,769 and 13,428 Mill. € and, for the environmental costs (which include Climate Change costs as well as noise or loss of biodiversity), between 13,886 and 21,263 Mill. €.

We proved that the approach and the selected methods lead to valid results. The report might be updated once or twice a year, depending on the publication by STATFOR.

Table of Contents

List of Abbreviations

ACE	Air Traffic Management Cost-Effectiveness
ANSP	Air Navigation Service Provider
ATCO	Air Traffic Control Officers
ATFM	Air Traffic Flow Management
ATC	Air Traffic Control
ATM	Air Traffic Management
ATMAP	Air Traffic Management Airport Performance
AUA	Air Traffic Control Unit Airspaces
CFP	Profile based on correlated positions report
CI	confidence interval
FAB	Functional Airspace Blocks
FEM	Fixed Effects Model
FIR	Flight Information Region
FTE	Full-Time Equivalence
FTFM	Last filed flight plan
GHG	Greenhouse Gas Emissions
HFE	Horizontal Flight Efficiency
KEA	Key performance Environment indicator based on Actual trajectory
KEP	Key performance Environment indicator based on last filed flight Plan
KPA	Key Performance Area
METAR	Meteorological Aviation Routine Weather Report
NEST	Network Strategic Tool
NOP	Network Operations Portal
OLS	Ordinary-Least-Squares
POLS	Pooled Ordinary-Least-Squares
PRU	Performance Review Unit
RP	Reference Period
SCR	Shortest Constrained Route
TRA	Temporary Restricted Areas
TSA	Temporary Segregated Area
WITI	Weather Impacted Traffic Index

Please note, that names/abbreviations of ANSPs, ACCs, Sector Groups and FABs are not listed.

List of Figures

List of Tables

1 Background

Air Navigation Service Providers (ANSPs) are responsible for the safe and efficient operation of air traffic. For this purpose, ANSP provides surveillance capacity (measured e.g., flight entries in sector per hour) which can be adjusted according to demand [1]. Obviously, this capacity is built upon human resources and as such incurs costs. In other words, ANSP's responsibility also comprises the efficient deployment of resources to ensure service provision at minimum costs to stakeholders. Therefore, resource planning relies on expected demand for a pre-set horizon. The optimum competes with sufficient resources for robust and safe operations, but minimum resources for cost-effectiveness [2,3].

Consequently, traffic forecasts have a significant influence on the cost- and resource planning of an ANSP. For an efficient operation, it is necessary to predict the demand as precisely as possible. To estimate future demand, STATFOR publishes three scenarios in its medium-term forecasts [4]: "high-level", "baseline" and a "low-level" scenarios. The difference between the high- and low-level scenarios can be considered as a confidence interval (CI) and interpreted as the implied resource and cost uncertainty for the ANSPs. However, previous studies showed that the majority of ANSPs face an inadequate forecast and the CI is in a majority of cases not met [2]. It has further been proven that imprecise forecasts hamper the performance of ANSPs significantly [5].

In the early 1990s, EUROCONTROL started to assess the European ANSPs [6,7]. In the currently valid performance scheme, four Key Performance Areas (KPAs) are defined: safety, capacity, cost efficiency, and environment. The latter is expressed by the indicator horizontal flight efficiency (HFE) and is mainly a metric expressing detours [8]. In the past years, regulators emphasized an enhancement of cost efficiency and capacity. However, social pressure (e.g., Fridays for Future) caused a shift towards environmental aspects of air traffic recently. As a consequence, the environmental indicators gain increasing importance in benchmarking exercises as well as their interdependency to other areas.

Although the importance of the environment KPA in performance benchmarking has increased, there have been no studies on the relationship between traffic forecasts and environmental impacts. This gap is filled by the present study. Based on the most recent STATFOR report [9], supplemented by two scenarios, the following questions are answered in this document:

1. How many ATCOs will be needed per year?
2. How much total delay and/ or CRSTMP delay will be created per year?
3. How much cost of total ATFM delay and/or CRSTMP delay for airspace users will be created per year?
4. What are the forecast values for Horizontal Flight Efficiency (KEA and/or KEP) per year?
5. What is the total amount of CO_2 emissions forecasted?
6. What is the total amount of climate costs (and potentially other environmental costs) per year?

Therefore, the document is structured as follows: In section two, we describe the forecast scenarios by STATFOR and our supplements. Furthermore, we determine the consequences for ANSPs with regards to resources and costs induced by the scenarios. Section 3 deals with the consequences of the predictions on the delays. Environmental consequences of demand, delay, and other factors are discussed in section 4, where we calculate how the predictions affect the horizontal flight efficiency. Based on the results, section 5 shows how the prediction scenarios affect emissions and environmental costs. A graphical scheme of the investigations is provided in Annex A1.

2 Traffic Scenarios and Implications

In October 2021, EUROCONTROL presented the most recent medium-term forecast, predicting traffic movements and service units for the years 2021-2027 [9]. Obviously, forecasting always inheres uncertainty due to global (e.g., financial crisis) or local (e.g., the Russian attack on Ukraine) events, leading to short-term changes in traffic demand. To cover these uncertainties, STATFOR published three scenarios (low, base, and high).

However, it was proven that the forecast quality is very limited and [5,10] showed that in the past the actual demand did not match the confidence interval in the majority of cases. In consequence, we created two further scenarios (super high and super low): the super low scenario assumes that traffic figures decrease again in 2022, e.g., due to a new corona virus mutation, followed by a growth rate below the low scenario for the years 2023-2027. The super high scenario expects that COVID was a tremendous, but short external shock and traffic figures recover faster as expected by STATFOR. The growth rates are expected to be slightly higher than the ones in the high scenario. The exact assumptions are shown in Annex A2.

Modeling of traffic scenarios considers applicability to all ANSPs. This is to avoid overfitting, e.g., by arbitrary adjustments. It should further be noted that the study is a snapshot of the current situation. It aims to show which consequences (in particular planning uncertainties) will be caused by the forecasted traffic. It is not meant to represent a specific use case, but to demonstrate the Effects of EUROCONTROL / STATFOR assumptions on ANSPs with regard to performance. The presented results reflect the perspective in autumn 2021 (STATFOR forecast date). Later geopolitical events are not integrated and effects (e.g., due to the Russian attack on Ukraine) are not taken into account.

STATFOR predicts traffic on a country basis and as such not for ANSPs. However, for our investigation it was necessary to have a database on an ANSP basis since operational and financial data is provided for ANSPs mainly, e.g., ACE data [11]. Further, the airspace of an ANSP does not match the airspace of a country in any case. In consequence, there are airspace-specific deviations between STATFOR actual demand (e.g., Germany) and the demand provided by the ACE database (e.g., for DFS). In addition, a country perspective disables the consideration of MUAC, which would mean a decisive disadvantage for our analyses. Finally, some data inconsistencies might not be caused by allocation problems. As an example, there are inconsistencies for DSNA 2017:

- STATFOR: 3.241.000 flights,
- ACE: 3.135.236 flights.

This emphasizes the necessity for a homogeneous database on an ANSP basis. In other words, country-based values (based on the dimension of FIRs that match the charging area for a country) have to be transformed into ANSP-related values in advance (based on AUA(s) size which may differ from FIR(s) size because of different areas of responsibility). There are two options to transform data. First, it is possible to use the demand forecasts and adjust the geographic units. However, data transformation is challenging concerning MUAC, Germany, Belgium/Luxemburg, and the Netherlands. The second option is to use the STATFOR prediction, calculate the growth rates (5-year horizon) and apply them to ACE data (flights). This option is expected to be more precise. Figure 1 shows the transformation scheme.

The calculations (Adjusted Database, orange) combine the STATFOR growth rates based on countries (blue) with the operational ACE data (red). For MUAC, the average change rate of Germany, Belgium, and the Netherlands is used. ANSP airspaces are expected to be within the borders of the corresponding country. However, this is relevant for illustrations only. Annex A3 provides a calculation example for the transformation.

We applied this method to all ANSPs, using the transformation procedure (state-related figures into ANSP-related figures) proposed by [5], as well as to all Functional Airspace Blocks (FABs) and the EUROCONTROL area (also further designated as “Europe”), the latter shown in Figure 1. Two further examples are shown in Annex A4.

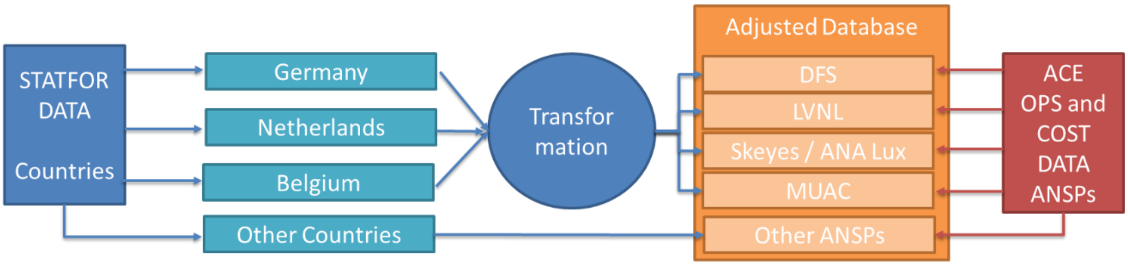
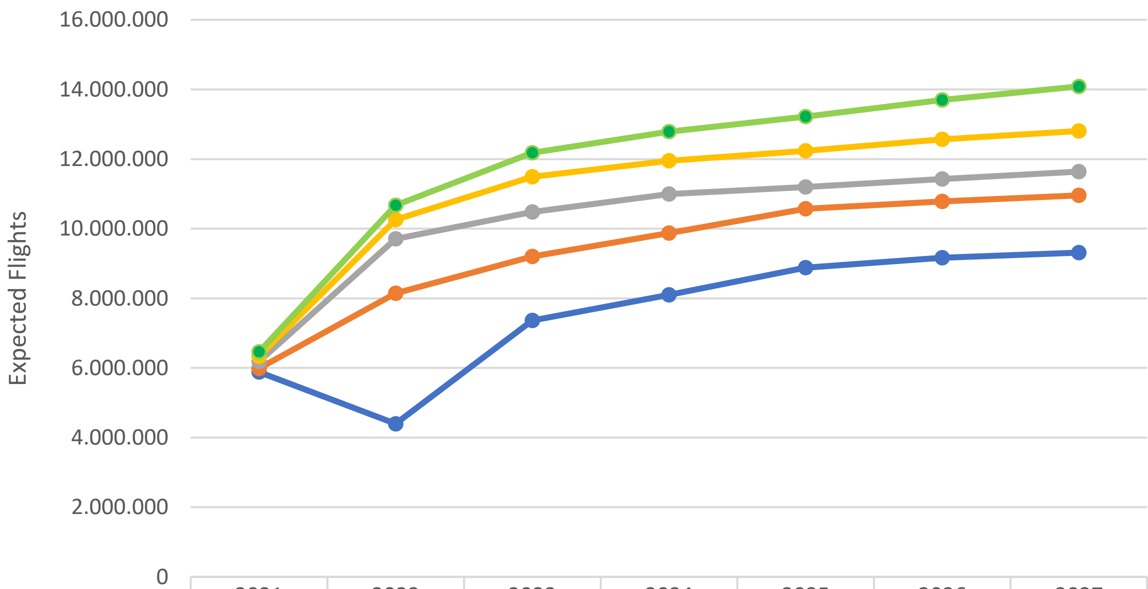


Figure 1: Data Transformation – From country-based to ANSP-based values

Figure 2 shows the expected number of flights between 2021 and 2027. Since the STATFOR report was published in the fall of 2021, a first deviation between the scenarios is visible for this year. The expected demand in 2027 may increase up to 14 Mill. flights in the most optimistic scenario. In the most pessimistic scenario, the demand will be about 9.3 Mill. flights and thus below the number in 2019. Concerning uncertainty, the STATFOR scenarios inhere a CI of 1.8 Mill. In flights, the range between super high and super low scenarios represents 4.8 Mill. flights.



	2021	2022	2023	2024	2025	2026	2027
Super Low	5.882.940	4.398.037	7.360.466	8.095.223	8.881.451	9.166.933	9.313.609
Low	5.986.840	8.142.106	9.200.583	9.872.223	10.573.156	10.784.627	10.957.187
Base	6.184.796	9.710.129	10.477.224	10.990.608	11.199.437	11.423.427	11.640.475
High	6.333.195	10.259.785	11.490.952	11.950.600	12.237.415	12.567.833	12.806.620
Super High	6.459.859	10.670.176	12.180.409	12.787.142	13.216.408	13.698.938	14.087.282

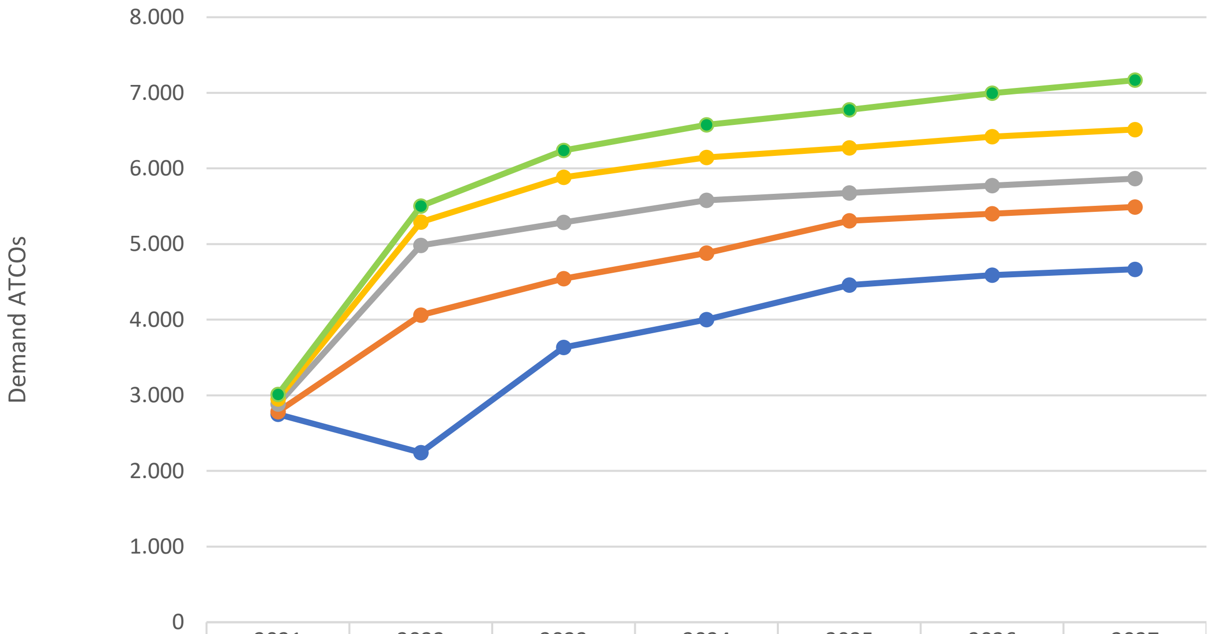
Figure 2: Traffic Scenarios, Europe

Please note that the traffic scenario results are not included in the appendix due to comprehensiveness. All graphs are provided in datasheets, which are available for all ANSPs, FABs, and Europe [12].

3 Expected Resources and Costs

It goes without saying that the implied confidence intervals lead to planning uncertainties for ANSPs. Resource planning relies on expected demand for a pre-set horizon. The most scarce and expensive resources are the Air traffic control officers (ATCOs). Using ACE data [13] and assuming a constant ATCO-productivity (the reference year 2019) [6,7], we can calculate the number of ATCOs and the corresponding employment costs for each ANSP as well as each scenario.

Unlike flights, resources and costs are clearly allocated to an ANSP. This means that the values can be aggregated and therefore the required controllers and subsequent employment costs can be calculated on the FAB level. As an example, the largest unit in meanings of demand, FABEC, employed 5,609 ATCOs in 2019. Using the forecasted traffic scenarios, the FAB will need between 4,668 and 7,167 ATCOs in the year 2027, respectively 5,865 ATCOs in the case of STATFORs baseline scenario (Figure 3). In other words, the uncertainty with regards to resources is 2,499 Full-Time Equivalences (FTEs) when comparing super high and super low scenarios. Further examples are shown in Annex A5.

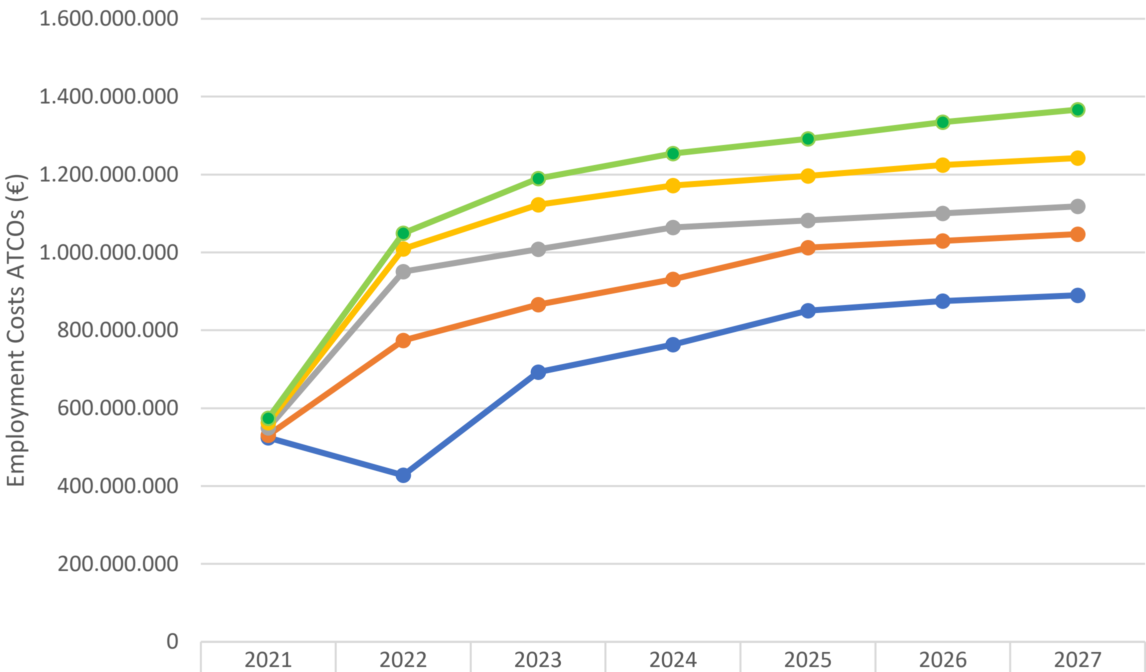


	2021	2022	2023	2024	2025	2026	2027
Super Low	2.748	2.244	3.633	4.002	4.460	4.590	4.668
Low	2.784	4.059	4.541	4.881	5.309	5.400	5.491
Base	2.884	4.985	5.288	5.580	5.674	5.772	5.865
High	2.953	5.291	5.885	6.146	6.274	6.420	6.515
Super High	3.012	5.502	6.238	6.576	6.776	6.997	7.167

Figure 3: Expected Need for ATCOs, FABEC

The need for resources directly affects the costs to be planned for Reference Period 3 (RP3) and beyond. In 2019, ATCO employment costs in FABEC summed up to 1.07 Bill. €. As shown in Figure 4, the expected costs for the year 2027 will be between 890 Mill. and 1.4 Bill. €, respectively 1.1 Bill. € in the most-likely scenario.

Further examples are shown in Annex A6. Please note that the results are not included in the appendix due to comprehensiveness. All graphs are provided in the traffic scenario data sheets, which are available for all ANSPs, FABs, and Europe [12].



	2021	2022	2023	2024	2025	2026	2027
Super Low	524.019.901	427.814.809	692.722.937	763.182.683	850.438.281	875.291.351	890.022.956
Low	530.944.697	774.060.076	865.903.671	930.710.589	1.012.426.5	1.029.754.5	1.047.085.8
Base	549.844.312	950.478.632	1.008.391.0	1.063.959.5	1.082.006.4	1.100.664.8	1.118.352.7
High	563.118.163	1.008.830.8	1.122.214.4	1.171.861.4	1.196.358.2	1.224.101.3	1.242.389.4
Super High	574.380.527	1.049.184.1	1.189.547.2	1.253.891.7	1.292.066.9	1.334.270.5	1.366.628.3

Figure 4: Expected ATCO Employment Costs, FABEC

The conversion of demand into resources (ATCOs) inheres some limitations. First, the assumption of a linear interdependency between resources/costs and demand might not be accurate, since scale effects are expected to have an influence. Thus, there is an over-estimation of resources and costs in case of increasing returns to scale, and an under-estimation of resources and costs in case of decreasing returns to scale. Second, the need for resources does consider ATCOs only. However, an increase in ATCOs may lead to the need for other resources as well (administrative staff, working positions, etc.), affecting costs as well. Third, the costs do not consider training costs, which are according to IFATCA up to 600.000 € per fully trained ATCO. Since the drop-out rate and inflation are not considered as well, the costs might be higher than calculated. Fourth, productivity is expected to be constant at the 2019 level. However, it might be expected that productivity increases, e.g., by innovative systems and tools. Fifth, the calculations do neither consider contractual or union aspects nor the availability of ATCOs. And finally, a change in traffic flows may lead to a higher or lower workload influencing the actual need of ATCOs and subsequently their productivity and costs.

4 Delay Forecast

4.1 Data and Method

An essential quality criterion of ANS service is represented by the punctuality of flights. If demand exceeds the available capacity, delays will occur, which can be due to various reasons, including weather, staffing, accidents, etc. Accordingly, in ANS provision delays are divided into total Air Traffic Flow Management (ATFM) delay (all causes) and CRSTMP delay (those causes which can be assigned to ANSPs).

EUROCONTROL publishes data for a number of flights as well as delay minutes (distinguished into causes) on daily basis [14]. We used this data (years 2015 to 2019) to derive the interdependency between demand and delay. Therefore, we first need to find the functional relationship between both indicators. In the second step, we use this formula to calculate the delay for each day and each year (see section 4.2), based on the expected flights (see section 2).

Earlier studies already proved that the relationship is expected to be exponential [15,16]. Thus, we imply the functional form shown in (1), where *y* stands for the delay, *x* for the flights, and *a*, *b* and *c* are parameters to be optimized. The parameter *c* represents an “offset” or “threshold” parameter, implying that delay does not occur below the corresponding demand.

$$Y=a(x-c)^b \tag{1}$$

The solver optimizes the parameters so that the quadratic distance between observations and function is minimized. This procedure was applied for both total and CRSTMP delay. To monitor the quality, we used the coefficient of determinations (R^2). Figure 5 shows an example of French DSNA. The blue dots represent the observations, the orange dots are based on the functional relationship between demand and delay.

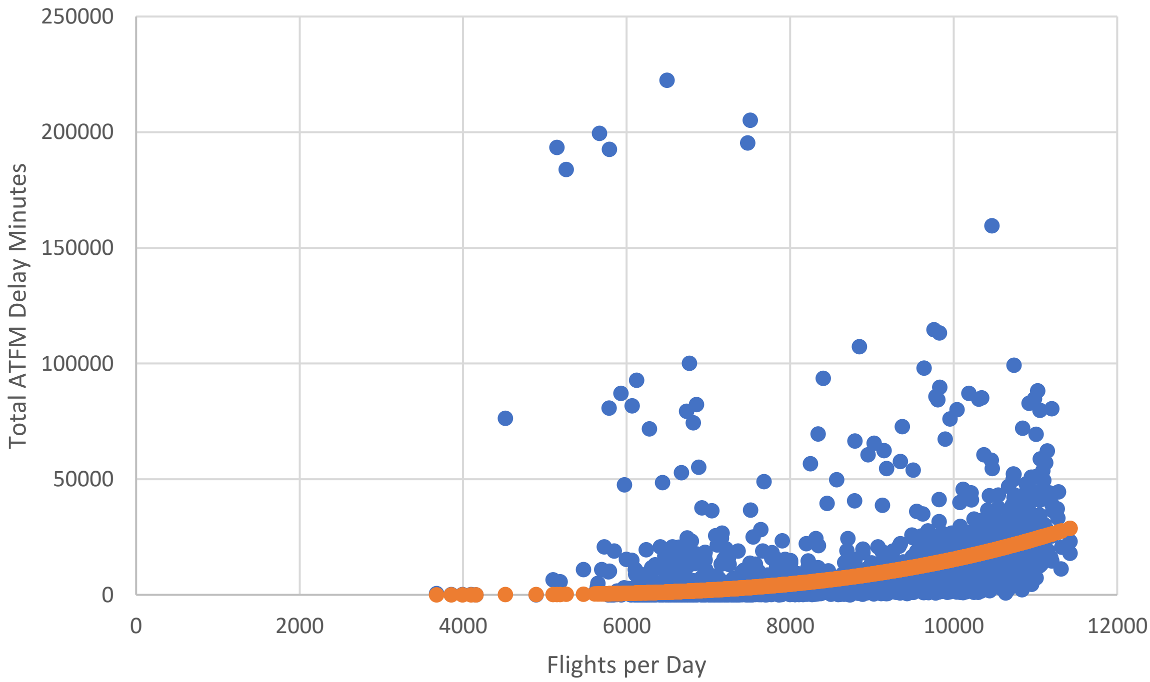


Figure 5: Interdependency between Demand and Total Delay, DSNA

The optimization model also considers two restrictions. First, the value *c* for CRSTMP delay is larger or equal to the one for the total delay. Otherwise, we would imply the possibility that CRSTMP delay could occur without the occurrence of total delay, which is obviously wrong. Second, the value for CRSTMP delay for one day can never be larger than the value for total delay. The model restriction assures that the CRSTMP delay is always smaller or equal to the total delay. Figure 6 compares both functions for DSNA. The curves increase exponentially and will eventually continue congruently.

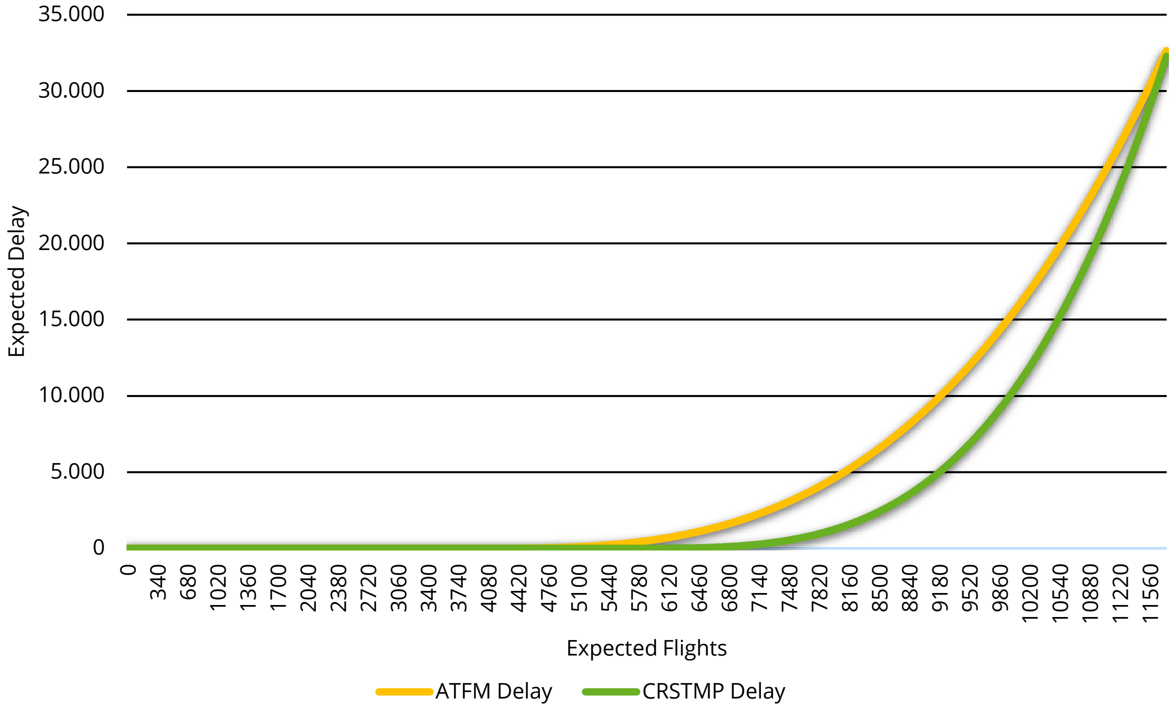


Figure 6: Interdependency between Demand and Total Delay, DFS

Due to the high heterogeneity in European Air Traffic Management (ATM) and the subsequent particularities of ANSPs, the analysis was executed for each ANSP separately. It can be observed that the relationship between demand and delay tends to be linear for smaller ANSPs ($b \approx 1$), while the exponential parameter for larger ANSPs results in a parabolic or hyperbolic function. This can be explained by the fact that the concerned small airspaces are also non-saturated. As a result, demand is not yet in the range of exponential growth and delay occurs due to capacity constraints in no or just a minor number of cases. Further, some of the ANSPs have no (reported) delay, or only a small number of observations, which also hampers a (precise) forecast.

The approach inheres some limitations. First, we assume that the temporal distribution of demand is relative to those of previous years. This is not necessarily the case: local or global events, such as the Russian attack on Ukraine, can change this distribution. In consequence, the delay for the day(s) and subsequently the year might be over- or underestimated. However, such events are not predictable for us and thus not included. Second, the delay is influenced not only by demand, but also by other factors such as weather, military activities, or low forecasting quality. Subsequently, there is a scattering of the observations as shown in Figure 5. Again, these effects are not predictable, at least not on a daily basis, and thus not included in the prediction. It might be assumed, that those effects offset each other – in other words: the overestimated delay on day one is compensated by the underestimated delay on day two. Nevertheless, the prediction inheres some uncertainty with regard to the actual values. Third, some ANSPs do not have or not have reported delays. Subsequently, we cannot predict any delay for those units.

4.2 Prediction of Delay Minutes

Based on the functional shape, as well as the predicted flights (section 2), the delay can be determined for each day of a year and be summed up for the annual value. For this purpose, the formula determined in the previous step (see section 4.1) is applied: The individually optimized parameter values (a and b) and the expected flights for x. Thus, a delay value y can be determined for each unit, for each day, and for each scenario. The procedure is applied to the years 2021-2027. Figure 7 shows the expected total delay minutes for French DSNA, Figure 8 illustrates the CRSTMP delay minutes.

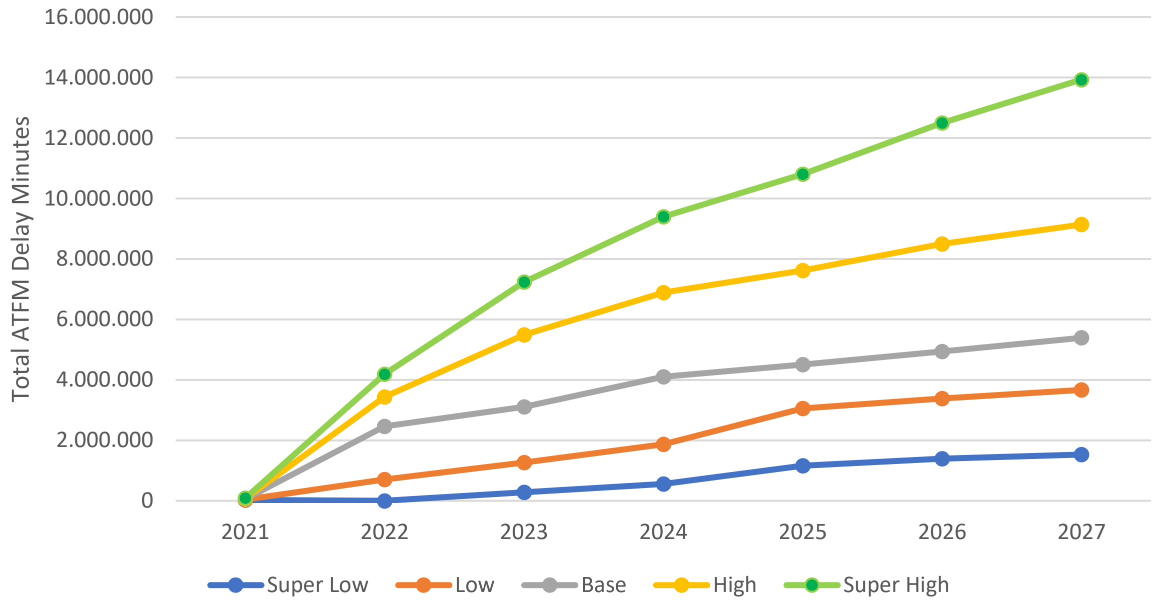


Figure 7: ATFM Delay Prediction, DSNA

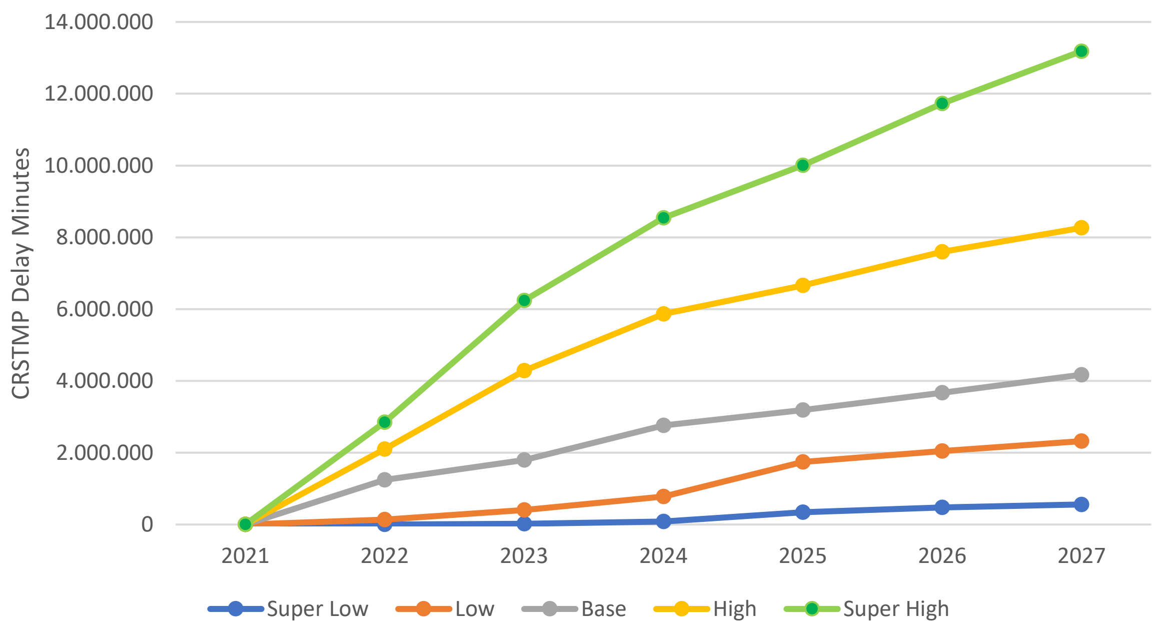


Figure 8: CRSTMP Delay Prediction, DSNA

According to the graphs, the ATFM delay in the French airspace will be between 1.5 and 13.9 Mill. delay minutes, which is rather high uncertainty. Even using the STATFOR scenarios will lead to a CI of 5.5 Mill. delay minutes. CRSTMP is generally lower, but the CI is larger: 5.9 Mill. minutes in the case of the STATFOR scenarios, and 12.6 Mill. minutes when comparing super high and super low scenarios.

Since delay minutes are aggregable, the values for FABs and Europe can be determined by summing up the minutes of the corresponding ANSPs. Further, it is possible to calculate the ATFM delay per flight, respectively CRSTMP-delay per flight, which might be beneficial for capacity target monitoring [17] or setting [18]. For example, the European capacity target represents a delay below 0.5 minutes per flight. As shown in Figure 9, the expectation is rather unrealistic, indicating that all scenarios will lead to a higher delay per flight in the years 2028 and 2029. However, it has to be considered that the analysis implies today's technology. Actual delay may be lower when ANSPs performance increases (see also [19]).

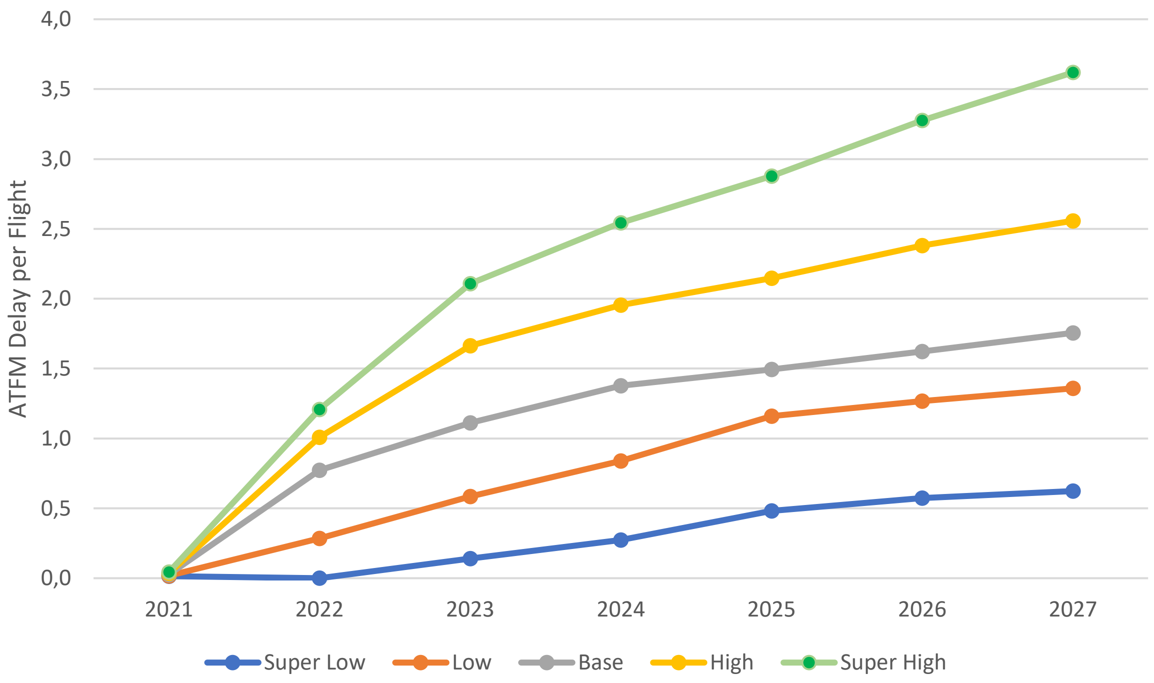


Figure 9: Expected Delay per Flight, Europe

Please note that the results are not included in the appendix due to comprehensiveness. All graphs are provided in the traffic scenario data sheets, which are available for all ANSPs, FABs, and Europe [12].

4.3 Expected Costs of Delay

The performance of air traffic control provision is measured by tracking its overall costs (cost-effectiveness), the attribution of ATFM delays to assisted flights, and the discrepancy of actual or planned routes with respect to the great circle distance linking the departure and destination airport pair (flight efficiency), while maintaining the highest level of safety [20][1].

[1] Note that ATFM Delay is often used to express the lack of capacity of a given airspace or airport, defined as the maximum aircraft throughput or occupancy per unit of time (usually an hour).

To assess the overall performance in these different areas, the concept of "total economic cost" has been developed [21]. The total economic cost recognizes that a delay for an airspace user, while desirable to optimize the air flow, carries a burden and a cost. Subsequently, a provision costs for ATC, the cost for safety oversight (this performance area is defined as paramount), and ATFM delay costs (due to the imbalance between demand and supply of air traffic management (ATM) capacity) are added to provide an overall view by bringing together two different Key Performance Areas. As a prerequisite, it is necessary to monetize delay.

In addition, ANSPs manage the capacity of their airspace. They, therefore, need to invest capital in both technology and staff. Ideally, by combining these measures, ATFM delay is avoided and safety levels are measured[2]. For any cost-benefit analysis, there is a need to arrive at a figure that quantifies this benefit. In order to have a common approach to this issue, EUROCONTROL has developed a publication with some Standard Inputs for Cost-Benefit Analysis in which the cost of delay is one of the most prominent figures [22].

The first attempt to monetize the cost of one minute of ATFM delay, as incurred by the Airliners in Europe, was made by the Transport Studies Group from the University of Westminster (2004) where such delays were measured relative to the last filed flight plan and with costs of 72 euros, in average per minute of delay. This is a very comprehensive and detailed report to serve as a basis for determining the true cost to airlines of one minute of airborne or ground delay [23], and it is probably the most relevant study performed until now.

The 2004 report differentiates between "short" (15 minutes) and "long" delays (65 minutes) and considers that there are neither passenger costs of delay nor crew costs for "short" delays and that the longer the delay, the higher the cost (for instance, the cost is less than 1 € per minute at-gate for short delays, while 289 € for long delays [23]. A differentiation between tactical (those incurred on the day of operations and not accounted for in advance) and strategic (those accounted for in advance) costs, and between gate-to-gate and at the network level is also made. All in all, the disaggregated calculation according to "long" and "short" delay types gave a range of the total cost of ATFM delay minutes of 840 – 1,200 Mill. €. Based on these delays, a network value of 72 € per minute for "long" delays was obtained. This average value includes reactionary delay costs but does not consider strategic costs associated with buffer minutes added to schedules.

Successive revisions were published, which included more aircraft types, a gate-to-gate perspective of delay cost, and some updates on the average cost of ATFM delay. Unlike the previous report, in this one costs were assigned to "short" delays, and tactical cost delays were given for nine delay ranges (5, 15, 30, 60, 90, 120, 180, 240, and 300 minutes) rather than for two ("short" and "long"), as before. The network total cost of ATFM delay (all causes) was 1,250 Mill. €, the average cost of delay of an ATFM delayed aircraft was 1,660 € and the network average cost of ATFM delay, per minute, was 81 € [24]. The methodology was substantially unchanged in the 2015 report. Only some minor specific modifications were included (e.g., more aircraft variants were considered, fuel burn was also included in the at-gate calculations, cost scenario values were increased and there was an average increase of 20% in the passenger cost of delay). As a result, the average cost of delay of an ATFM

[2] It is true that some ATFM delay problems can be solved by contracting new ATCOs. However, we cannot ignore the fact that many delays are attributed to the elementary capabilities of the sector, so in these cases the delays stem from an airspace problem, not a resource problem.

delayed aircraft was 1,970 €, the ATFM delay cost averaged over all flights was 103 € and the network average cost of ATFM delay, per minute, was 100 € [25].

However, using the average values does not seem to be a good representation of the real costs, as not all flights are subject to the same amount of delay. This means that the use of the average value overestimates the total cost. Thus, it is crucial to determine the distribution of these delays and how they affect the total cost. That is, to have a precise picture of the number of delays but also of how long these delays were, and consequently a more accurate estimate of the cost.

One way to do so is to propose a cost curve (mathematical) function per minute of delays based on the earlier values. If, in addition to the distribution of delays, we want to obtain the values resulting from using different costs for different ranges of delays, we can do the following (the full procedure can be thoroughly explained in [26]: first, starting from the average cost per range of delays from [24], we can calculate the cost per minute by dividing the average cost by the midpoint of the range, and update it to 2015 values, as shown in Table 1.

Delay range (min)	01-04	05-14	15-29	30-59	60-89	90-119	120-179	180-239	240-299	300+
Average total cost (€)	39,50	259,25	1074,02	4,78	14,74	31,55	49,02	65,70	86,97	99,09
Cost per minute (€)	15,80	27,29	48,82	107,36	197,85	301,95	327,91	313,60	322,71	330,32

Table 1. ATFM delay ranges and weighted costs – total and per minute – (in 2015 €) for ten delay ranges (adaptation from Table J5 (2010 values) in[24]

Once the cost per minute has been estimated, the next step consists of multiplying the number of minutes of delay considering the full distribution for the delays ranges by the cost of them. Using the information in Table 1, we can estimate a cost function to be used for calculations.

Deriving a function is potentially more appropriate, but the results obtained with it will depend largely on the quality and stability of the base data available. In any case, it is a step forward in terms of methodology.

The function should meet the following theoretical conditions:

a) Only make sense for positive delay values;
b) Goes through the origin;
c) Must be a growing function, that is, the first derivative should be positive; and
d) As values are expected to grow rapidly with delays, the second derivative should also be positive.

The function proposed (2) is as follows [26]:

$$Cost=a(y)^b \tag{2}$$

y being delays and *a* and *b* parameters.

Equation (2) is equivalent to (3):

$$ln(Cost)=ln(a)+bln(y) \tag{3}$$

In addition, annual data on total delays have been used to estimate the costs of delays with the average, while in the case of functions, the calculation has been made with daily data for ANSPs. In the absence of information, annual data have been used for FABs and Europe.

Table 2 shows the cost of delays for FABEC, whether the average value of 100 € per minute or the function is applied. Results are based on total delay, not CRSTMP delay.

AVERAGE	2022	2023	2024	2025	2026	2027
Super low	0.03	34.56	79.74	200.76	251.06	282.12
Low	94.51	219.23	375.66	676.60	754.44	831.55
Base	450.59	649.70	909.39	1002.00	1107.20	1213.97
High	672.83	1277.36	1635.58	1833.92	2076.03	2237.72
Super high	855.43	1763.23	2345.83	2744.07	3234.00	3631.80
FUNCTION	2022	2023	2024	2025	2026	2027
Super low	0.02	29.82	70.86	184.32	232.32	262.139
Low	84.50	201.89	352.59	648.36	725.73	802.658
Base	425.63	621.70	880.57	973.57	1079.57	1187.528
High	644.62	1251.79	1616.86	1820.26	2069.61	2236.704
Super high	826.53	1747.68	2348.67	2762.62	3274.77	3692.665

Table 2. Cost of delays for FABEC, 2022-2027 (in Mill. €) for the five scenarios and using the average and function

As the function takes into consideration the distribution of delays, this makes the estimate more accurate. Moreover, using the average cost value tends to overestimate the cost[3]. The difference is illustrated in Table 3. A result of 0.68 indicates that the function is 68% of the mean value. In other words, the function makes the value 32% less than the mean.

DIFFERENCE	2022	2023	2024	2025	2026	2027
Super low	0.68	0.86	0.89	0.92	0.93	0.93
Low	0.89	0.92	0.94	0.96	0.96	0.97
Base	0.94	0.96	0.97	0.97	0.98	0.98
High	0.96	0.98	0.99	0.99	1.00	1.00
Super high	0.97	0.99	1.00	1.01	1.01	1.02

Table 3. Difference between the average cost of delays and the costs calculated by applying the function (FABEC, 2022-2027)

Further examples are shown in Annex A6. However, all results are presented in data sheets, which are available for all ANSPs, FABs, and Europe.

[3] This is true in most cases. However, it is not impossible that, in certain scenarios, the function of slightly above average values. This has to do with the fact that "long" delays are expected to be much longer than "short" delays, so that the mean does not adequately capture this distribution.

5 Prediction of Horizontal Flight Efficiency

5.1 Definition and Metrics

In the EUROCONTROL benchmarking scheme, environment-related performance is assessed by the horizontal en-route flight efficiency [8]. The HFE is expressed as a ratio of distances and is, therefore, an average per distance within given airspace: All portions *p* of a flight *f* traversing an airspace *j* are considered, comparing flown (*L*) and achieved (*H*) distance as shown in (4).

$$HFE_j = \frac{\sum L_{fjp} - \sum H_{fjp}}{\sum H_{fjp}} \tag{4}$$

EUROCONTROLs Performance Review Unit (PRU) publishes the achieved and flown distance for each day. The corresponding indicators may be referred to as three different trajectory data [27]:

- The shortest constrained trajectory (SCR),
- The last filed flight plan trajectory (FTFM),
- The actual trajectory (CPF).

Official reports as well as the provided database use indicators to express the HFE, representing a proxy for detours. The higher the indicator, the lower the efficiency. In our study, we focus on the indicators of the planned (KEP) and actual trajectory (KEA). The indicators are calculated as shown for KEA in formula (5). The yearly values for KEA or KEP represent the average of the daily values; however, the ten highest and ten lowest values are excluded. In our analysis, we use all values.

$$KEA = \frac{L}{H} - 1 \tag{5}$$

It should be noted that the methodology and significance of the indicator might be debatable. As an example, [28] showed that the achieved distance concept leads to biases, in particular for small airspaces. The authors recommend not comparing HFE scores spatially (e.g., in a ranking or on a map). Despite the weaknesses, the indicator is still used in official benchmarking. We use the indicator to estimate the environmental consequences of different traffic scenarios.

5.2 Data

Before we can predict HFE scores based on the traffic scenarios, we need to examine which factors influence the horizontal flight efficiency, measured by the indicators KEA and KEP [8], and how high this influence is. Therefore, in the first step, a long list of factors is compiled, e.g., demand, complexity, weather, military airspaces, etc. In a second step, it is checked which factors are quantifiable and which only have qualitative characteristics. For the quantifiable factors, a suitable metric is sought, otherwise, they cannot be considered in the analysis. As an example, there is a metric that is supposed to define the complexity of demand [29,30], but it has already been shown that this indicator is not applicable due to methodological weaknesses [31]. Military data, while available in principle, is sensitive and therefore not usable. Nevertheless, operational experts expect that military activities have a tremendous influence on the HFE. To emphasize this situation, we provide a case study in section 5.6. The third step is to examine how high the correlation between the factors is. It is not advisable to use highly correlated factors in one analysis model.

Table 4 shows all potential factors, whether it was included or not (also in test models), the expected influence as well as the data source. Some factors correlate with each other, as shown in Figure 10. Included are also KEA (HFE_CPF) and KEP (HFE_FTFM). The dark blue and dark red points represent a strong positive or negative correlation. In consequence, these factors should not be included in one model. However, this issue mainly affects the complexity indicators.

Factor	Acronym	Expected Influence	Considered	Data Source
Demand	DEM	+	YES	PRU [32]
Airspace Sze	SIZE	-	YES	ACE [6,13]
Density	DENS	+	YES	Calculated
Adjusted Density	ADENS	+	YES	EUROCONTROL [29]
Horizontal Score	HS	+	YES	EUROCONTROL [29]
Vertical Score	VS	+	YES	EUROCONTROL [29]
Speed Score	SS	+	YES	EUROCONTROL [29]
Complexity Score	COMP_S	+	YES	EUROCONTROL [29]
ATFM Delay	ATFM_DEL	+	YES	PRU [32]
CRSTMP Delay	CRSTM_DEL	+	YES	PRU [32]
Weather	ATMAP	-	YES	METAR, Own Calculations
CO2 Price	CO2P	-	YES	
Fuel Price	FUELP	-	YES	
Charge	CHARGE	-	YES	CRCO [33]
Wealth	WEALTH	+	YES	World bank [34]
Military Area	MIL	+	No	
Flexibility Staff Scheduling	FLEX	-	No	
2016	Y2016	-	Yes	Dummy
2017	Y2017	-	Yes	Dummy
2018	Y2018	-	Yes	Dummy
2019	Y2019	-	Yes	Dummy

Table 4: Factors influencing HFE

Weather is one of those factors that operational experts rank as significant for HFE. Severe weather can lead to detours, which would affect particularly the KEA score. Despite there being approaches to quantify en-route weather, such as the Weather Impacted Traffic Index (WITI) [35,36], there is no reliable dataset for the time period and spatial scope considered in the study. For this reason, we developed an approximation based on the concept of weather evaluation for airports. Data and evaluation were provided by Prof. Michael Schultz.

Usually, weather conditions are recorded at each airport using the Meteorological Aviation Routine Weather Report (METAR) and reported every 30 or 60 minutes (depending on the airports' importance). Current and historical weather data are accessible on different publicly available websites. In addition to information about the location, the day of the month, and the UTC, METAR contains relevant information for airport operations, such as wind speed and direction, visibility, precipitation, clouding, air temperature, and pressure.

Besides this general weather information, additional measurements were available related to adverse weather situations, such as information about wind gusts, runway conditions (e.g., ice layer), thunderstorm-related cloud formations, or measurements of runway visual range. For the following analysis, METAR messages are parsed and filtered to enable the quantification of weather measurements regarding their impacts on the aviation domain.

EUROCONTROL provides a framework for measuring airport airside and nearby airspace performance for this quantification [37]. Here, weather conditions are generally separated into nominal, degraded, and disruptive conditions with an increasing impact on airport performance. We used the implementation [38] of the Air Traffic Management Airport Performance (ATMAP) algorithm [39] for the quantification of weather conditions.

ATMAP algorithm quantifies and aggregates major weather conditions at airports, significantly impacting airport operations. Five different weather classes with significant influence on aircraft and airport operations include visibility and cloud ceiling, wind, precipitation, freezing conditions, and dangerous phenomena.

These five different weather classes are related to particular meteorological conditions, which are linked to an associated coefficient. More severe weather conditions lead to higher coefficients, equivalent to a high impact on the performance of the air traffic/airport system. The sum of all five coefficients represents a quantified weather score (cf. [40]).

To obtain a quantitative value for the weather we first created a list of airports for each ANSP. An ATMAP score was then determined for these airports on a daily basis. The score for the corresponding ANSP is defined by the mean of the airport values. Although this approach is very rough, it yielded good results. Countries with frequent severe weather conditions achieved a higher score, e.g., countries in the north and/or with a high percentage of mountainous terrain. Moreover, the test regressions have already shown that this value significantly improves the prediction model.

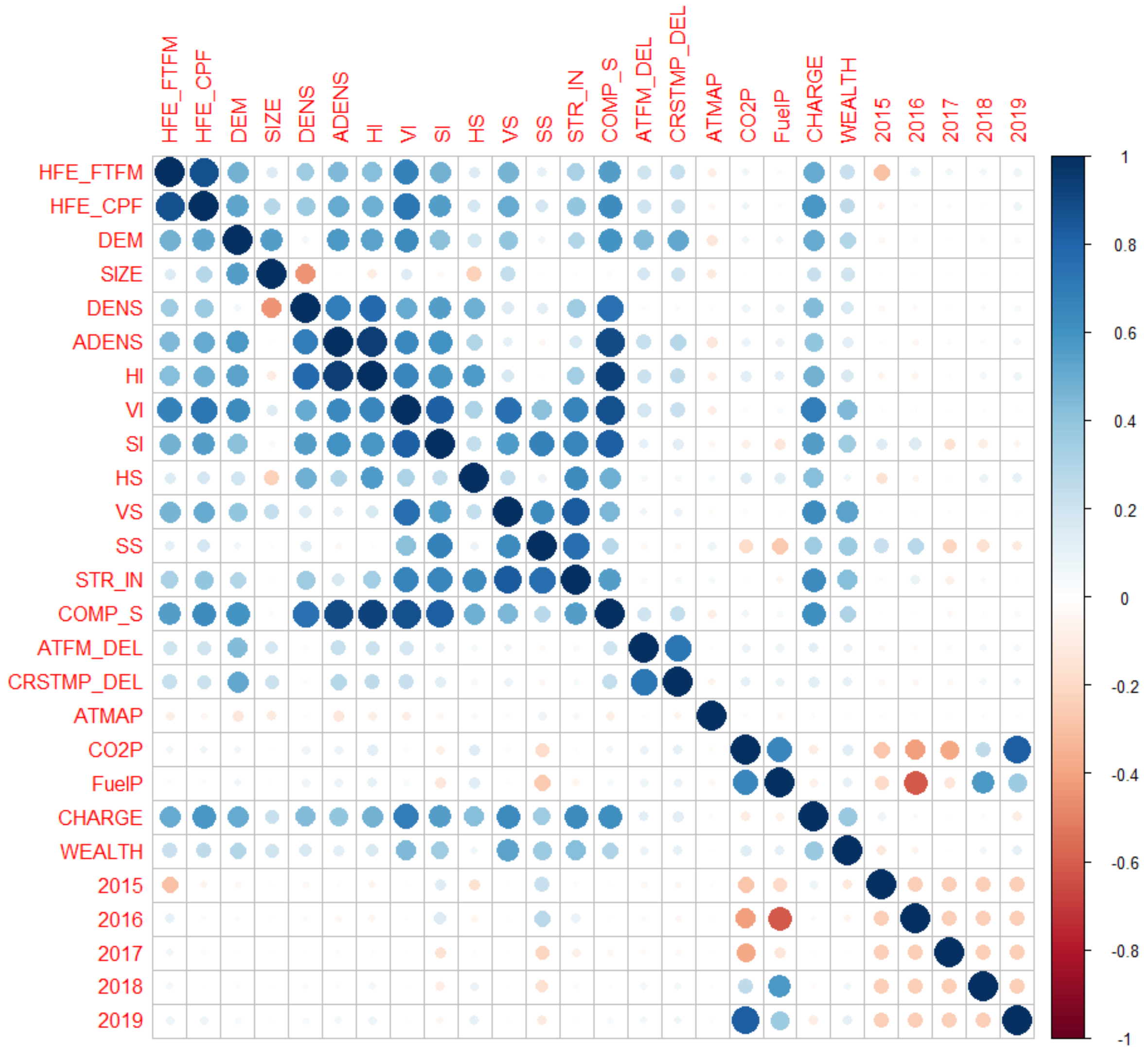


Figure 10: Correlation between factors

5.3 Approach and Methodology

Since it is expected that several factors significantly influence the HFE, a pure correlation analysis (e.g., by using scatter plots) is not applicable. Subsequently, we need to apply methods that can map multiple interdependencies. One of these methods is regression analysis.

Regression analysis allows the quantification of one or more independent variables (factors) on one or more dependent variables. As an example, the speed of an athlete may depend on multiple factors, such as age, muscles, training, food, etc. These factors may or may not be measurable (e.g., due to qualitative nature or missing determinability). The regression calculates how to weight the measurable factors ("coefficients") in order to estimate the speed of the athlete *v* as precisely as possible (see Figure 11 and formula 6). The term *c* represents the constant of the formula, which means the speed when all observed influences would be zero.

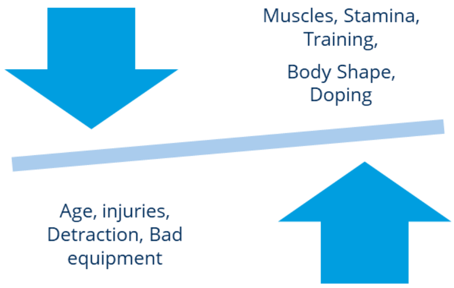


Figure 11: Aim of a Regression Analysis

$$v = c + w_1 \cdot age + w_2 \cdot stamina + \ldots \quad (6)$$

In our investigation, the dependent variable is the KEA or the KEP indicator. The independent variables are represented by (potential) influencing factors on KEA or KEP, e.g., demand, delay, or weather. In the first approach, we calculated one regression using whole ANSPs. However, due to the high level of heterogeneity in European Airspace and the particularities of each ANSP, we decided to calculate one regression model for each ANSP, each FAB, and Europe. Aggregations (FABs, Europe) partly use average data to predict scores, e.g., for wealth.

The type of regression is dependent on the characteristics of the dependent variable and the data (cross-sectional versus panel data). Cross-sectional data means that data is available for one time period and all firms. The advantage is, that no time effects have to be considered. Panel data shows the data for each firm for multiple years. Thus, more observations are available, enabling the consideration of a higher number of factors. In other words, the model might be more precise than a cross-sectional model. Depending on data characteristics, different regression types might be applied. If panel data is available, panel regression models like Pooled, Fixed- or Random-Effect Models might be applied. For cross-sectional data, Ordinary-Least-Squares (OLS) regression is the most common method. However, if the dependent variable is restricted, OLS is model misspecification and Tobit- or Truncated models are to be preferred [41].

There are mainly two ways to apply regression. The most common method is to maximize model quality (e.g., adjusted R^2) by variable reduction. That means, that statistically insignificant variables are excluded successively from the regression model. Another possibility is the sequential inclusion of variable clusters. As an example, potential factors might be distinguished into endogenous and exogenous variables. Those applications however also lead to other model quality criteria, such as Akaike. Our study focuses on variable reduction and model quality maximization.

The accuracy of the regression model is evaluated by model quality criteria. Good model quality is e.g., expressed by a high coefficient of determination (R^2): The closer the indicator is to 100%, the more variance is resolved by the considered factors. We used three different model quality criteria, depending on the regression model:

- Adjusted R^2 for Pooled OLS (incl. constant).
- Non-centred R^2 for Pooled OLS (excl. constant),
- Dummy R^2 for Fixed Effects Model.

The resolved variance is the most commonly used model quality criterion in scientific research and is therefore used in this study. The distinction is necessary due to the differences in the mathematical background of the regression models. As an example, models tend to have a higher R^2 in case there are more explanatory variables (even if they might not be significant. Therefore, the "adjusted" only considers the independent variables which actually influence the dependent variable. Due to the calculation procedure of R^2 (squares of deviation), the adjusted R^2 represent a centred value since it is "corrected" (or centred) by the observed mean. However, this is only valid if the regression formula considers the constant *c*. In case the model does not consider a constant, the regression line intersects the coordinate origin. Due to the calculation scheme of R^2, this would lead to negative values, and thus the criterion is invalid. In consequence, an adjusted formula is used, where the squats of deviation are not centred by the empirically observed mean. Therefore, it is called "non-centred" R^2. Considering time effects (fixed or random effects) influences the regression formula itself. It is supplemented by an independently and identically distributed disturbance term. The solution of the regression model is often found by using dummy variables by applying the Least Squares Dummy Variables (LSDV) method. Subsequently, the R^2 for the fixed effect model is also called "Dummy-R^2" [42,43].

Although the working principle is similar for all three criteria, the values are not comparable due to the different mathematical calculation schemes. For example, the non-centred R^2 will always lead to high values. In this respect, only the values of the same calculation basis, i.e. the same indicator, can be compared.

The regression analysis provides the strength (value of the coefficient), direction (the sign of the coefficient), and significance (p-value of the model statistic) of the influence of all factors considered. The model can now be used to determine the KEA and KEP values for the following years. Further, model quality criteria are indicated. However, if the non-quantifiable factors have a significant influence as well, model quality will decrease. The prediction nevertheless might lead to useful results.

The figure on the right side (Figure 12) describes the procedure. Regression analysis is applied to each ANSP separately. Based on an ANSP-specific dataset, an initial model (base model) is calculated. By adding / removing / substituting factors, the model quality is increased (adjustments). The best model is used for the HFE prediction. In case the results are significantly counter-intuitive, the previous step is repeated. Otherwise, the results are used for the HFE prediction.

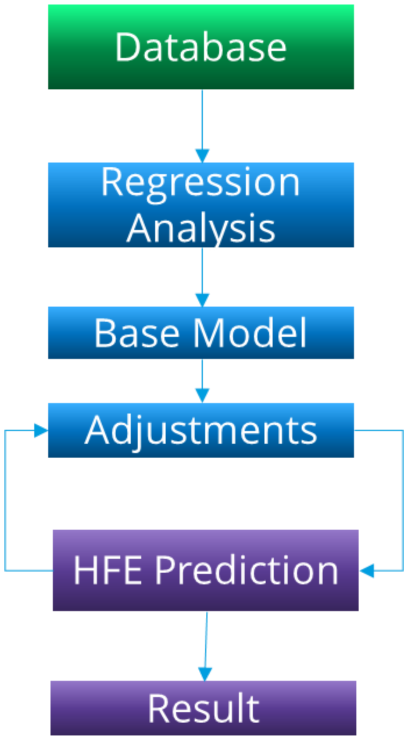


Figure 12: HFE Prediction Scheme

Expected demand and delay for 2021 to 2027 are extracted from the traffic scenario study. Other expected values are based on official documents (e.g., charges and CO_2 prices) or own assumptions. In general, the following assumptions have been made:

- HFE decreases slightly (expressed by yearly dummies)
- Fuel Prices and CO_2 Prices increase
- Charges decrease
- The weather becomes worse (extreme weather situations will be more often)
- Wealth increase

5.4 Prediction Models

For each ANSP, two optimized models are set up for prediction: One for KEA and one for KEP. This allows us to consider that a certain factor influences ANSP A, but not ANSP B. Furthermore, it is taken into account that a factor might be important for the KEA, but not significant for the KEP indicator.

The tables below show, which factors were included in the optimized regression model, the corresponding model quality criterion, and which type of regression was used. The type was chosen based on statistical tests (e.g., Breusch Pagan Test or Hausman Test) as well as based on model optimization mechanisms. FEM stands for Fixed Effects Model, POLS for Pooled Ordinary Least Squares. Results are shown on ANSP- (Table 5), FAB- (Table 6), and European level (Table 7). Please note that the Coefficient of Determination (R^2) is comparable only between models based on the same regression method and whether the "constant" was included or not:

- Fixed Effects Model: Dummy R^2
- Pooled OLS (incl. constant): Adjusted R^2
- Pooled OLS (excl. constant): Non-centred R^2

ANSP	KEP									KEA								
	Type	R^2	CONST	DEM	ATFM_DEL	ATMAP	CO2P	FuelP	CHARGE	Type	R^2	CONST	DEM	ATFM_DEL	ATMAP	CO2P	FuelP	CHARGE
Albcontrol	FEM	46%	X	X		X		X		POLS	28%	X	X		X			
ANS CR	POLS	4%	X	X	X	X	X			FEM	59%	X	X	X	X		X	
ARMATS	POLS	89%		X		X	X			POLS	4%	X	X		X		X	
AustroControl	POLS	94%		X		X	X			FEM	59%	X	X		X		X	
Avinor	FEM	44%	X	X	X	X	X			FEM	19%	X	X		X			
BULATSA	FEM	33%	X	X		X			X	POLS	97%		X	X	X	X	X	X
Croatia Control	POLS	87%		X		X	X			FEM	56%	X	X		X			
DCAC	POLS	95%		X		X	X			FEM	30%	X	X		X		X	
DFS	FEM	42%	X	X		X	X	X		FEM	58%	X	X		X	X	X	
DSNA	POLS	97%		X		X	X			POLS	98%		X		X	X		
EANS	FEM	61%	X	X		X	X	X		FEM	34%	X	X		X			
ENAIRE	POLS	9%	X	X	X	X				POLS	29%	X	X	X	X	X	X	
ENAV	POLS	93%		X		X	X			FEM	21%	X	X	X	X	X		
Fintraffic ANS	FEM	37%	X	X				X		FEM	30%	X	X	X	X			X
HCAA	POLS	42%	X	X		X	X			POLS	41%	X	X		X			X
Hungaro Control	POLS	40%	X	X	X	X	X	X		FEM	63%	X	X	X	X		X	
IAA	POLS	92%		X	X	X	X			POLS	95%		X		X	X		

LFV	FEM	39%	X	X			X	X		FEM	36%	X	X		X			X
LGS	FEM	20%	X	X		X	X	X		FEM	47%	X	X	X	X		X	
LPS	POLS	94%		X		X				FEM	43%	X	X		X		X	
LVNL	FEM	59%	X	X	X	X	X	X		FEM	40%	X	X	X	X		X	X
MATS	POLS	2%	X	X		X				FEM	59%	X	X		X	X	X	X
M-NAV	POLS	68%		X		X				POLS	12%	X	X		X			
MoldATSA	POLS	68%		X		X	X			FEM	24%	X	X		X		X	
NATS	FEM	45%	X	X		X	X	X		FEM	54%	X	X		X		X	X
NAV Portugal	FEM	22%	X	X		X				FEM	24%	X	X		X			
NAVIAIR	FEM	48%	X	X		X	X	X		FEM	42%	X	X		X		X	X
Oro Navigacija	FEM	41%	X	X		X	X			FEM	54%	X	X		X			
PANSA	POLS	97%		X		X	X			FEM	47%	X	X	X	X		X	X
ROMATSA	FEM	16%	X	X		X		X		FEM	37%	X	X	X	X			
Sakaeronavigatsia	FEM	48%	X	X		X	X	X	X	POLS	80%		X		X			
skeyes	FEM	59%	X	X		X		X	X	FEM	53%	X	X		X		X	X
skyguide	POLS	97%		X		X	X			POLS	20%	X	X	X	X	X	X	X
Slovenia Control	POLS	88%		X		X	X			POLS	40%	X	X	X	X	X	X	
SMATSA	POLS	90%		X		X				FEM	51%	X	X	X	X		X	
UkSATSE	FEM	50%	X	X	X		X	X		FEM	27%	X	X				X	

Table 5: Regression Models on ANSP Level

FAB	KEP									KEA								
	Type	R^2	CONST	DEM	ATFM_DEL	ATMAP	CO2P	FuelP	CHARGE	Type	R^2	CONST	DEM	ATFM_DEL	ATMAP	CO2P	FuelP	CHARGE
Baltic FAB	FEM	30%	X	X	X	X	X	X	X	FEM	49%	X	X	X	X	X	X	
BLUE MED FAB	POLS	37%	X	X		X	X			POLS	13%	X	X		X	X		
DANUBE FAB	POLS	12%	X	X	X	X				POLS	36%	X	X	X	X			
DK-SE FAB	FEM	47%	X	X	X		X	X		FEM	41%	X	X	X				X
FAB CE	POLS	95%		X		X	X			FEM	64%	X	X		X		X	
FABEC	FEM	33%	X	X	X		X	X		FEM	54%	X	X	X	X	X	X	
NEFAB	FEM	55%	X	X	X		X	X		FEM	22%	X	X		X	X		X
SW FAB	POLS	10%	X	X	X	X	X	X	X	POLS	27%	X	X	X	X	X	X	X
UK-Ireland FAB	FEM	47%	X	X	X	X	X	X		FEM	53%	X	X	X	X	X	X	

Table 6: Regression Models on FAB Level

Unit	KEP									KEA								
	Type	R^2	CONST	DEM	ATFM_DEL	ATMAP	CO2P	FuelP	CHARGE	Type	R^2	CONST	DEM	ATFM_DEL	ATMAP	CO2P	FuelP	CHARGE
EUROCONTROL	FEM	54%	X	X	X	X	X	X		FEM	69%	X	X	X	X	X	X	X

Table 7: Regression Models on European Level

The results show that different factors influence the HFE of an ANSP, FAB, or Europe. Keeping in mind that some significant factors (e.g., military airspaces) could not be included in the model, the regression lead to appropriate results for the majority of ANSPs. As expected, the POLS without a constant lead to higher R^2, which does not necessarily mean that the HFE can be predicted more precisely than using a POLS with a constant. In fact, there is no threshold dividing the results into "good" and "bad" models. However, some examples (e.g., KEP for MATS) can be identified to be insufficient.

The model quality also differs according to the unit considered. A (relatively) lower model quality is caused by unobserved effects, either because a significant factor was not included (availability) or not quantifiable (qualitative nature). Lower quality scores as well as the individual analysis of KEA and KEP (different regression models) may lead to counterintuitive predictions or inconsistencies. As an example, the KEA might be higher than the KEP. Table 8 shows the average model quality per Indicator and regression model. Overall, the regression models for KEA achieve higher quality. Thus, it might be assumed that also the prediction of HFE scores is more precise than those for KEP.

	ANSP		FAB	
	KEP	KEA	KEP	KEA
Dummy R^2	41,8%	42,7%	42,4%	47,2%
Adjusted R^2	19,4%	24,9%	19,7%	25,3%
Non-Centered R^2	89,2%	92,5%	95,0%	-

Table 8: Comparison of model quality criteria

Some factors are very important for HFE, while other factors only affect a minor number of units. These differences can be observed when comparing units, but also indicators (KEA vs. KEP). Table 9 ranks the factors according to their impact, distinguishing KEA and KEP. The maximum value is 46 (36 ANSP + 9 FABs + Europe).

Demand is the only factor affecting all units and both HFE scores. The second most influencing factor is the weather, affecting 87% (KEP), respectively 97% (KEA) of the units. In contrast, the route charges influence the HFE for just 5, respectively 15 units. Please note that other factors (e.g., wealth) were considered, but never included in the optimized models which were used for the predictions.

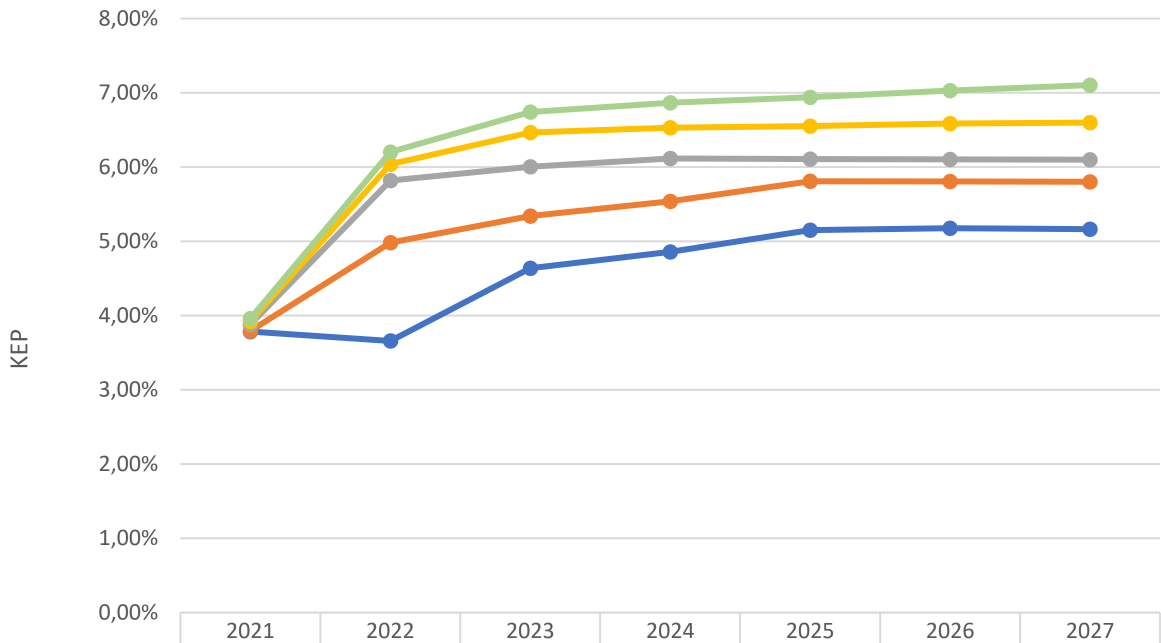
KEP		KEA	
Factor	Impact	Factor	Impact
DEM	46	DEM	46
ATMAP	40	ATMAP	44
CO2P	34	FuelP	27
FuelP	21	ATFM_DEL	20
ATFM_DEL	15	CO2P	16
CHARGE	5	CHARGE	15

Table 9: Comparison of impacts by factors of 46 units

5.5 Results

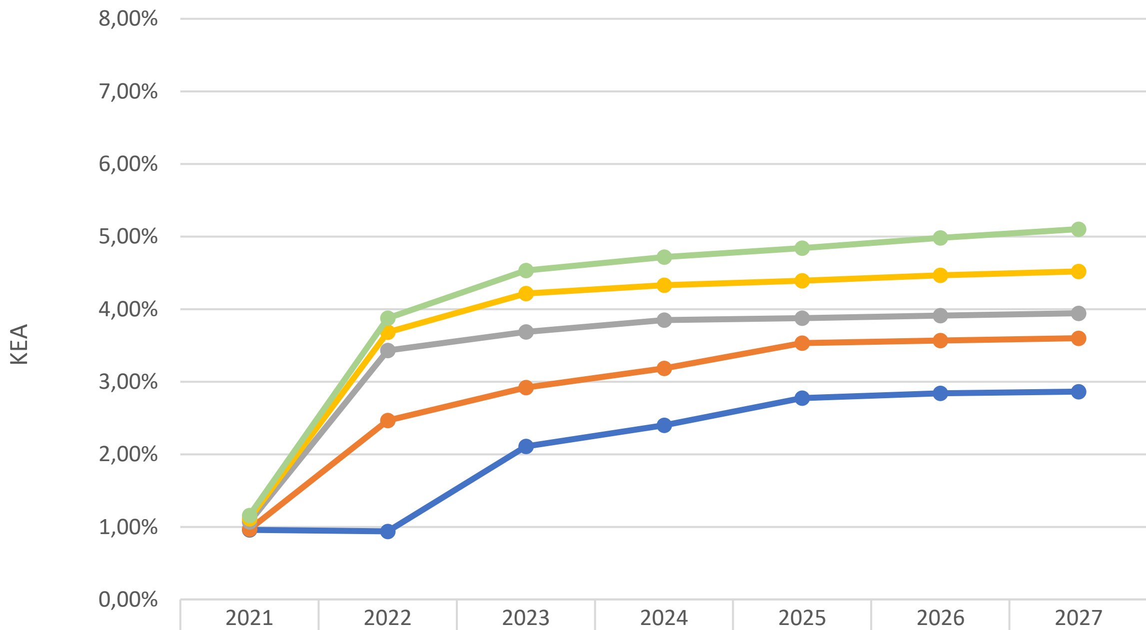
Based on the regression model and the expected values of the factors (see section 5.3), KEA and KEP are estimated for all scenarios and all years. The expected values are available for each ANSP, FAB, and Europe. Figure 13 shows the expected KEP, and Figure 14 the expected KEA values on the ANSP level for the British NATS. Figure 15 and Figure 16 illustrate the results for FABEC, Figure 17 and Figure 18 show the prediction on the European level.

Please note that the scale (y-axis) might differ between KEA and KEP figures and that the scale might not start with 0. This is due to illustrational reasons. Further results can be found in Annex A7 and A9. However, due to the amount of data, only excerpts of the results are included in this document. A detailed description is provided in [44].



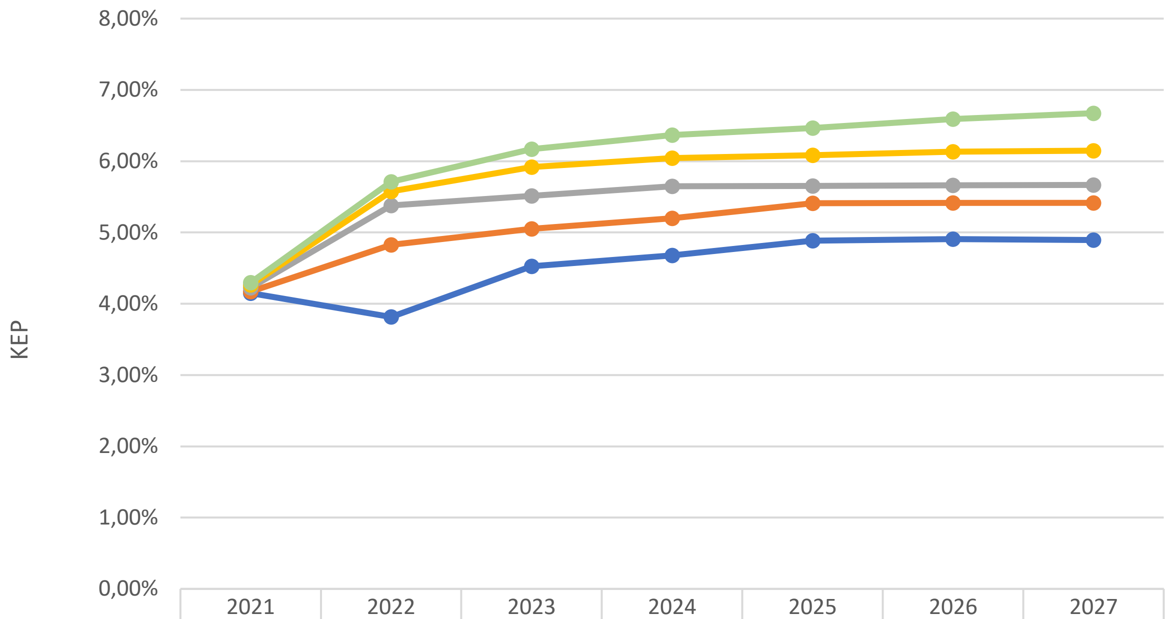
	2021	2022	2023	2024	2025	2026	2027
Super Low	3,79%	3,66%	4,64%	4,86%	5,15%	5,18%	5,16%
Low	3,79%	4,98%	5,34%	5,54%	5,81%	5,81%	5,80%
Base	3,88%	5,82%	6,01%	6,12%	6,11%	6,10%	6,10%
High	3,92%	6,04%	6,46%	6,53%	6,55%	6,59%	6,60%
Super High	3,96%	6,20%	6,74%	6,87%	6,94%	7,03%	7,10%

Figure 13: HFE on ANSP Level - Predicted KEP for NATS



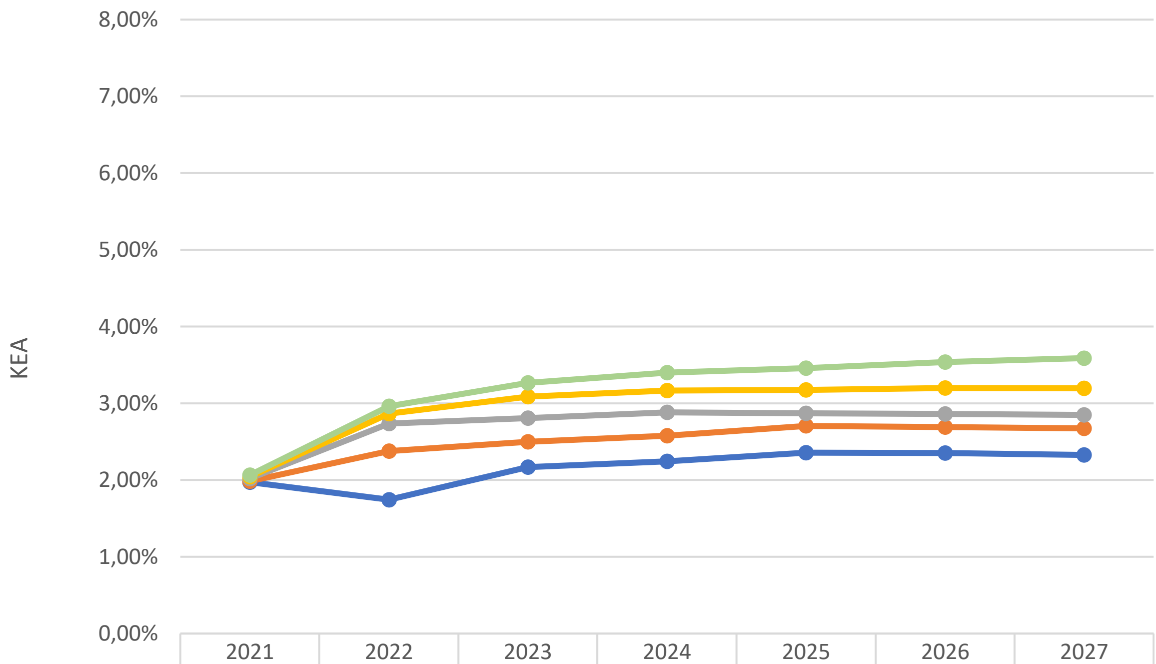
	2021	2022	2023	2024	2025	2026	2027
Super Low	0,96%	0,94%	2,11%	2,40%	2,77%	2,84%	2,86%
Low	0,97%	2,46%	2,92%	3,18%	3,53%	3,57%	3,60%
Base	1,07%	3,43%	3,69%	3,85%	3,88%	3,91%	3,94%
High	1,11%	3,68%	4,21%	4,33%	4,39%	4,47%	4,52%
Super High	1,16%	3,87%	4,53%	4,72%	4,84%	4,98%	5,10%

Figure 14: HFE on ANSP Level - Predicted KEA for NATS



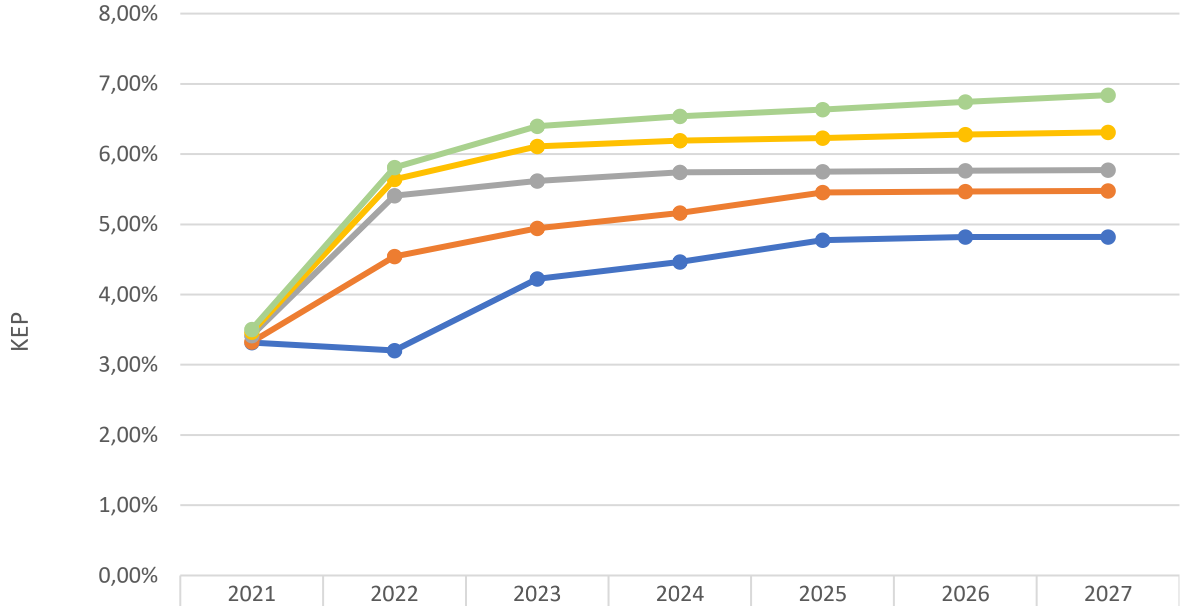
	2021	2022	2023	2024	2025	2026	2027
Super Low	4,15%	3,81%	4,53%	4,68%	4,89%	4,91%	4,90%
Low	4,17%	4,83%	5,05%	5,20%	5,41%	5,41%	5,42%
Base	4,23%	5,38%	5,51%	5,65%	5,65%	5,66%	5,67%
High	4,26%	5,57%	5,92%	6,05%	6,08%	6,13%	6,15%
Super High	4,30%	5,71%	6,17%	6,37%	6,47%	6,59%	6,67%

Figure 15: HFE on FAB Level - Predicted KEP for FABEC



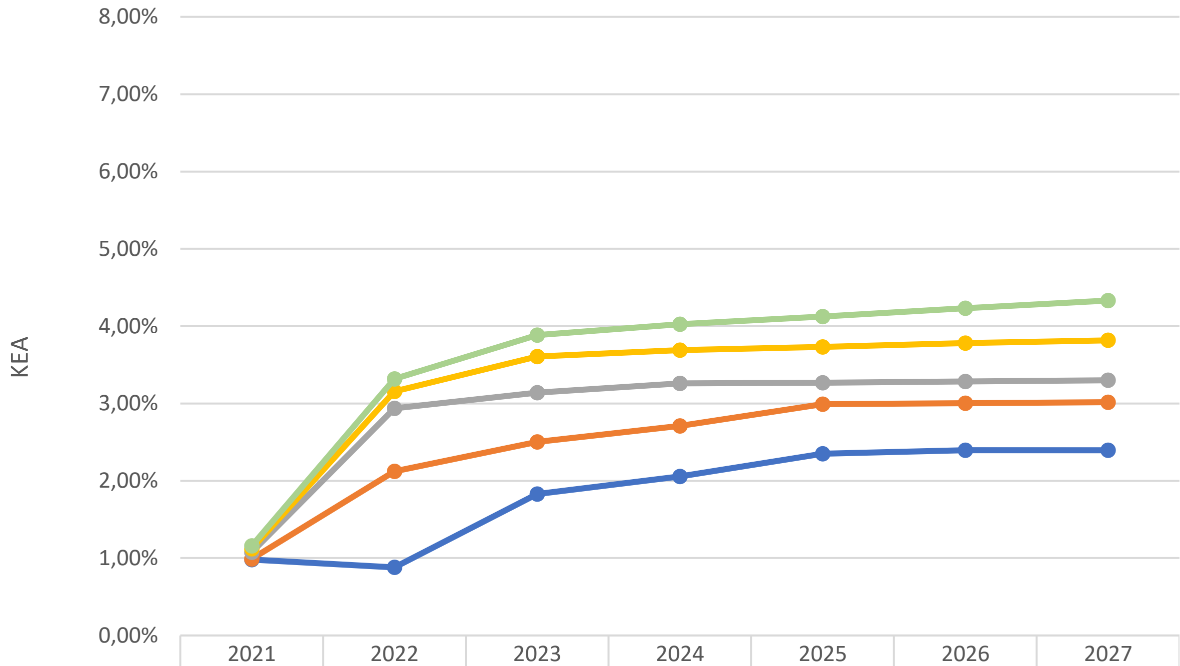
	2021	2022	2023	2024	2025	2026	2027
Super Low	1,97%	1,74%	2,17%	2,24%	2,36%	2,35%	2,33%
Low	1,99%	2,38%	2,50%	2,58%	2,71%	2,69%	2,67%
Base	2,02%	2,74%	2,81%	2,88%	2,87%	2,86%	2,85%
High	2,04%	2,87%	3,09%	3,16%	3,18%	3,20%	3,20%
Super High	2,06%	2,96%	3,27%	3,40%	3,46%	3,54%	3,59%

Figure 16: HFE on FAB Level - Predicted KEA for FABEC



	2021	2022	2023	2024	2025	2026	2027
Super Low	3,32%	3,20%	4,22%	4,46%	4,78%	4,82%	4,82%
Low	3,32%	4,54%	4,94%	5,16%	5,45%	5,47%	5,48%
Base	3,42%	5,41%	5,62%	5,74%	5,75%	5,76%	5,77%
High	3,46%	5,64%	6,11%	6,19%	6,23%	6,28%	6,31%
Super High	3,51%	5,81%	6,40%	6,54%	6,63%	6,74%	6,84%

Figure 17: HFE on European Level - Predicted KEP for EUROCONTROL Area



	2021	2022	2023	2024	2025	2026	2027
Super Low	0,98%	0,88%	1,83%	2,06%	2,35%	2,39%	2,39%
Low	0,99%	2,12%	2,50%	2,71%	2,99%	3,01%	3,02%
Base	1,08%	2,94%	3,14%	3,26%	3,27%	3,29%	3,30%
High	1,12%	3,16%	3,61%	3,69%	3,73%	3,78%	3,82%
Super High	1,16%	3,32%	3,89%	4,03%	4,12%	4,23%	4,33%

Figure 18: HFE on European Level - Predicted KEA for EUROCONTROL Area

Methodology and results have already been discussed with operational experts and found to be realistic. Significant deviations are only to be expected for those national airspaces controlled by multiple ANSPs, especially the Benelux countries. Since the HFE score is based on states, the ANSP-specific HFE score will be higher, which was also demonstrated in a case study for Skeyes (Belgium), see section 5.7.

5.6 Case Study: Military Influence

According to operational experts, military areas have a significant impact on HFE. The influence is emphasized in Figure 19, showing the airspaces (such as temporarily restricted airspaces, TRAs) across Europe. There are data sources such as PRISMIL, which are, however, sensitive and thus not publicly available. Subsequently, data could not be provided by the client. Public data (e.g., Network operations portal, NOP) is not available at the granularity needed [45].

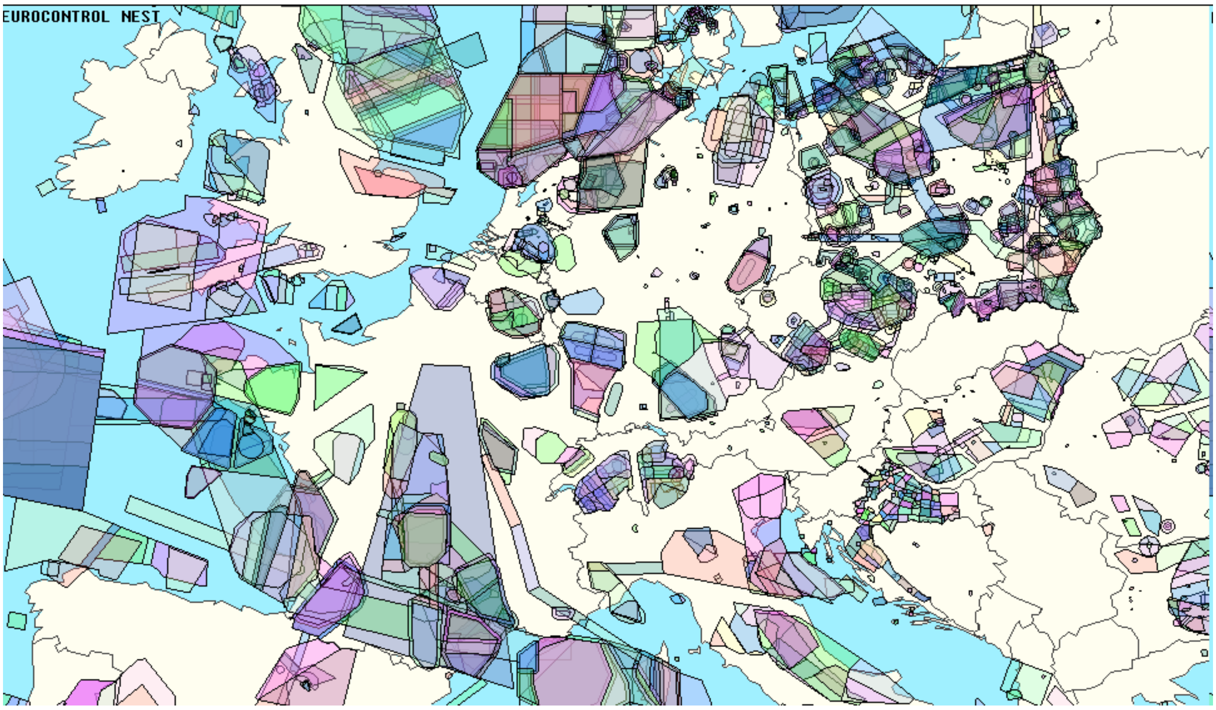


Figure 19: Military Airspaces in Europe

As shown before, HFE predictions lead to satisfactory results. Thus, military areas might be seen as one of the "particularities" which are covered by ANSP Individual regressions. The only biasing factor would be significant differences between the years. External shocks, such as the downing of MH17 by Russian separatists, the annexation of Crimea by Russia, or the Russian war against Ukraine leads to significant traffic shifts. Smaller events, such as the hijacking of a Ryanair plane by Belarus, can trigger such effects as well.

Several analysis options are available to visualize these effects. As an example, density plots of the trajectories show shifts in traffic flows. The plots can be created and evaluated by applying EUROCONTROL tool NEST [46,47]. The data were provided by DFS [48]. It is visible that the traffic flows shifted, comparing the situation before (Figure 20) and after (Figure 21) the downing of MH17 and the Crimea annexation. Similar effects are visible for Belarus (not illustrated).

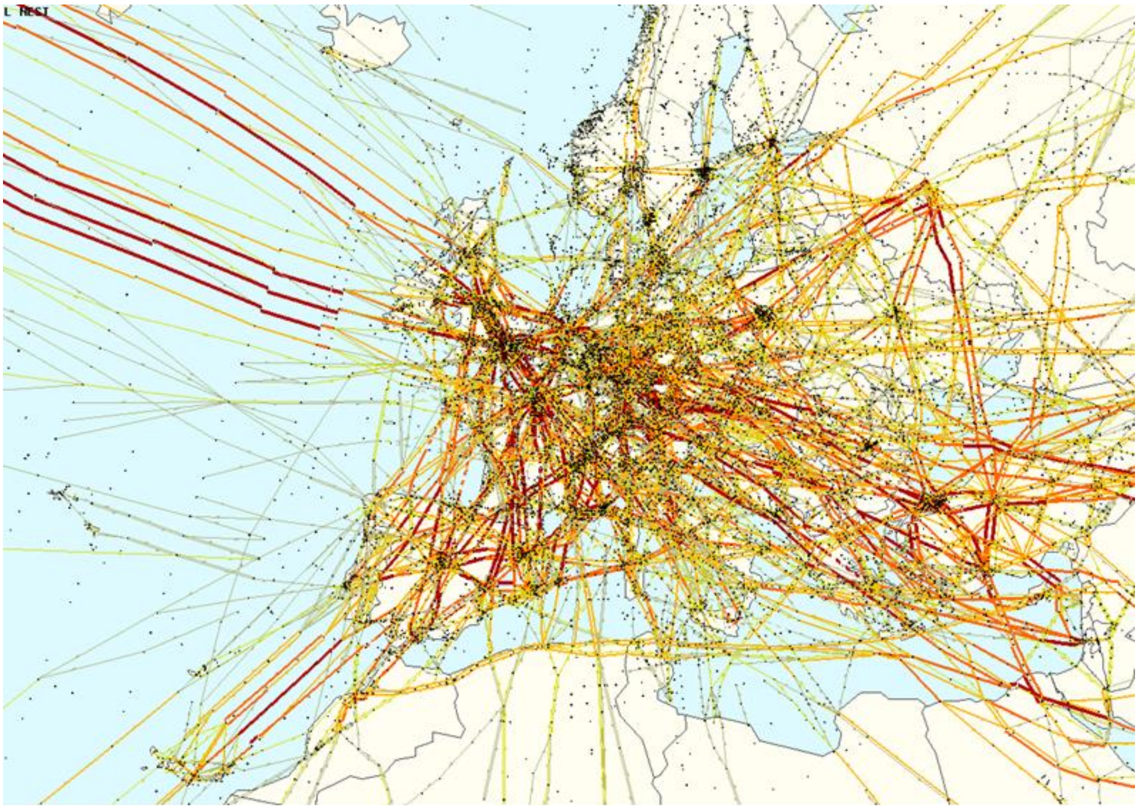


Figure 20: Density Plot Actual Trajectories in European Airspace, 18.07.2012

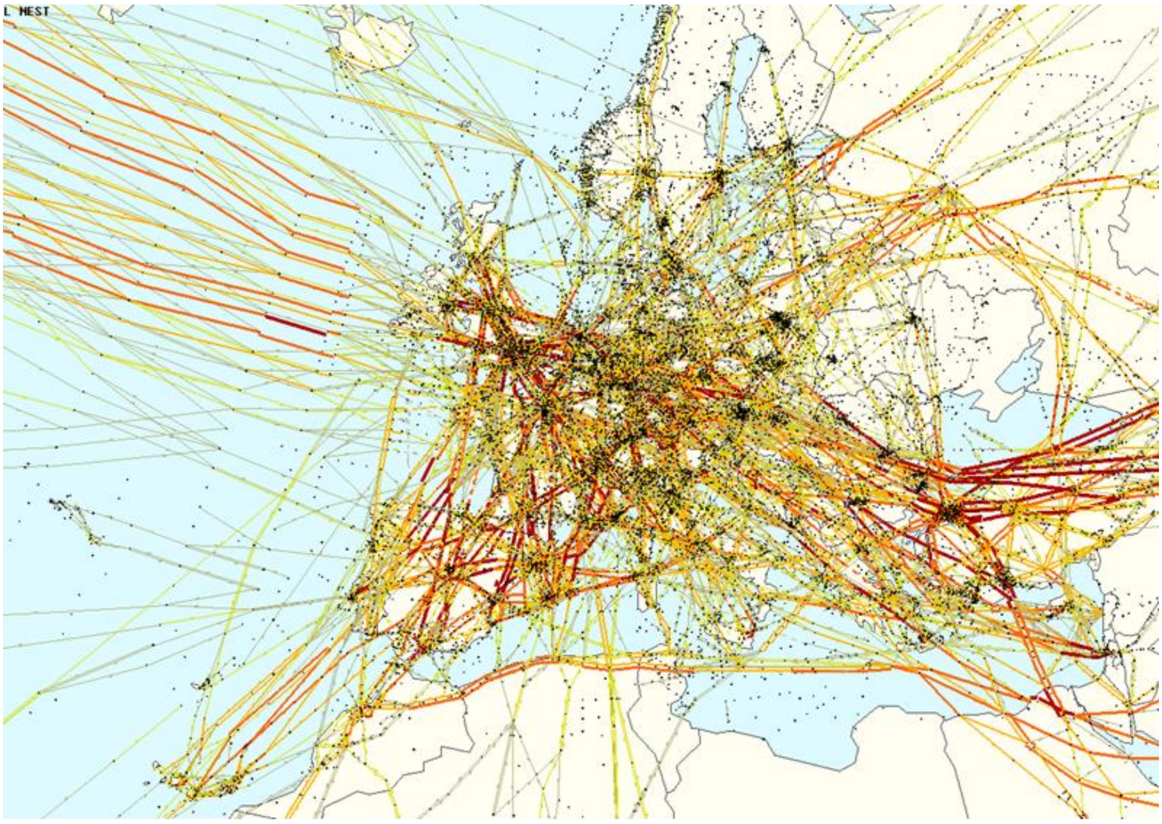


Figure 21: Density Plot Actual Trajectories in European Airspace, 13.07.2016

The shift in traffic flows also affects the HFE scores significantly. For example, the downing of MH17 caused a sharp increase in the HFE scores in Ukraine's neighboring states. Figure 22 shows the development of KEA in 2014 for Poland and Lithuania based on daily data, and Figure 23 for the corresponding FAB based on monthly data.

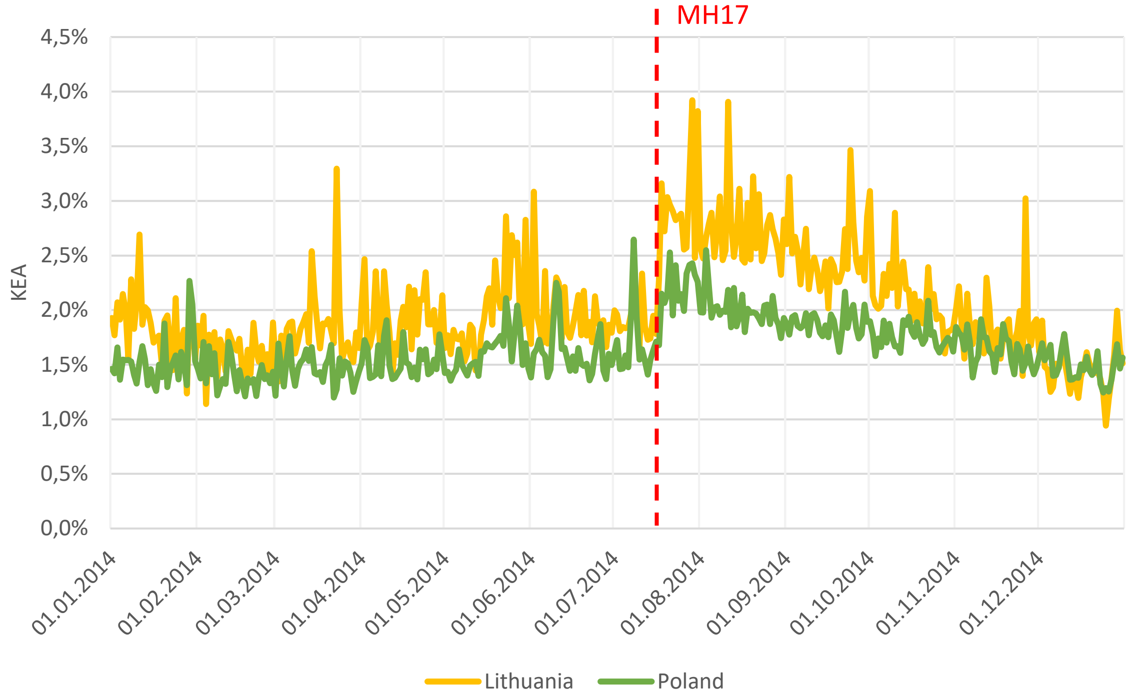


Figure 22: KEA of Poland and Lithuania, 2014

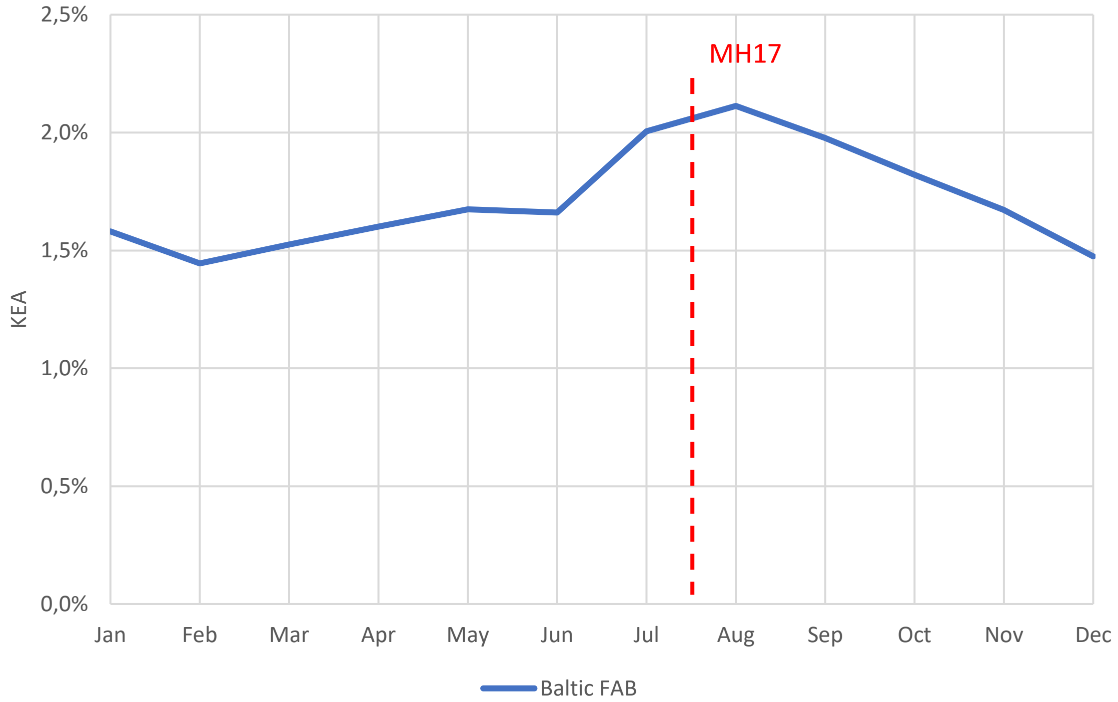


Figure 23: KEA of Baltic FAB, 2014

The same effect can be observed triggered by the Russian attack on Ukraine in February 2022, as shown in Figure 24 (ANSP level) and Figure 25 (FAB level). Surprisingly, the HFE did not increase significantly in Danube FAB and the associated ANSPs.

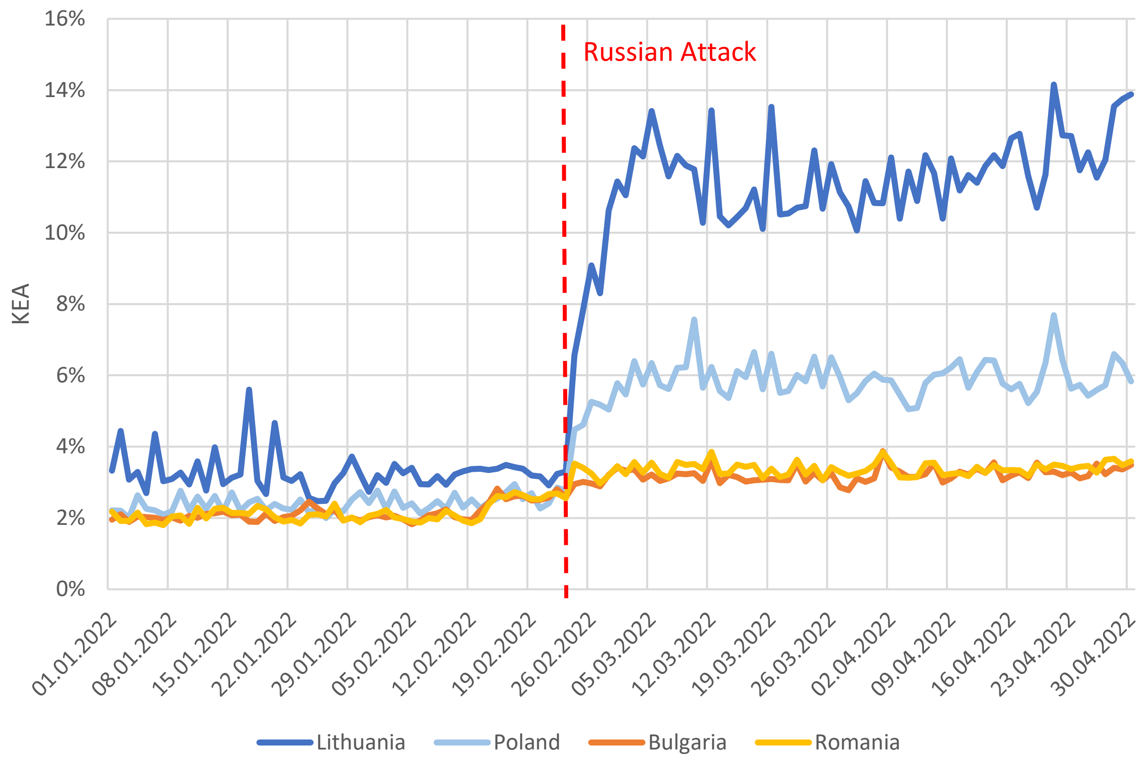


Figure 24: KEA in various countries after the Russian attack on Ukraine

Figure 25: KEA in Baltic FAB and Danube FAB after the Russian attack on Ukraine

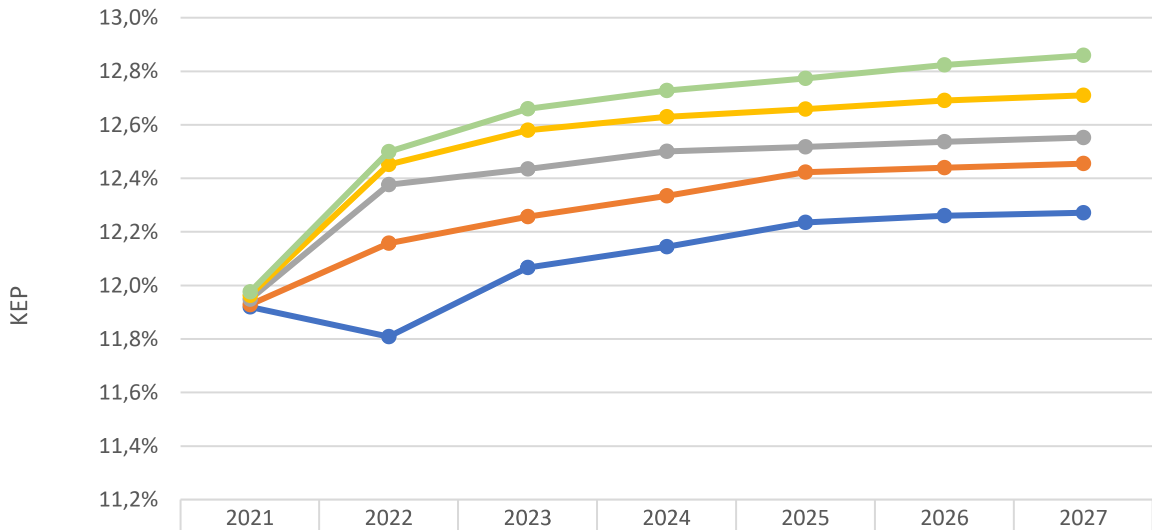
The analyses emphasize the importance of military traffic on HFE. Therefore, a consideration of the military in the regressions and predictions would be desirable. However, it can also be shown that political conflicts in one country can affect the HFE of other countries tremendously. These effects in turn are hard to model and impossible to predict. In this respect, we argue that the inclusion could improve the regression model, but the high uncertainty of future events would make a meaningful prediction rather difficult. In this respect, the results obtained are to be regarded as appropriate and sufficient estimates, even though new military airframes will impact the activation of TRA/TSA and thus also HFE which might lead to biased results.

5.7 Case Study: HFE Prediction for Skeyes

The prediction of KEA and KEP is done on an ANSP basis. This is because the factors in the regression model, with a few exceptions, contain ANSP-related values. For example, demand is represented by the traffic scenarios, and the corresponding flights were calculated on an ANSP basis. The regression method establishes a functional relationship between the dependent variable and the independent variable. This model can then be applied to other units of investigation (e.g., to other years). However, in case the dependent variable has significant other variance, this may cause problems.

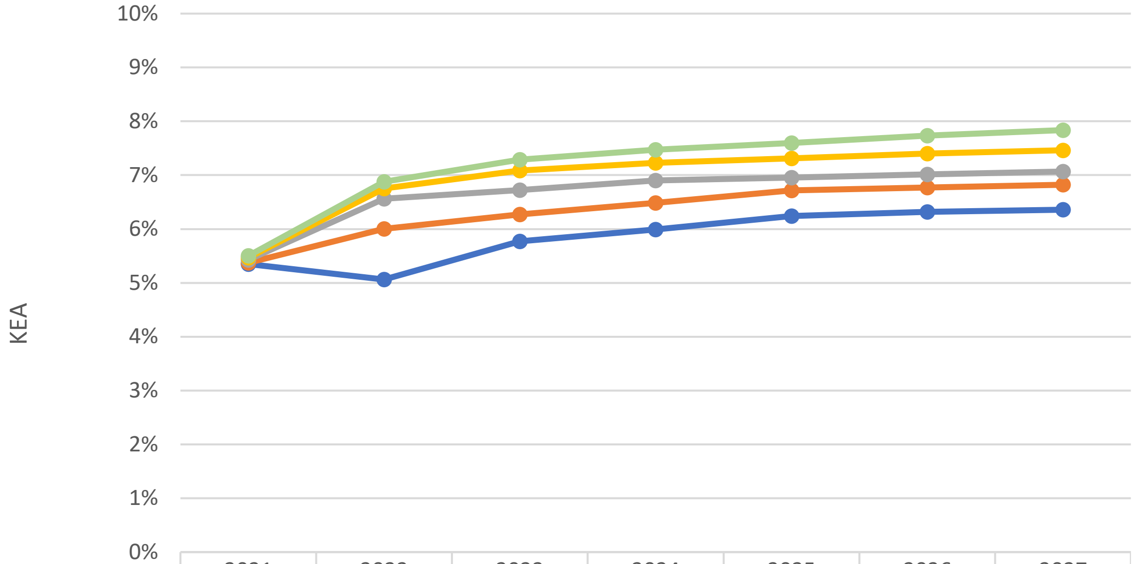
In the European context, this problem occurs when several ANSPs control a (national) airspace. The HFE value provided by PRU then represents the average of the participating ANSPs. This is mainly the case for LVNL, MUAC, and skeyes, partly also for DFS. As an example, the values for Belgium are composed of the scores for MUAC and skeyes. However, since MUAC controls mainly the upper airspace, the HFE scores are rather low. Conversely, the values for skeyes should be higher and thus the predictions may have to be corrected upwards.

To illustrate this effect, the prediction was repeated using specific values for skeyes. HFE data was provided by skeyes [49], using the FABEC tool Carpe Diem. It should be noted that the calculation method is similar to the PRU method but may lead to slightly deviating scores [50]. The application of the data to the regression model indeed led to higher HFE scores, as shown in Figure 26 and Figure 27. The initial results for skeyes are illustrated in Annex A7 (Figure A 14, and Figure A 15).



	2021	2022	2023	2024	2025	2026	2027
Super Low	11,92%	11,81%	12,07%	12,14%	12,24%	12,26%	12,27%
Low	11,93%	12,16%	12,26%	12,33%	12,42%	12,44%	12,45%
Base	11,95%	12,38%	12,44%	12,50%	12,52%	12,54%	12,55%
High	11,96%	12,45%	12,58%	12,63%	12,66%	12,69%	12,71%
Super High	11,98%	12,50%	12,66%	12,73%	12,77%	12,82%	12,86%

Figure 26: HFE Forecast for skeyes, KEP



	2021	2022	2023	2024	2025	2026	2027
Super Low	5,35%	5,06%	5,77%	5,99%	6,24%	6,32%	6,36%
Low	5,37%	6,00%	6,27%	6,48%	6,72%	6,77%	6,82%
Base	5,43%	6,56%	6,73%	6,90%	6,96%	7,01%	7,07%
High	5,47%	6,75%	7,09%	7,23%	7,31%	7,40%	7,46%
Super High	5,50%	6,88%	7,29%	7,47%	7,60%	7,74%	7,84%

Figure 27: HFE Forecast for skeyes, KEA

The results emphasize the importance of a valid dataset. Since we apply regression on individual units (and not Europe), with the specific particularities, regression models and subsequently HFE prediction differ significantly with changes in the input data of the model. In this case, the characteristics of Belgium airspace strongly differ from the one assigned to skeyes, and thus the HFE scores as an input for the regression model as well. This mainly affects the constant of the regression model, but also (to a lower extent) the factor coefficients. Thus, also the predicted HFE scores differ significantly. Based on this finding, we recommend for units where state and ANSP-related airspaces differ significantly to estimate the HFE scores for both airspaces to emphasize the differences.

6 Environmental Influences

A shortfall of capacity leads to delay costs and considerable environmental costs (i.e. changes in air-traffic management capacity may lead to an increase in distances flown and therefore in fuel burn for airlines who prefer to reroute rather than accept the initial delay). And all this leads to significant increases in environmental costs). Therefore, considering that capacity is planned for the medium and long term, traffic forecasts are a crucial element. This means that further research on the interdependency of traffic forecasts, capacity, and environmental costs is justified. In this respect, it is essential to analyze the efficiency of flight paths in order to optimize and balance delays and, consequently, possible environmental costs. This means exploring other variables such as CO_2 emissions and its likely rising cost. An exercise for forecasting CO_2 prices has been conducted in this study. Note that estimates of future emissions costs are not included in the studies by the Transport Studies Group from the University of Westminster, so this should be added to these calculations.

Nevertheless, climate and environmental costs go beyond mere CO_2 costs. They also include factors such as non-CO_2 emissions that also cause climate change, noise, or habitat damage. Therefore, in this study, we first focus on CO_2 costs and then move on to a broader definition of climate and environmental costs.

6.1 CO_2 Emissions and Climate Costs

In the assessment of HFE targets, the regulation does not consider actual wind – and temperature conditions – nor the presence of significant weather along the route, which may have a comparable impact on the flight time and fuel burn. However, although a higher horizontal flight efficiency measurement usually means a more direct flight trajectory, this does not necessarily translate into a climate optimal trajectory. The optimal climate trajectory refers to the flying trajectory that minimizes the amount of Greenhouse Gas Emissions (GHG). In consequence, in particular for long-haul flights, flying in a straight line may not be the most efficient option. For short-haul flights, a longer route might be preferred when then the shortest route is impacted by level-capping measures.

There is also an interdependency between airspace and ATM Capacity and Environment: when the offered capacity falls short of the demand for flights, ground delays, holdings and traffic shifts to adjacent areas occur. This entails detours and a deterioration of the HFE indicator. In addition to this, there are the countermeasures: If it takes longer to complete the flight or if the flight is delayed due to low ATM capacity, pilots may speed up to arrive on time which will increase fuel consumption and therefore costs (and also CO_2 emissions).

Interdependency between Cost-Efficiency and Environment leads also to a decrease in HFE. When the unit rate of a country becomes too expensive compared to a neighboring country, or when the price of fuel becomes cheaper, airlines do not hesitate to file and fly on longer routes.

Aviation warms Earth's surface through both CO_2 and net non-CO_2 contributions. According to [51], CO_2 emissions are responsible for only 34% of the total climate change impact, meaning that aviation emissions are currently warming the climate at approximately three times the rate associated with aviation CO_2 emissions alone[4]. Thus, non-CO_2 impacts (e.g., nitrogen oxides (NOx), water vapor, soot and sulfate aerosols, and increased cloudiness due to contrail formation) comprise about two-thirds of the net radiative forcing (the remaining 66%).

[4] This study is based on CO2-warming-equivalent emissions based on global warming potentials (GWP method).

On this basis, in this study, we assume that the cost of CO_2 emissions also accounts for 34% of the total cost of climate change, with the remaining 66% coming from other sources.

6.2 Environmental Costs

Nevertheless, aviation causes other environmental impacts which, although not directly related to climate change, are environmentally damaging, such as noise, local air pollution, well to tank, or habitat damage.

In order to estimate the environmental cost, [52] provides average external costs for selected EU28 (air)ports, concluding with the following (see Table 10):

Cost category	**Aviation passenger**		
	Short-haul	Medium haul	Long haul
	€-cent/pkm	€-cent/pkm	€-cent/pkm
Accidents	0.04	0.01	0.00
Air pollution	0.30	0.13	0.06
Climate	2.39	1,85	2,24
Noise	0.46	0.11	0.01
Well to tank	1.06	0.70	0.91
Habitat damage	0.03	0.01	0.00
Total	**4.28**	**2.81**	**3.22**
Environmental costs[a]	**4.24**	**2.8**	**3.22**

a: Air pollution, climate, well to tank, noise and habitat damage costs

Table 10. Average external costs for selected EU(28) air(ports)

This allows us to calculate the following shares (Table 11):

Cost category	**Aviation passenger**				
	Short-haul	Medium haul	Long haul	Average	%
	€-cent/pkm	€-cent/pkm	€-cent/pkm	€-cent/pkm	
Air pollution	0.30	0.13	0.06	0.16	4.78
Climate	2.39	1,85	2,24	2.16	63.16
Noise	0.46	0.11	0.01	0.19	5.65
Well to tank	1.06	0.70	0.91	0.89	26.02
Habitat damage	0.03	0.01	0.00	0.01	0.39
Environmental costs[a]	**4.24**	**2.8**	**3.22**	**3.42**	**100**

Table 11. Share of average external costs for selected EU(28) air(ports)

According to Table 11, it can be seen that climate change (CO_2 + nonCO_2 effects) represents 63.16% of the total environmental cost, so it is possible to estimate how much the rest of the categories amount to (see Table 12). This is for all ANSPs and FABs.

Environmental cost = climate cost + non-climate costs	**100%**
Climate cost	**63,16%**
Co2 (34% of climate cost)	21,47%
Non-CO2 (66% of climate cost)	41,68%
Non-climate costs	**36,84%**
Local air pollution	4,78%
Noise	5,65%
Well to tank	26,02%
Habitat damage	0,39%

Table 12. Distribution of environmental costs by type of costs

6.3 Methodology to estimate environmental costs

This sub-section presents the full methodology and steps taken to estimate environmental costs for each ANSP, FAB, as well as for Europe as a whole (see Figure 28).

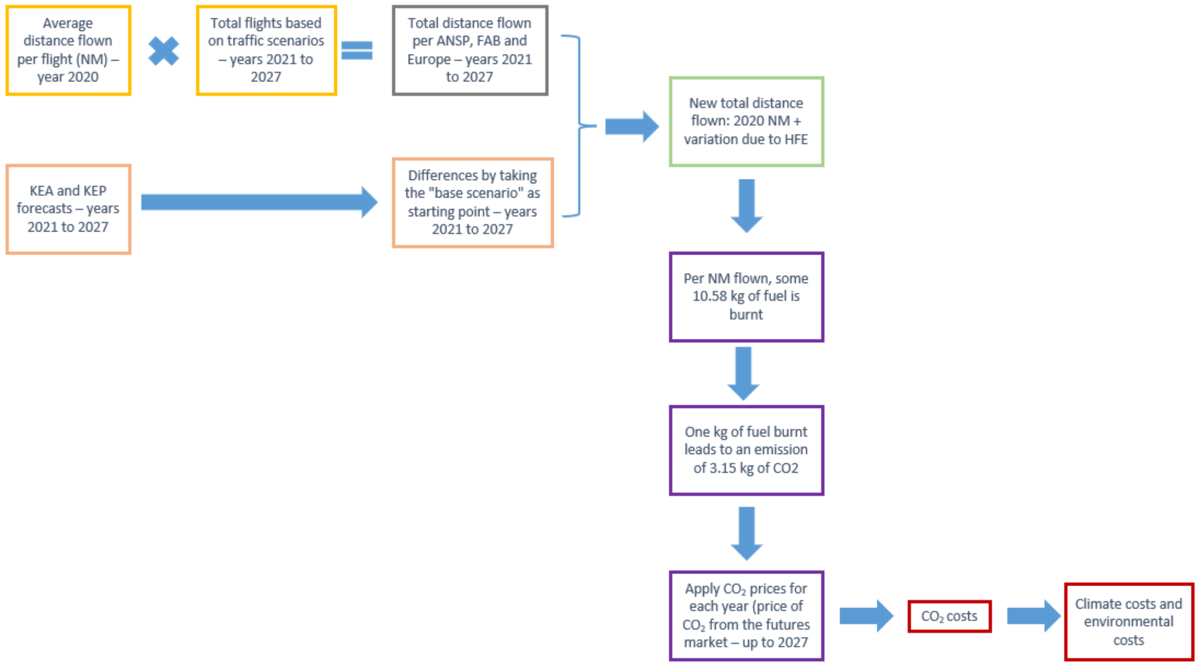


Figure 28. Steps taken to estimate environmental costs

From the 2020 Key operational annual data, the total distance (in km) controlled by the ANSP (or FAB) is divided by the values of the total IFR flights controlled by the ANSP (or FAB) to obtain the average distance flown per flight (per ANSP and FAB). This value corresponds to the year 2020. Km is then converted into nautical miles (NM)[5].

In the previous stages of the study, the total number of flights was calculated for the 5 scenarios (super low, low, base, high, and super high) from 2021 to 2027. Taking these flights as a variable, they are multiplied by the average distance flown per flight already estimated (in NM), so as to obtain the total distance flown per ANSP, FAB, and Europe. It has been assumed that the average distance will remain the same over the years (from 2021 to 2027).

In parallel, KEA and KEP have also been foreseen in previous steps. In order to find out the difference between the scenarios, the base scenario is taken as a starting point and then the values of the other scenarios are compared with this baseline scenario (see the example shown in Figure 29).

Expected Horizontal Flight Efficiency

KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	4,2%	3,8%	4,5%	4,7%	4,9%	4,9%	4,9%
Low	4,2%	4,8%	5,0%	5,2%	5,4%	5,4%	5,4%
Base	4,2%	5,4%	5,5%	5,6%	5,7%	5,7%	5,7%
High	4,3%	5,6%	5,9%	6,0%	6,1%	6,1%	6,1%
Super High	4,3%	5,7%	6,2%	6,4%	6,5%	6,6%	6,7%

Differences

KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	-0,07%	-1,56%	-0,99%	-0,97%	-0,77%	-0,75%	-0,77%
Low	-0,05%	-0,55%	-0,46%	-0,45%	-0,24%	-0,25%	-0,25%
Base	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
High	0,04%	0,20%	0,40%	0,40%	0,43%	0,47%	0,48%
Super High	0,07%	0,33%	0,66%	0,72%	0,82%	0,93%	1,01%

Figure 29. KEP estimates – FABEC (2021-2027) and differences between scenarios

[5] 1 NM is equivalent to 1,852 km.

For FABEC, KEP for 2024 is 4.7% for the super low scenario, compared to 5.6% in the base scenario. This results in a difference of - 0.97%, which means that there will be an improvement in this indicator for this year. In other words mean, FABEC will be more efficient in 2024 and the cost will be reduced. If the difference were positive, then inefficiency would occur and the cost would increase.

In summary, information on total distance, on the one hand, and variations in KEA and KEP, on the other hand, are available so far. With both variables in place, the next step is to estimate the "new" total distance flown after considering KEA and KEP. This is done by adding the variation due to HFE to the total distance flown (on a 2020 basis). Back to the FABEC example (Figure 30), as the difference in 2024 was -0.97%, the new total distance flown is less than that given without taking into account the KEP differences because there has been an improvement.

	2021	2022	2023	2024	2025	2026	2027
Super Low	565.579.312	461.744.306	747.661.991	823.709.818	917.885.556	944.709.694	960.609.646
Low	573.053.306	835.449.884	934.577.489	1.004.524.168	1.092.720.900	1.111.423.169	1.130.128.995
Base	593.451.828	1.025.859.991	1.088.365.359	1.148.340.903	1.167.819.152	1.187.957.297	1.207.048.015
High	607.778.413	1.088.840.104	1.211.215.930	1.264.800.449	1.291.240.078	1.321.183.454	1.340.921.897
Super High	619.933.981	1.132.393.709	1.283.888.886	1.353.336.481	1.394.539.284	1.440.089.965	1.475.014.087

Total miles (2020 NM + Extra (or minus) miles due to HFE)

KEP	2021	2022	2023	2024	2025	2026	2027
Super Lo	565155254	454519989	740290763	815732368	910863391	937589537	953200718
Low	572738888	830834333	930247871	1000014881	1090098559	1108676900	1127284827
Base	593451828	1025859991	1088365359	1148340903	1167819152	1187957297	1207048015
High	608012689	1090965620	1216108821	1269842143	1296790932	1327426005	1347368920
Super Hig	620375890	1136172017	1292319107	1363087901	1405907931	1453471722	1489858490

Figure 30. New total distance flown – FABEC (2021-2027)

Once the total distance flown is available (per ANSP, FAB, and Europe), environmental equivalencies can be applied.

According to [53] there was an average fuel burn for departing and arriving Instrument Flight Rules flights in the European Civil Aviation Conference (ECAC) region of 10.011 kg on an average flight length of 946 NM (see page 55 of [53]). This means that per NM flown, some 10.58 kg of fuel was burnt. In addition, one kg of fuel burnt leads to an emission of 3.15 kg of CO_2; 1.237 kg of H2O; and 0.00084 kg of SO_2 (see pages 24 of [53] and [54].

With all this information, it is possible to extract the emissions generated (in million tonnes) by aviation in each ANSP, FAB, and at the European level and for each of the 5 scenarios and 7 years.

Finally, the CO_2 prices for each year can be applied to calculate the CO_2 costs. Note that the price of CO_2 from the futures market has been used directly, as this information is available until 2027 (CE EUA FUTURES PRICES (EUR)). Considering that CO_2 costs represent only a small part of environmental costs (see table 12), then it is straightforward to estimate both climate and environmental costs (see Figure 31 for FABEC results).

CO2 costs (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	836,65	682,99	1129,16	1262,95	1431,47	1495,65	1543,44
Low	847,87	1248,47	1418,89	1548,27	1713,14	1768,57	1825,32
Base	878,54	1541,53	1660,07	1777,91	1835,29	1895,04	1954,47
High	900,09	1639,36	1854,91	1966,03	2037,97	2117,52	2181,68
Super High	918,40	1707,29	1971,16	2110,39	2209,45	2318,59	2412,40
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	836,89	686,98	1133,10	1267,14	1435,11	1499,35	1547,30
Low	848,05	1250,89	1421,11	1550,52	1714,44	1769,93	1826,73
Base	878,54	1541,53	1660,07	1777,91	1835,29	1895,04	1954,47
High	899,96	1638,32	1852,64	1963,75	2035,47	2114,72	2178,79
Super High	918,15	1705,46	1967,32	2106,11	2204,51	2312,83	2406,06

Climate costs (CO2 + non-CO2) (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	2461,23	2009,21	3321,73	3715,33	4211,06	4399,87	4540,45
Low	2494,26	3672,72	4174,08	4554,66	5039,69	5202,73	5369,68
Base	2584,46	4534,83	4883,56	5230,23	5399,01	5574,78	5749,63
High	2647,88	4822,63	5456,75	5783,62	5995,26	6229,27	6418,03
Super High	2701,72	5022,47	5798,71	6208,32	6499,73	6820,77	7096,76
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	2461,93	2020,93	3333,32	3727,66	4221,77	4410,75	4551,82
Low	2494,78	3679,85	4180,60	4561,30	5043,51	5206,75	5373,84
Base	2584,46	4534,83	4883,56	5230,23	5399,01	5574,78	5749,63
High	2647,49	4819,58	5450,05	5776,91	5987,91	6221,03	6409,51
Super High	2700,99	5017,09	5787,42	6195,71	6485,18	6803,84	7078,09

Environmental costs (climate + local air pollution + noise + well to tank + habitat damage) (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	3897,44	3181,65	5260,06	5883,34	6668,35	6967,32	7189,95
Low	3949,74	5815,86	6609,78	7212,45	7980,51	8238,69	8503,06
Base	4092,58	7181,05	7733,27	8282,23	8549,50	8827,83	9104,71
High	4192,99	7636,79	8640,93	9158,54	9493,69	9864,24	10163,15
Super High	4278,25	7953,24	9182,44	9831,06	10292,52	10800,90	11237,94
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	3898,55	3200,21	5278,42	5902,86	6685,31	6984,55	7207,95
Low	3950,56	5827,16	6620,10	7222,96	7986,56	8245,05	8509,65
Base	4092,58	7181,05	7733,27	8282,23	8549,50	8827,83	9104,71
High	4192,38	7631,95	8630,32	9147,92	9482,04	9851,20	10149,66
Super High	4277,10	7944,73	9164,57	9811,10	10269,48	10774,10	11208,38

Figure 31. CO_2 costs, climate costs and environmental costs for FABEC, 2021-2027

Further examples are shown in Annex A10 However, all results are presented in data sheets, which are available for all ANSPs, FABs, and Europe.

7 Conclusion

The report discusses the impact of STATFOR's traffic forecast, extended by two scenarios, on the performance of ANSPs, FABs, and Europe. In the light of current social, political, and economic preferences, we focus on the environmental domain. This is reported by EUROCONTROL through the indicator Horizontal Flight Efficiency. Although this score has significant methodological weaknesses, it is still a frequently used metric, especially in the official reports. It can be assumed that the diversions factor is indirectly or directly dependent on demand. Uncertainty in actual transport demand is therefore also accompanied by uncertainty in HFE, and thus in environmental consequences and their costs.

We have shown that uncertainties in demand lead to uncertainties in resource and cost planning. As some airspaces are already operating at capacity limits, an increase in delay can be assumed. The expected values were determined and mapped using functional relationships. The interdependency was exponential for the majority of units. For FABEC we expect between 5.2 Mill. and 8.0 Mill. flights in 2027, which leads to a need for resources of between 4,668 and 7,167 ATCOs. The respective employment costs are up to 1.4 Bill. €, not considering inflation. Based on the delay of the assigned ANSPs, a total delay between 2.8 Mill. and 36.3 Mill. minutes is expected. This large span is due to the exponential interdependency between demand and delay. These delays will result in associated costs of between 262 and 3,692 Mill. €, depending on the scenario and whether the average or the function is considered.

Based on the traffic scenarios, delay values, and other endogenous and exogenous influences, the influence of various factors on the HFE was determined utilizing regression analysis. The pan-European approach is not practicable. However, the ANSP-specific approach led to appropriate results, both in terms of regression and prediction. The models lead to appropriate results concerning significance and quality for the majority of units.

Using this method, it was possible to predict the HFE scores for the years 2021 to 2027. The comparison with the 2022 values gives confidence in the quality of the method. One limitation might be that the HFE is very sensitive to demand, but during the Corona pandemic, it was found that the HFE hardly decreased despite the absence of traffic. This can be attributed both to the fact that the calculation method of the HFE has weaknesses and that no COVID years were included in the regression. As a consequence, the values for 2021 should be interpreted accordingly. The shown results reflect the perspective in autumn 2021 (STATFOR forecast date). Later geopolitical events are not integrated and effects (e.g., due to the war in Ukraine) are not taken into account. For FABEC, we expect a KEP between 4.9% and 6.7% in 2027. The KEA will most probably be between 2.3% and 3.59%. However, these values may change significantly due to current political conflicts and the subsequent investment in military equipment.

The HFE results were used to determine the emissions, CO_2 costs, climate costs (both CO_2 and non- CO_2), and environmental costs depending on the scenarios. The CO_2 costs in 2027 would amount to approximately 1,543 to 2,412 Mill. €, depending on the scenario and whether KEA or KEP is considered. The range of values for the climate costs would be between 4,540 and 7,097 Mill. € and, for the environmental costs, between 7,190 and 11,238 Mill. €. This means that FABEC alone would represent around 52-53% of total CO_2, climate, and environmental costs in Europe.

Acknowledgments

The authors would like to thank Prof. Michael Schultz for the provision of ATMAP data for the en-route weather quantification. Further, we thank all InterFAB members who supported the work with their operational and environmental expertise.

References

[1] FABEC (2019): *ACC Capacity Benchmarking Report - An analysis of difference in capacity and operational practices applied across selected FABEC ACCs*, FABEC Performance Management Group, PBTF. Contributors: Maja Marciniak-Cork, Thomas Hellbach, Juan Espinar-Nova, Thomas Standfuß, Stéphane Mariétan, Riccardo Massacci, and Christoph Czech, Langen.

[2] Fricke, H., and Standfuss, T. (2021): *Accuracy of Air Traffic Forecasts - Causes and Consequences*, InterFAB Expert Talks: ATM performance data - can we do better?, TU Dresden, Institute of Logistics and Aviation.

[3] Fricke, H., Vogel, M., and Standfuss, T. (2021): *Reducing Europe's Aviation Impact on Climate Change using enriched Air Traffic Forecasts and improved Efficiency Benchmarks*, FABEC Research Workshop "Climate Change and the Role of Air Traffic Control, Vilnius.

[4] EUROCONTROL (2021): *Forecasting*, https://www.eurocontrol.int/forecasting (10.05.2021).

[5] Standfuss, T., and Whittome, M. (2021): *Forecasting European Air Traffic Demand - How deviations in traffic affect ANS performance*, INAIR Conference, Malta.

[6] EUROCONTROL (2021): *ATM Cost-Effectiveness (ACE) 2019 Benchmarking Report with Special Focus on COVID-19 Impacts in 2020*, Performance Review Unit, ACE Working Group, Brussels.

[7] EUROCONTROL (2020): *Performance Review Report of the European Air Traffic Management System in 2019*, Performance Review Commission, Brussels.

[8] EUROCONTROL (2021): *Performance Indicator - Horizontal Flight Efficiency*, https://ansperformance.eu/methodology/horizontal-flight-efficiency-pi (04.05.2021), Brussels.

[9] EUROCONTROL (2021): *Forecast Update 2021-2027 - European Flight Movements and Service Units - Three Scenarios for Recovery from COVID-19*, STATFOR, Brussels.

[10] FABEC (2021): *Forecasting European Air Traffic Demand - How deviations in traffic affect ANS performance*, Study for InterFAB., Langen.

[11] EUROCONTROL (2019): *Air traffic management cost-effectiveness (ACE) benchmarking report for 2017*, Performance Review Unit, Brussels.

[12] Standfuss, T. (2022): *Traffic Scenario Datasheets*, https://cloudstore.zih.tu-dresden.de/index.php/s/qNNgDTHNBsc4par, Dresden.

[13] EUROCONTROL (2020): *OneSky Online*, ACE Working Group, Brussels. Available at: https://extra.eurocontrol.int/Pages/default.aspx (04.03.2020).

[14] EUROCONTROL (2021): *En-route IFR flights and ATFM delays*, Performance Review Unit, https://ansperformance.eu/data/ (02.09.2021).

[15] Galarraga, I., Abadie, L.M., Standfuss, T., Whittome, M., and Ruiz-Gauna, I. (2021): *Approximation to flights, delays and costs for different forecast scenarios: a backcasting exercise*, Study for FABEC, Bilbao / Dresden.

[16] Standfuss, T., and Galarraga, I. (2021): *Traffic Forecasts, Delay and Costs - A Backcasting Exercise*, FABEC Expert Talk, ATM performance data - can we do better?

[17] FABEC (2018): *Performance Report 2015-2019 - Capacity*, Performance Management Group, Langen.

[18] PRB (2018): *PRB Advice to the Commission in the setting of Union-wide performance targets for RP3*, Brussels.

[19] Standfuss, T. (2021): *Performance Benchmarking in Air Traffic Management - Methodology, Analysis, and Evaluation*, Technische Universität Dresden, Dresden.

[20] PERFORMANCE REVIEW UNIT (2019a): *ATM Cost-Effectiveness (ACE) 2017 Benchmarking Report with 2018-2022 outlook*.

[21] PERFORMANCE REVIEW UNIT (2019b): *PRR 2018: Performance Review Report. An Assessment of Air Traffic Management in Europe during the Calendar Year 2018.PRB (2018)*. PRB Advice to the Commission in the setting of Union-wide performance targets for RP3, Brussels.

[22] EUROCONTROL (2018a): *Standard Inputs for EUROCONTROL Cost-Benefit Analyses. Edition Number: 8.0*.

[23] Cook, A. (2004): *Evaluating the true cost to airlines of one minute of airborne or ground delay*. Prepared for the Performance Review Unit – EUROCONTROL.

[24] Cook, A., and Tanner, G. (2011): *European airline delay cost reference values*. Prepared for the Performance Review Unit – EUROCONTROL.

[25] Cook, A., and Tanner, G. (2015): *European airline delay cost reference values*. Prepared for the Performance Review Unit – EUROCONTROL.

[26] Abadie, L. M., Galarraga, I., and Ruiz-Gauna, I. (2022): *Flight Delays in Germany: a Model for Evaluation of Future Cost Risk*. European Journal of Transport and Infrastructure Research 22(1): 93–117.

[27] EUROCONTROL (2021): *SES Performance Scheme Reference Period 3 (2020-2024)*, Single European Sky Portal: https://www.eurocontrol.int/prudata/dashboard/metadata/rp3/ (10.05.2021).

[28] Sitova, I. (2016): *KEP/KEA methodology review*, MUAC, Maastricht.

[29] EUROCONTROL (2020): *Traffic Complexity Score Dataset*, http://ansperformance.eu/references/dataset/Traffic_Complexity_Score.html (10.02.2020), Performance Review Unit.

[30] EUROCONTROL (2008): *Airspace Complexity For Regulation Purposes*, EEC Note No. 13/2008.

[31] Standfuss, T., and Rosenow, J. (2020): *Applicability of Current Complexity Metrics in ATM Performance Benchmarking and Potential Benefits of Considering Weather Conditions*, Digital Avionics Systems Conference (DASC), San Antonio.

[32] EUROCONTROL (2020): *Daily IFR traffic and en-route ATFM delay by entity and delay cause*, https://ansperformance.eu/data/ (22.06.2020), Brussels, PRU.

[33] EUROCONTROL (2016): *Monthly Adjusted Unit Rates*, Central Route Charges Office, https://www.eurocontrol.int/services/monthly-adjusted-unit-rates, Brussels.

34] Worldbank (2019): *World Bank Open Data - Free and open access to global development data*, https://data.worldbank.org/ (20.04.2019).

[35] Cook, L., Wood, B., Klein, A., Lee, R., and Memarzadeh, B. (2009): *Analyzing the Share of Individual Weather Factors Affecting NAS Performance Using the Weather Impacted Traffic Index*, Aviation Technology, Integration, and Operations Conference, Hilton Head.

[36] Klein, A., MacPhail, T., Kavoussi, S., Hickman, D., Phaneuf, M., Lee, R.S., and Simenauer, D. (2009): *NAS Weather Index: Quantifying Impact of Actual and Forecast En-Route And Surface Weather on Air Traffic*, 14th Conference on Aviation, Range and Aerospace Meteorology, Phoenix.

[37] EUROCONTROL (2009): *ATM Airport Performance (ATMAP) Framework*, Performance Review Commission, Brussels.

[38] Schultz, M., Lorenz, S., Schmitz, R., and Delgado, L. (2018): *Weather Impact on Airport Performance*, MDPI Aerospace

[39] EUROCONTROL (2011): *Algorithm to describe weather conditions at European airports, Technical Report*, PRU, Brussels.

[40] Schultz, M., Reitmann, S., and Alam, S. (2020): *Predictive classification and understanding of weather impact on airport performance through machine learning*, Transportation Research Part C: Emerging Technologies

[41] Welc, J., and Esquerdo, P.J.R. (2017): *Applied Regression Analysis for Business: Tools, Traps and Applications*, Springer International Publishing, Cham.

[42] Baum, C.F. (2006): *An Introduction to Modern Econometrics Using Stata*, Taylor & Francis.

[43] Clark, T.S., and Linzer, D.A. (2015): *Should I Use Fixed or Random Effects?*, Political Science Research and Methods, pp. 399–408.

[44] Standfuss, T., Galarraga, I., and Ruiz-Gauna, I. (2022): *Prediction of Horizontal Efficiency - Preliminary Results*, https://cloudstore.zih.tu-dresden.de/index.php/s/x6tKfPjzgFg39YS, Dresden.
[45] EUROCONTROL *Network operations portal - Connecting operational stakeholders to the EUROCONTROL Network Manager Operations Centre.*, https://www.eurocontrol.int/portal/network-operations-portal, Brussels.
[46] EUROCONTROL (2020): *NEST User Guide*, Ch. 6.6, Brussels / Paris.
[47] EUROCONTROL (2018): *NEST modelling tool*, http://www.eurocontrol.int/services/nest-modelling-tool, Brussels.
[48] Espinar-Nova, J. (2021): *NEST data analysis of flights on hourly basis*, DFS Deutsche Flugsicherung GmbH, Langen.
[49] FABEC (2022): *HFE scores for Skeyes*, Dataset provided by Skeyes, Brussels.
[50] FABEC (2015): *FABEC Implementation Phase - Comparison between CarpeDiem and PRU KEA results*, DSNA / CarpeDiem Team, Brussels.
[51] Lee, D.S. et al. (2021): T*he contribution of global aviation to anthropogenic climate forcing for 2000 to 2018*. Atmospheric Environment 244: 117834.
[52] European Commission (2019): *Sustainable Transport Infrastructure Charging and Internalisation of Transport Externalities: Main Findings*.
[53] EUROCONTROL (2020f): *ECTL Standard Inputs for economic analysis (2020)*, edition 9. December.
[54] Goicoechea, N., Galarraga, I., Abadie, L.M., Pümpel, H., and Ruiz-Gauna, I. (2021): *Insights on the Economic Estimates of the Climate Costs of the Aviation Sector due to Air Management in 2018-2019*. Dyna 96(6).
[55] STATFOR (2019): *Seven-year Forecast of Flight Movements and Service Units - Autumn 2019*, EUROCONTROL, Brussels.
[56] EUROCONTROL (2020g): *ATM Cost-Effectiveness (ACE) 2018 Benchmarking Report*, Performance Review Unit, Brussels.

ANNEX

A1 Analysis Scheme

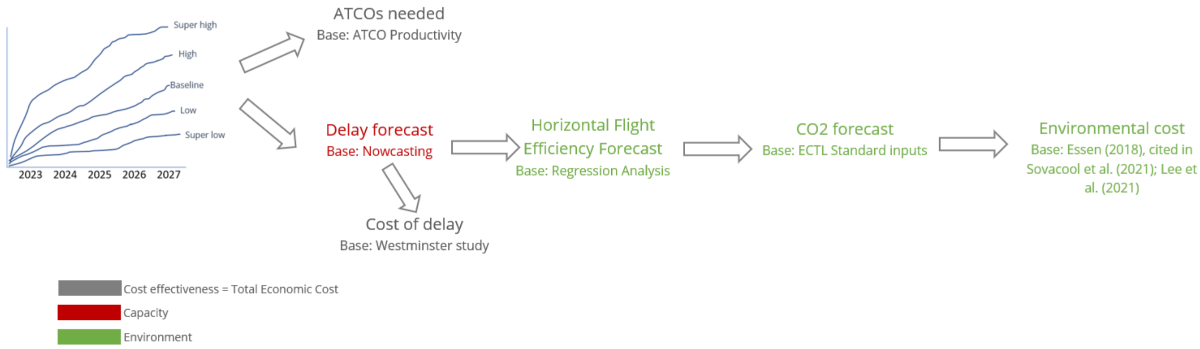


Figure A 1: Components of the Study

A2 Assumptions for super-high and super-low Scenarios

Year	Super-low	Super High
2021	90% of the growth rate in the low scenario	2% above high level
2022	40% of mov. in 2019	4% above high level
2023	80% of mov. in low scenario.	6% above high level
2024	82% of mov. in low scenario.	7% above high level
2025	84% of mov. in low scenario.	8% above high level
2026	85% of mov. in low scenario.	9% above high level
2027	85% of mov. in low scenario.	10% above high level

Table A 1: Extension of Traffic Scenarios

A3 Calculation Example for State-ANSP-Transformation

The STATFOR reports provide the predicted movements as well as the seven-year average annual growth rate (AAGR). The AAGR was adjusted to fit the 5-year-horizon. On a 5-year basis, the predicted AAGR for Germany until 2023 is 2.2% (Baseline Scenario). The predicted total growth rate (TGR) is 11.3% (see [55], Annex 3).

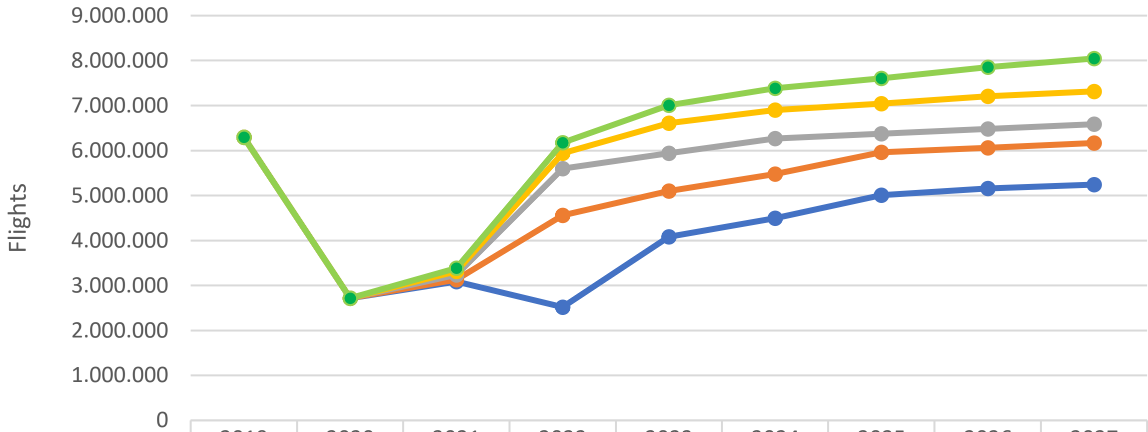
Country	Sz	2018	2019	2020	2021	2022	2023	2024	2025	AAGR 2019-2025	AAGR 2019-2023	TGR 2009-2023
Germany	H	3404	3.562	3.705	3.804	3.891	3.974	4.062	4.130	2,8%	3,1%	16,7%
Germany	B	3.404	3.519	3.623	3.676	3.737	3.787	3.837	3.877	1,9%	2,2%	11,3%
Germany	L	3404	3.465	3.521	3.508	3.519	3.524	3.536	3.525	0,5%	0,7%	3,5%

Table A 2: STATFOR Predictions for Germany, Spring Report 2019

In Spring 2019, the actual flights 2019 are yet unknown. Thus, growth rates are related to the year 2018. Since it is beneficial to have a homogenous database, the flights of 2018 were extracted from the ACE database [56]. In 2018, the German ANSP DFS was responsible for 3,113,468 flights. Applying the forecasted 11.3% growth, STATFOR predicts 3,463,779 flights for DFS in 2023. The induced CI reflects the uncertainty of 13.2 percentage points, respectively 411,592 flights:

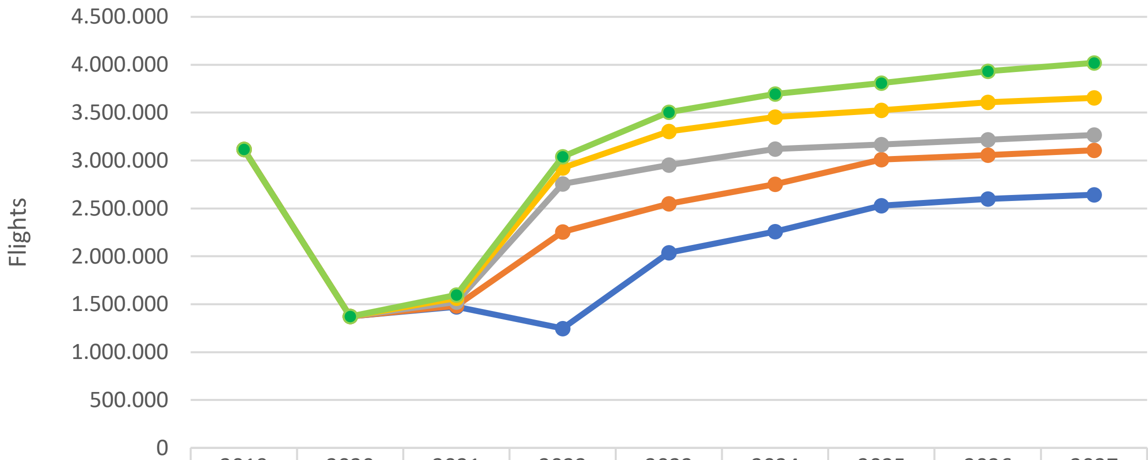
- High-Level-Scenario: 3,634,818 movements
- Low-Level-Scenario: 3,223,26 movements

A4 Traffic Scenarios on Different Operational Levels



	2019	2020	2021	2022	2023	2024	2025	2026	2027
Super Low	6.297.681	2.718.577	3.085.550	2.519.072	4.078.913	4.493.796	5.007.577	5.153.918	5.240.661
Low	6.297.681	2.718.577	3.126.325	4.557.845	5.098.641	5.480.239	5.961.401	6.063.433	6.165.483
Base	6.297.681	2.718.577	3.237.610	5.596.638	5.937.639	6.264.839	6.371.104	6.480.969	6.585.119
High	6.297.681	2.718.577	3.315.770	5.940.229	6.607.858	6.900.191	7.044.434	7.207.792	7.315.476
Super High	6.297.681	2.718.577	3.382.085	6.177.838	7.004.329	7.383.204	7.607.989	7.856.493	8.047.023

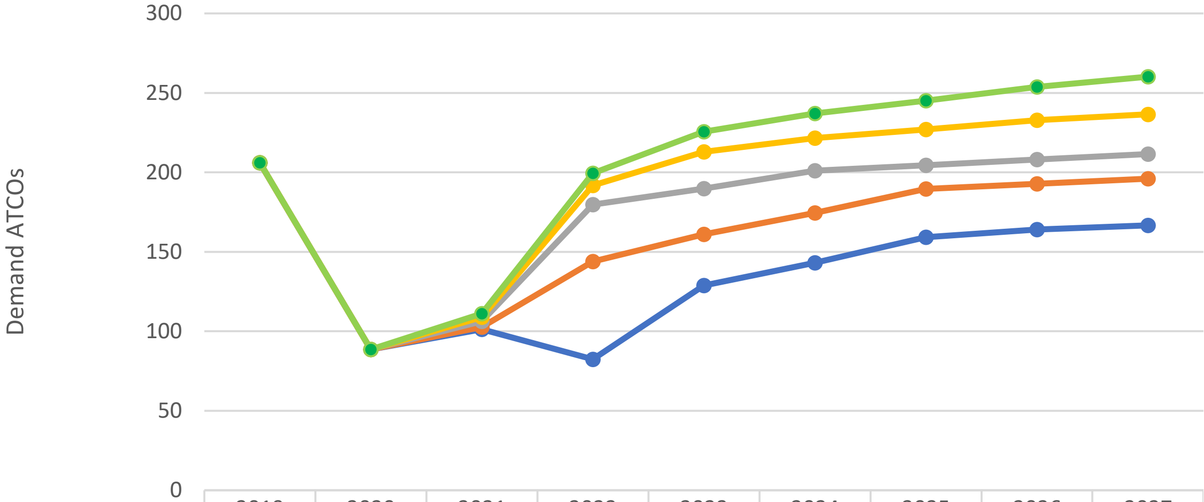
Figure A 2: Traffic Scenarios FABEC



	2019	2020	2021	2022	2023	2024	2025	2026	2027
Super Low	3.118.176	1.372.003	1.472.027	1.247.270	2.037.964	2.258.116	2.528.314	2.599.350	2.640.936
Low	3.118.176	1.372.003	1.483.136	2.254.371	2.547.455	2.753.800	3.009.898	3.058.059	3.106.983
Base	3.118.176	1.372.003	1.522.921	2.756.476	2.954.945	3.120.421	3.167.231	3.217.910	3.266.187
High	3.118.176	1.372.003	1.564.086	2.924.842	3.305.080	3.453.809	3.526.336	3.607.444	3.654.333
Super High	3.118.176	1.372.003	1.595.368	3.041.836	3.503.385	3.695.576	3.808.443	3.932.114	4.019.766

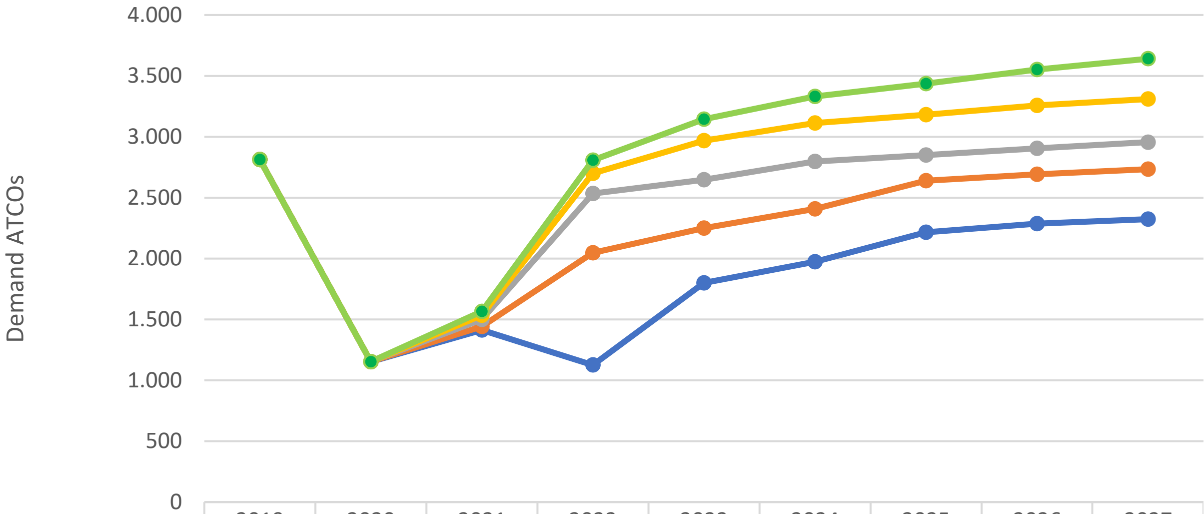
Figure A 3: Traffic Scenarios, DFS

A5 Need for Resources



	2019	2020	2021	2022	2023	2024	2025	2026	2027
Super Low	206	89	101	82	129	143	159	164	167
Low	206	89	103	144	161	174	189	193	196
Base	206	89	106	180	190	201	205	208	212
High	206	89	109	192	213	222	227	233	237
Super High	206	89	111	199	226	237	245	254	260

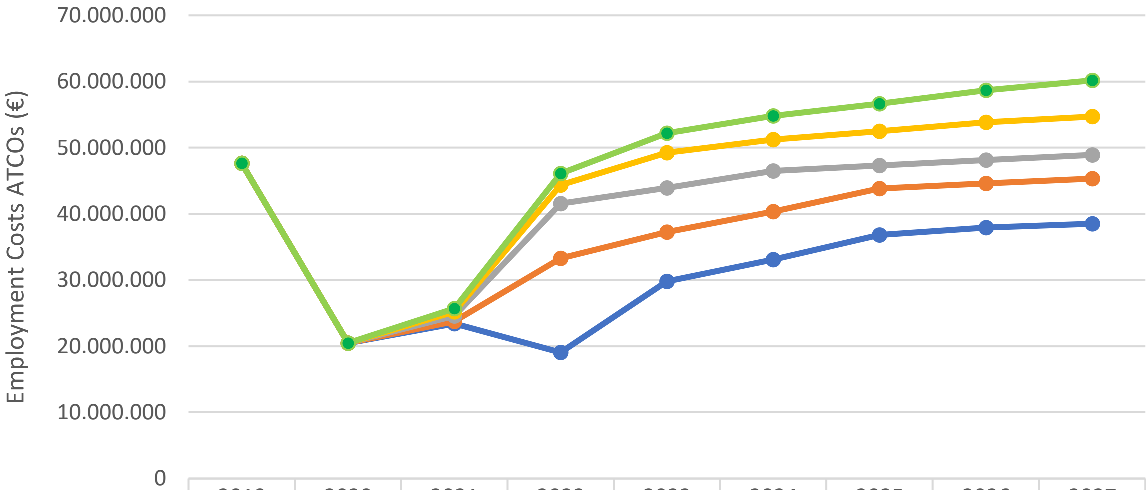
Figure A 4: Expected need for ATCOs, skeyes



	2019	2020	2021	2022	2023	2024	2025	2026	2027
Super Low	2.813	1.153	1.413	1.125	1.800	1.974	2.216	2.288	2.324
Low	2.813	1.153	1.442	2.047	2.250	2.407	2.639	2.691	2.734
Base	2.813	1.153	1.499	2.534	2.648	2.796	2.849	2.903	2.956
High	2.813	1.153	1.534	2.700	2.967	3.112	3.181	3.257	3.309
Super High	2.813	1.153	1.565	2.808	3.145	3.330	3.435	3.550	3.640

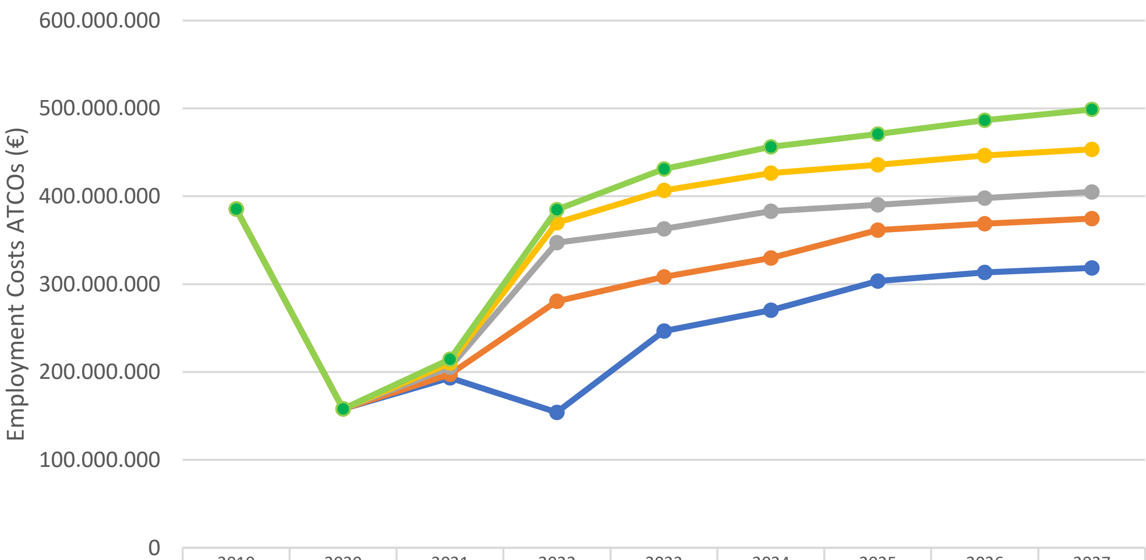
Figure A 5: Expected need for ATCOs, DSNA

A6 Expected Employment Costs



	2019	2020	2021	2022	2023	2024	2025	2026	2027
Super Low	47.638.7	20.485.1	23.435.0	19.055.4	29.806.4	33.087.2	36.809.6	37.917.9	38.524.3
Low	47.638.7	20.485.1	23.761.2	33.266.3	37.258.0	40.350.3	43.821.0	44.609.3	45.322.7
Base	47.638.7	20.485.1	24.582.6	41.544.1	43.911.6	46.502.5	47.292.1	48.142.9	48.913.3
High	47.638.7	20.485.1	25.196.9	44.346.9	49.225.3	51.243.3	52.473.5	53.838.3	54.699.9
Super High	47.638.7	20.485.1	25.700.8	46.120.8	52.178.8	54.830.4	56.671.4	58.683.7	60.169.9

Figure A 6: Expected Employment Costs, skeyes



	2019	2020	2021	2022	2023	2024	2025	2026	2027
Super Low	385.458.234	158.038.407	193.596.737	154.183.294	246.637.705	270.500.968	303.700.426	313.461.197	318.477.129
Low	385.458.234	158.038.407	197.552.591	280.525.022	308.297.131	329.879.230	361.548.126	368.777.879	374.678.975
Base	385.458.234	158.038.407	205.451.225	347.212.590	362.838.028	383.157.073	390.436.671	397.855.766	405.017.463
High	385.458.234	158.038.407	210.190.709	369.937.273	406.561.143	426.482.712	435.865.259	446.326.070	453.467.106
Super High	385.458.234	158.038.407	214.394.523	384.734.764	430.954.812	456.336.502	470.734.479	486.495.416	498.813.816

Figure A 7: Expected Employment Costs, DSNA

A7 Further Results of Cost of Delays

AVERAGE	2022	2023	2024	2025	2026	2027
Super low	0.00	5.65	20.95	65.33	83.53	95.71
Low	20.56	69.93	134.96	263.53	294.77	329.06
Base	136.01	230.80	338.95	374.98	416.89	459.74
High	214.11	496.38	655.35	744.34	853.37	921.18
Super high	283.97	715.33	983.83	1170.21	1400.92	1582.22
FUNCTION	2022	2023	2024	2025	2026	2027
Super low	0.00	3.82	14.74	47.60	61.32	70.56
Low	14.46	51.05	100.57	200.64	225.24	252.33
Base	101.38	174.97	260.17	288.77	322.16	356.41
High	161.93	385.79	514.03	586.29	675.22	730.74
Super high	216.72	562.70	782.15	935.73	1126.99	1278.06

Table 13. Cost of delays for DFS, 2022-2027 (in Mill. €) for the five scenarios and using the average and function

DIFFERENCE	2022	2023	2024	2025	2026	2027
Super low		0.68	0.70	0.73	0.73	0.74
Low	0.70	0.73	0.75	0.76	0.76	0.77
Base	0.75	0.76	0.77	0.77	0.77	0.78
High	0.76	0.78	0.78	0.79	0.79	0.79
Super high	0.76	0.79	0.80	0.80	0.80	0.81

Table 14. Difference between the average cost of delays and the costs calculated by applying the function (DFS, 2022-2027)

AVERAGE	2022	2023	2024	2025	2026	2027
Super low	0.04	28.62	55.40	115.65	139.42	152.82
Low	70.50	126.47	186.48	305.35	338.20	366.71
Base	246.67	311.04	410.41	450.61	494.21	538.88
High	343.68	548.86	688.77	762.18	849.97	913.62
Super high	418.92	723.14	940.07	1080.48	1249.45	1393.13
FUNCTION	2022	2023	2024	2025	2026	2027
Super low	0.02	20.31	40.13	85.74	103.98	114.31
Low	51.45	94.03	140.39	233.60	259.60	282.23
Base	187.39	238.10	317.04	349.17	384.13	420.05
High	263.95	428.09	541.30	601.02	672.70	724.83
Super high	323.83	569.24	746.53	862.05	1001.76	1121.07

Table 15. Cost of delays for DSNA. 2022-2027 (in Mill. €) for the five scenarios and using the average and function

DIFFERENCE	2022	2023	2024	2025	2026	2027
Super low	0.58	0.71	0.72	0.74	0.75	0.75
Low	0.73	0.74	0.75	0.77	0.77	0.77
Base	0.76	0.77	0.77	0.77	0.78	0.78
High	0.77	0.78	0.79	0.79	0.79	0.79
Super high	0.77	0.79	0.79	0.80	0.80	0.80

Table 16. Difference between the average cost of delays and the costs calculated by applying the function (DSNA, 2022-2027)

AVERAGE	2022	2023	2024	2025	2026	2027
Super low	0.00	0.19	2.21	6.58	8.27	9.26
Low	2.38	7.24	12.50	19.20	20.76	22.18
Base	14.75	19.38	24.56	26.16	27.89	29.47
High	20.24	30.11	34.26	36.82	39.67	41.49
Super high	23.79	36.21	41.76	45.63	49.86	52.99
FUNCTION	2022	2023	2024	2025	2026	2027
Super low	0.00	0.12	1.47	4.45	5.62	6.31
Low	1.58	4.91	8.56	13.29	14.40	15.41
Base	10.14	13.41	17.11	18.26	19.50	20.64
High	14.02	21.10	24.11	25.96	28.04	29.36
Super high	16.56	25.52	29.56	32.39	35.49	37.79

Table 17. Cost of delays for Skeyes. 2022-2027 (in Mill. €) for the five scenarios and using the average and function

DIFFERENCE	2022	2023	2024	2025	2026	2027
Super low		0.64	0.66	0.68	0.68	0.68
Low	0.66	0.68	0.69	0.69	0.69	0.69
Base	0.69	0.69	0.70	0.70	0.70	0.70
High	0.69	0.70	0.70	0.71	0.71	0.71
Super high	0.70	0.70	0.71	0.71	0.71	0.71

Table 18. Difference between the average cost of delays and the costs calculated by applying the function (Skeyes, 2022-2027)

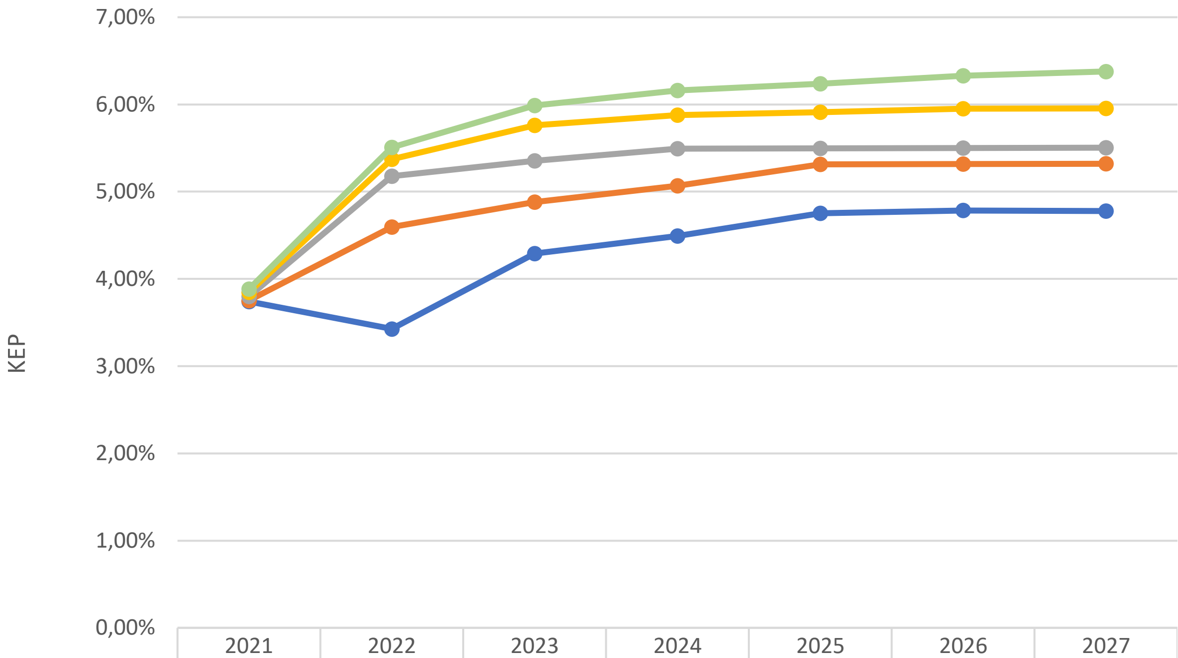
AVERAGE	2022	2023	2024	2025	2026	2027
Super low	0.31	64.69	148.01	343.25	434.54	484.46
Low	153.66	369.97	620.64	1075.77	1213.62	1329.43
Base	726.32	1072.96	1458.02	1616.90	1801.70	1991.87
High	1066.14	2019.05	2542.59	2872.80	3293.48	3603.85
Super high	1339.66	2743.82	3590.81	4223.58	5027.30	5711.46
FUNCTION	2022	2023	2024	2025	2026	2027
Super low	0.19	44.63	104.00	246.51	313.94	351.07
Low	108.76	266.31	452.81	798.91	904.38	993.62
Base	533.49	795.55	1092.15	1214.97	1358.13	1505.92
High	792.23	1528.65	1941.12	2201.17	2533.26	2778.51
Super high	1002.65	2098.68	2773.22	3278.45	3922.89	4473.44

Table 19. Cost of delays for Europe. 2022-2027 (in Mill. €) for the five scenarios and using the average and function

DIFFERENCE	2022	2023	2024	2025	2026	2027
Super low	0.59	0.69	0.70	0.72	0.72	0.72
Low	0.71	0.72	0.73	0.74	0.75	0.75
Base	0.73	0.74	0.75	0.75	0.75	0.76
High	0.74	0.76	0.76	0.77	0.77	0.77
Super high	0.75	0.76	0.77	0.78	0.78	0.78

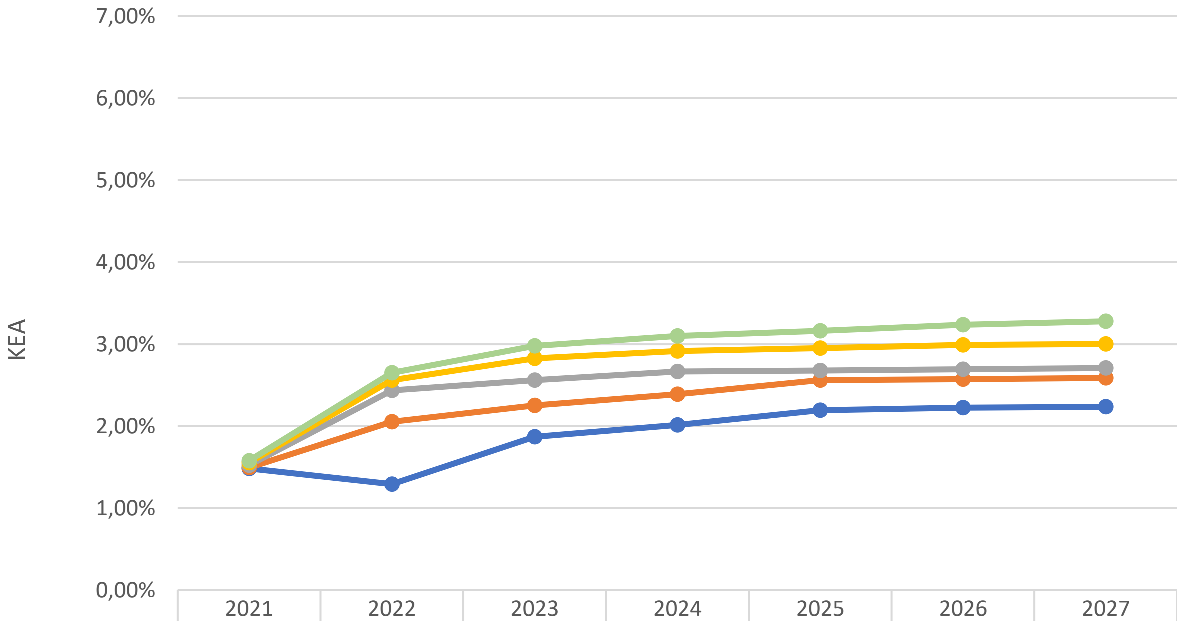
Table 20. Difference between the average cost of delays and the costs calculated by applying the function (Europe, 2022-2027)

A8 Further Results of HFE Predictions – ANSP Level



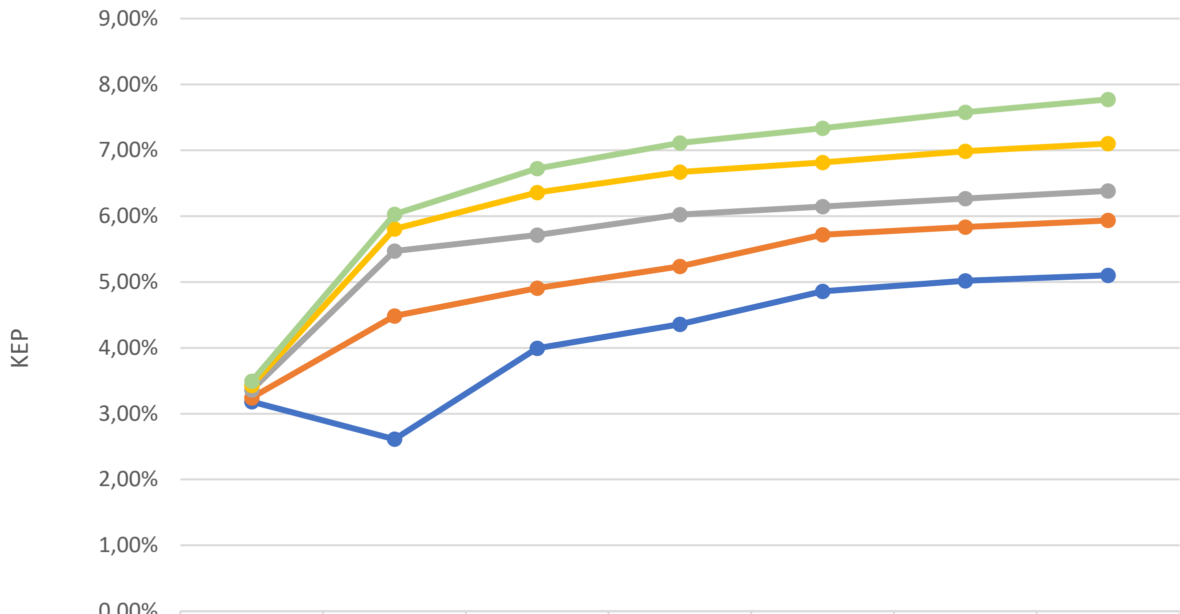
	2021	2022	2023	2024	2025	2026	2027
Super Low	3,74%	3,43%	4,29%	4,49%	4,75%	4,78%	4,78%
Low	3,75%	4,59%	4,88%	5,07%	5,31%	5,32%	5,32%
Base	3,80%	5,18%	5,35%	5,49%	5,50%	5,50%	5,50%
High	3,85%	5,37%	5,76%	5,88%	5,91%	5,95%	5,95%
Super High	3,88%	5,51%	5,99%	6,16%	6,24%	6,33%	6,38%

Figure A 8: Predicted KEP, DFS



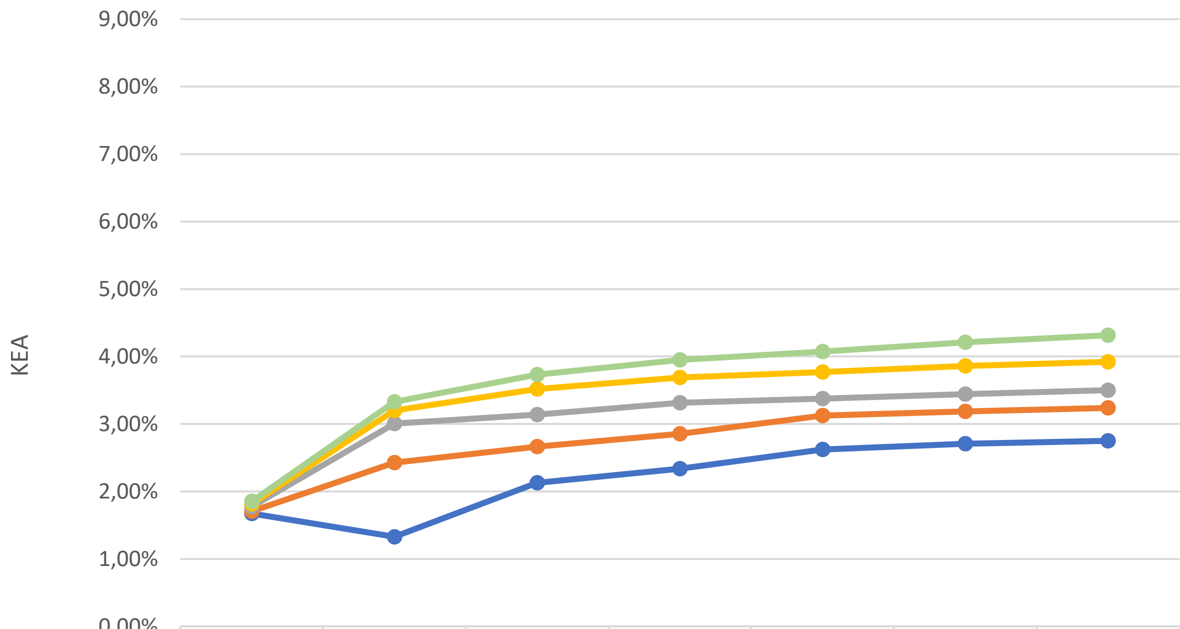
	2021	2022	2023	2024	2025	2026	2027
Super Low	1,49%	1,29%	1,87%	2,01%	2,20%	2,23%	2,24%
Low	1,49%	2,06%	2,26%	2,39%	2,56%	2,57%	2,59%
Base	1,52%	2,44%	2,56%	2,67%	2,68%	2,69%	2,71%
High	1,56%	2,56%	2,83%	2,92%	2,95%	2,99%	3,00%
Super High	1,58%	2,65%	2,98%	3,10%	3,16%	3,24%	3,28%

Figure A 9: Predicted KEA, DFS



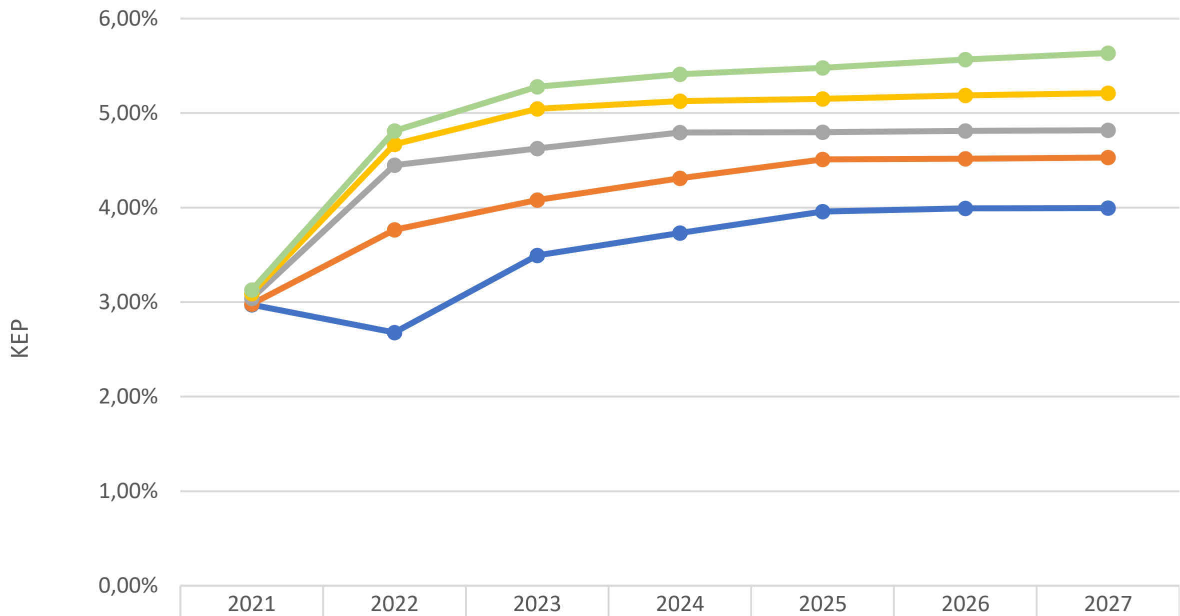
	2021	2022	2023	2024	2025	2026	2027
Super Low	3,18%	2,61%	3,99%	4,36%	4,86%	5,02%	5,10%
Low	3,24%	4,48%	4,91%	5,24%	5,72%	5,84%	5,93%
Base	3,36%	5,47%	5,71%	6,03%	6,14%	6,27%	6,38%
High	3,43%	5,81%	6,36%	6,67%	6,82%	6,98%	7,10%
Super High	3,49%	6,03%	6,72%	7,11%	7,33%	7,58%	7,77%

Figure A 10: Predicted KEP, DSNA



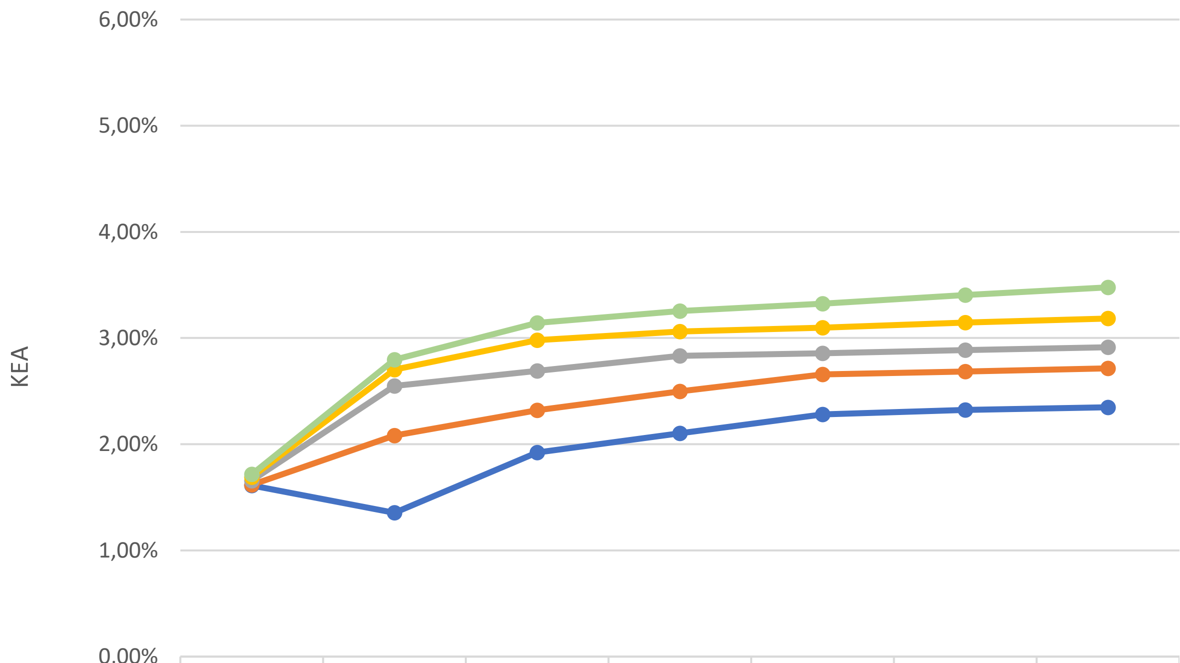
	2021	2022	2023	2024	2025	2026	2027
Super Low	1,67%	1,33%	2,13%	2,34%	2,62%	2,71%	2,75%
Low	1,71%	2,42%	2,66%	2,85%	3,13%	3,19%	3,24%
Base	1,77%	3,00%	3,14%	3,31%	3,38%	3,44%	3,50%
High	1,81%	3,20%	3,52%	3,69%	3,77%	3,86%	3,92%
Super High	1,85%	3,33%	3,73%	3,95%	4,07%	4,21%	4,32%

Figure A 11: Predicted KEA, DSNA



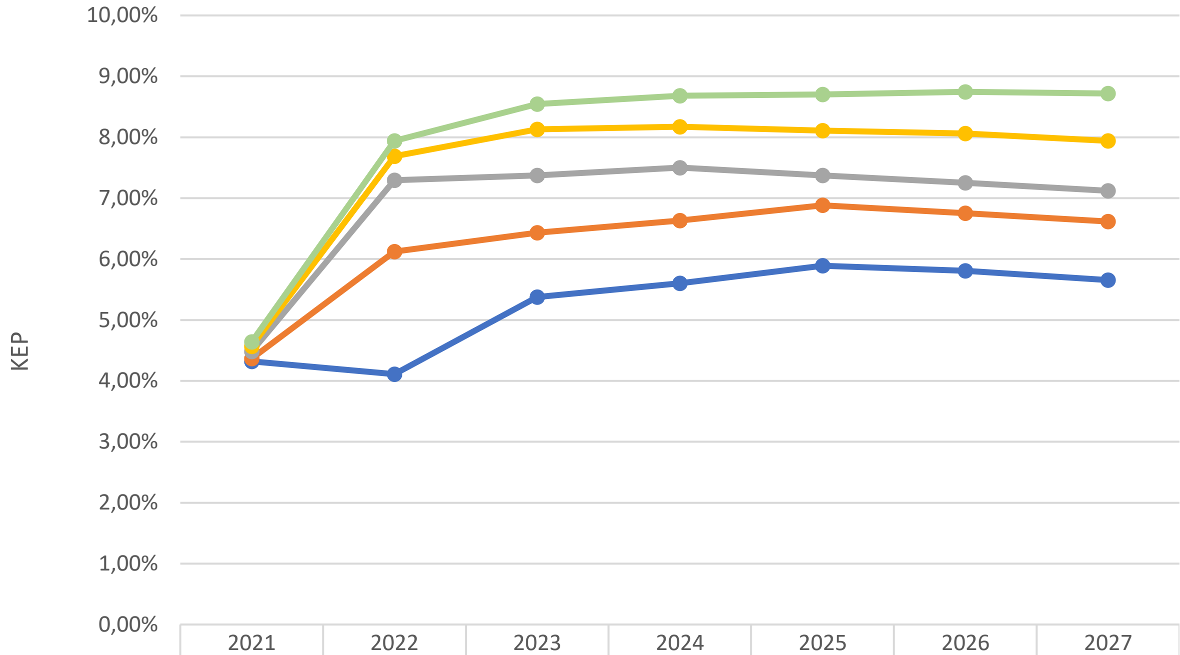
	2021	2022	2023	2024	2025	2026	2027
Super Low	2,97%	2,68%	3,50%	3,73%	3,96%	3,99%	4,00%
Low	2,98%	3,77%	4,08%	4,31%	4,51%	4,52%	4,53%
Base	3,04%	4,45%	4,62%	4,80%	4,80%	4,81%	4,82%
High	3,09%	4,67%	5,04%	5,13%	5,15%	5,19%	5,21%
Super High	3,13%	4,81%	5,28%	5,41%	5,48%	5,57%	5,64%

Figure A 12: Predicted KEP, LVNL



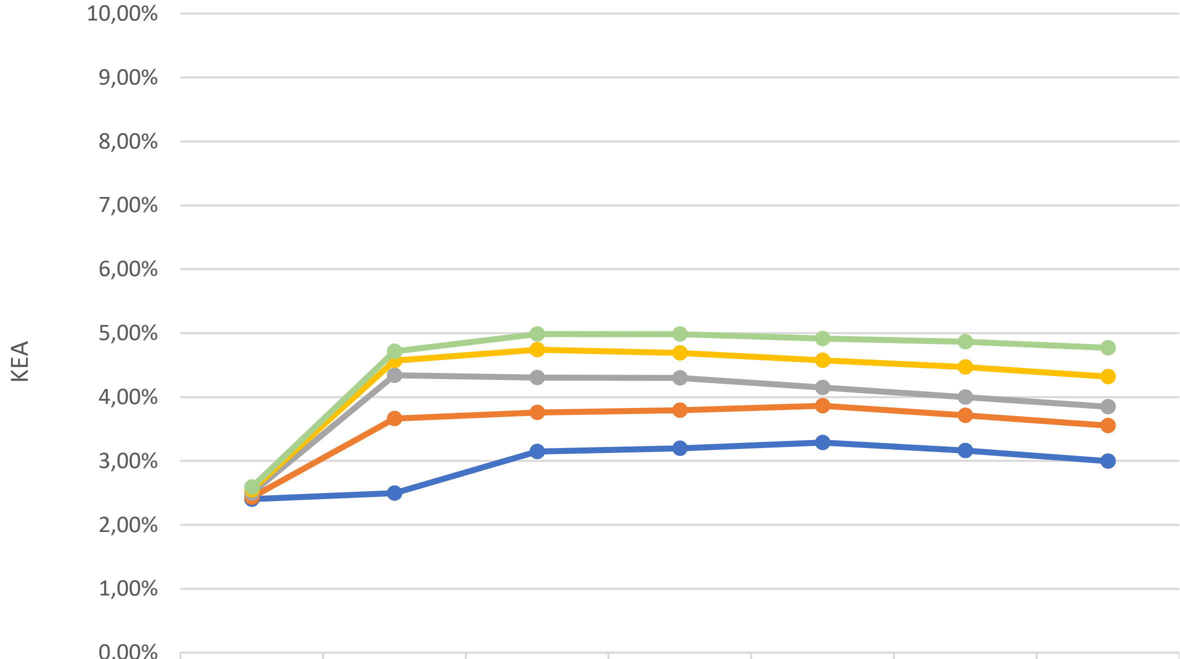
	2021	2022	2023	2024	2025	2026	2027
Super Low	1,61%	1,35%	1,92%	2,10%	2,28%	2,32%	2,35%
Low	1,62%	2,08%	2,32%	2,50%	2,66%	2,68%	2,71%
Base	1,66%	2,55%	2,69%	2,83%	2,86%	2,89%	2,91%
High	1,69%	2,70%	2,98%	3,06%	3,10%	3,15%	3,18%
Super High	1,72%	2,80%	3,14%	3,26%	3,33%	3,41%	3,48%

Figure A 13: Predicted KEA, LVNL



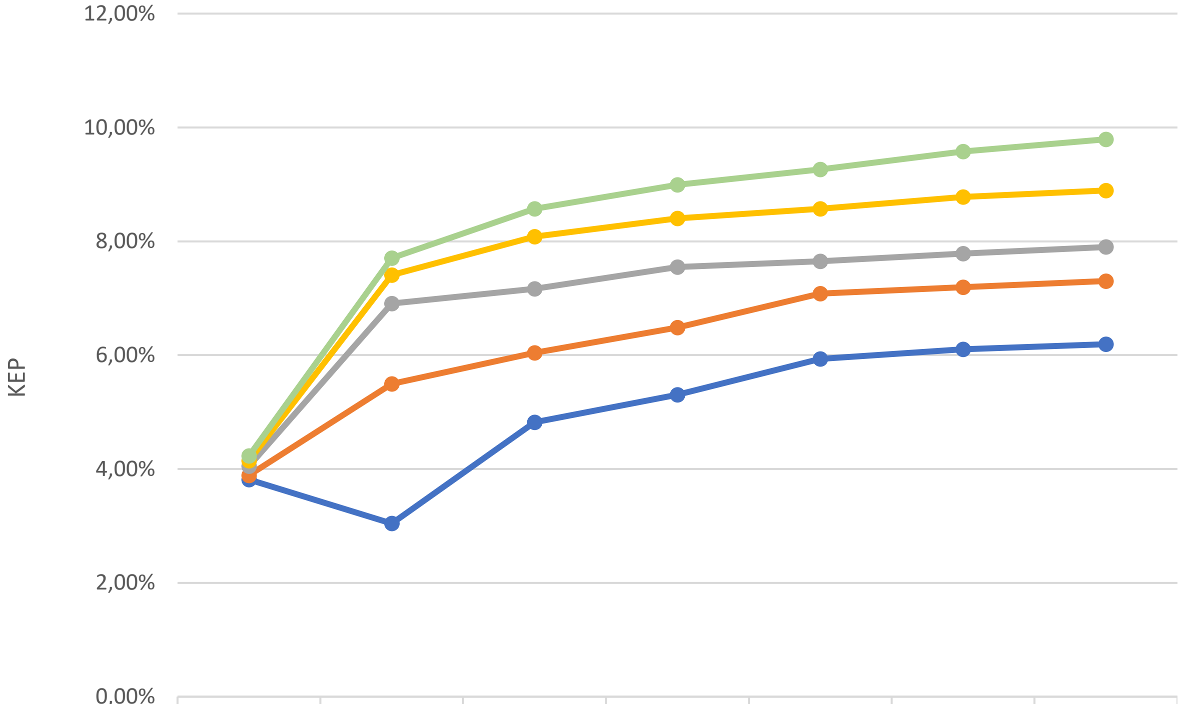
	2021	2022	2023	2024	2025	2026	2027
Super Low	4,32%	4,11%	5,38%	5,60%	5,89%	5,81%	5,65%
Low	4,37%	6,12%	6,43%	6,63%	6,88%	6,75%	6,61%
Base	4,48%	7,29%	7,38%	7,50%	7,37%	7,25%	7,12%
High	4,57%	7,69%	8,13%	8,17%	8,11%	8,06%	7,94%
Super High	4,64%	7,94%	8,55%	8,68%	8,70%	8,75%	8,72%

Figure A 14: Predicted KEP, Skeyes



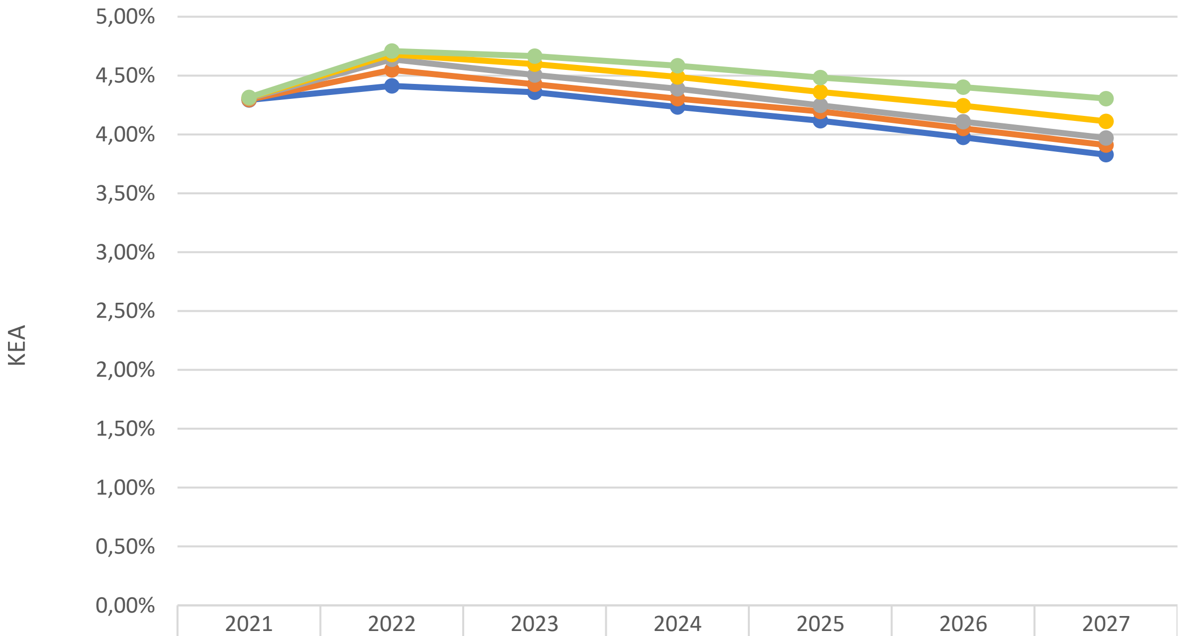
	2021	2022	2023	2024	2025	2026	2027
Super Low	2,40%	2,50%	3,15%	3,20%	3,29%	3,16%	2,99%
Low	2,43%	3,66%	3,76%	3,79%	3,86%	3,71%	3,55%
Base	2,50%	4,34%	4,30%	4,30%	4,15%	4,00%	3,85%
High	2,55%	4,57%	4,74%	4,69%	4,57%	4,47%	4,32%
Super High	2,59%	4,72%	4,98%	4,98%	4,92%	4,86%	4,77%

Figure A 15: Predicted KEA, Skeyes



	2021	2022	2023	2024	2025	2026	2027
Super Low	3,81%	3,04%	4,82%	5,31%	5,94%	6,10%	6,19%
Low	3,89%	5,50%	6,04%	6,49%	7,08%	7,19%	7,30%
Base	4,05%	6,91%	7,16%	7,55%	7,65%	7,78%	7,90%
High	4,14%	7,41%	8,08%	8,40%	8,57%	8,78%	8,89%
Super High	4,23%	7,70%	8,57%	8,99%	9,26%	9,58%	9,79%

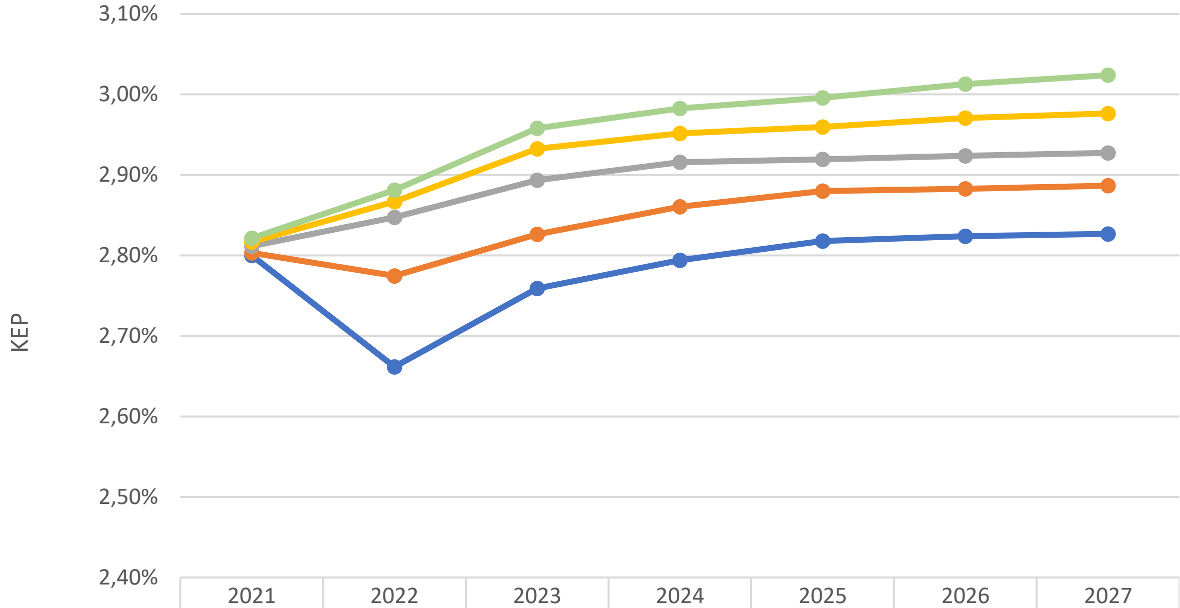
Figure A 16: Predicted KEP, Skyguide



	2021	2022	2023	2024	2025	2026	2027
Super Low	4,29%	4,41%	4,36%	4,23%	4,12%	3,97%	3,83%
Low	4,30%	4,55%	4,43%	4,30%	4,20%	4,05%	3,91%
Base	4,31%	4,64%	4,51%	4,39%	4,25%	4,11%	3,97%
High	4,31%	4,68%	4,60%	4,49%	4,36%	4,24%	4,11%
Super High	4,32%	4,71%	4,66%	4,58%	4,48%	4,40%	4,31%

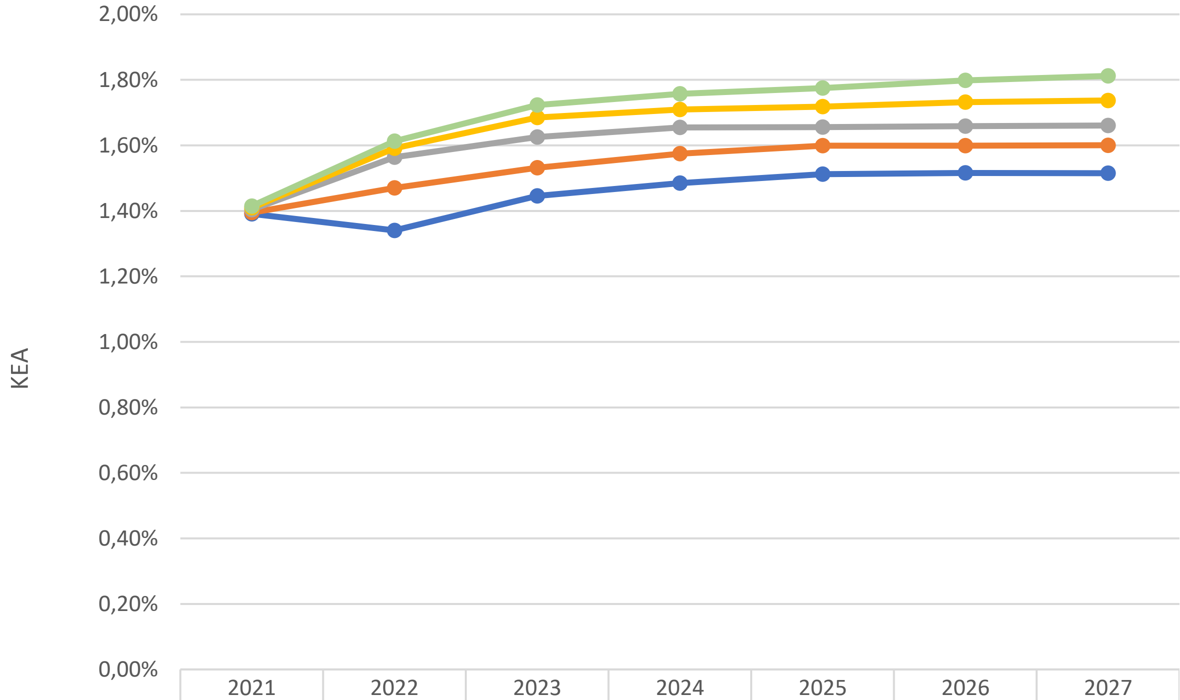
Figure A 17: Predicted KEA, Skyguide

A9 Further Results of HFE Predictions – FAB Level



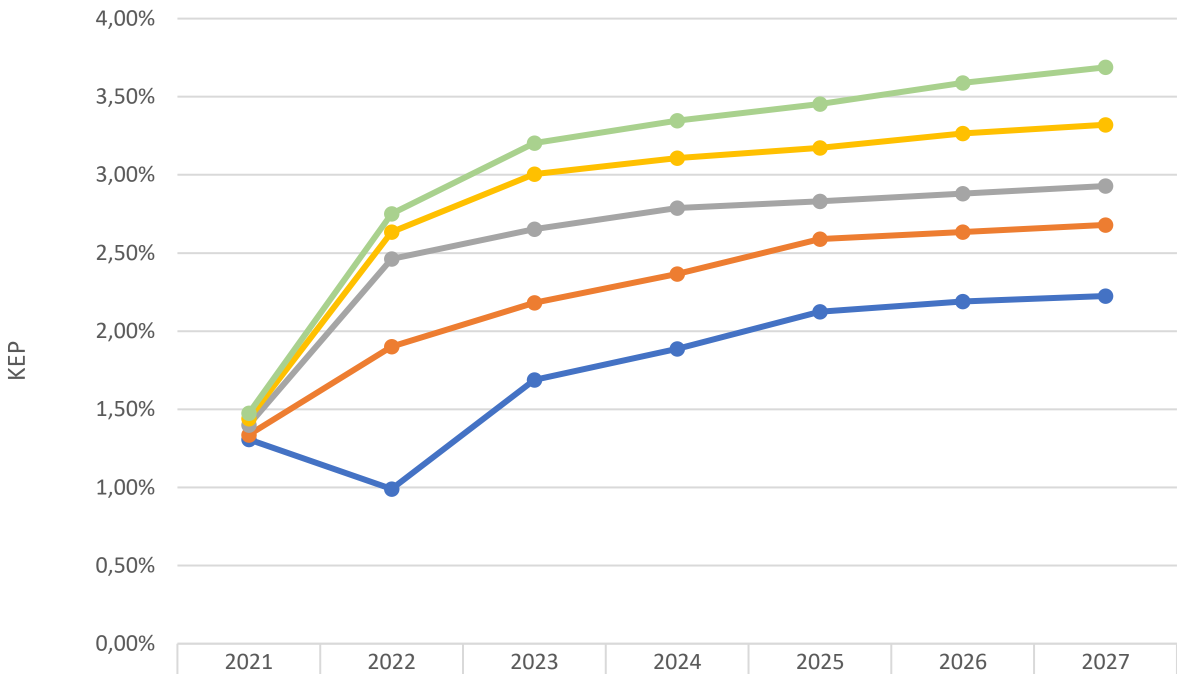
	2021	2022	2023	2024	2025	2026	2027
Super Low	2,80%	2,66%	2,76%	2,79%	2,82%	2,82%	2,83%
Low	2,80%	2,77%	2,83%	2,86%	2,88%	2,88%	2,89%
Base	2,81%	2,85%	2,89%	2,92%	2,92%	2,92%	2,93%
High	2,82%	2,87%	2,93%	2,95%	2,96%	2,97%	2,98%
Super High	2,82%	2,88%	2,96%	2,98%	3,00%	3,01%	3,02%

Figure A 18: Predicted KEP, Baltic FAB



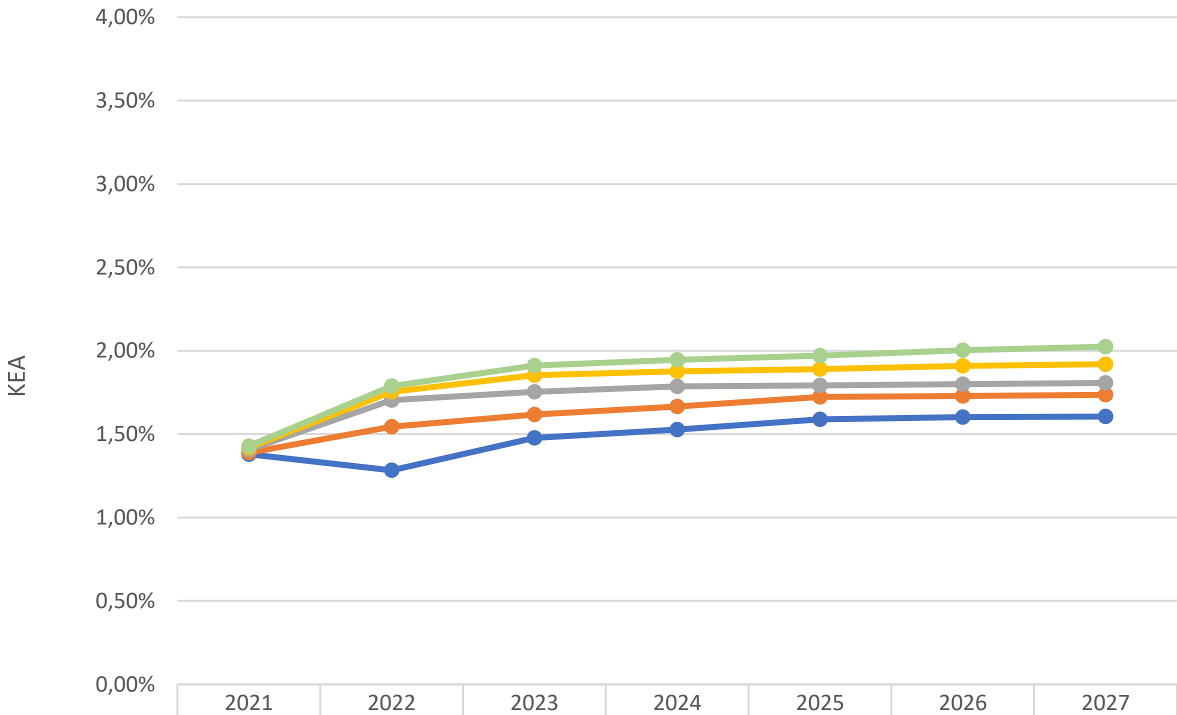
	2021	2022	2023	2024	2025	2026	2027
Super Low	1,39%	1,34%	1,45%	1,49%	1,51%	1,52%	1,51%
Low	1,39%	1,47%	1,53%	1,57%	1,60%	1,60%	1,60%
Base	1,40%	1,56%	1,63%	1,65%	1,66%	1,66%	1,66%
High	1,41%	1,59%	1,68%	1,71%	1,72%	1,73%	1,74%
Super High	1,41%	1,61%	1,72%	1,76%	1,77%	1,80%	1,81%

Figure A 19: Predicted KEA, Baltic FAB



	2021	2022	2023	2024	2025	2026	2027
Super Low	1,31%	0,99%	1,69%	1,89%	2,12%	2,19%	2,22%
Low	1,34%	1,90%	2,18%	2,37%	2,59%	2,63%	2,68%
Base	1,40%	2,46%	2,65%	2,79%	2,83%	2,88%	2,93%
High	1,44%	2,63%	3,01%	3,11%	3,17%	3,26%	3,32%
Super High	1,47%	2,75%	3,20%	3,35%	3,45%	3,59%	3,69%

Figure A 20: Predicted KEP, FAB CE



	2021	2022	2023	2024	2025	2026	2027
Super Low	1,38%	1,28%	1,48%	1,53%	1,59%	1,60%	1,61%
Low	1,39%	1,54%	1,62%	1,67%	1,72%	1,73%	1,74%
Base	1,41%	1,70%	1,75%	1,79%	1,79%	1,80%	1,81%
High	1,42%	1,75%	1,85%	1,88%	1,89%	1,91%	1,92%
Super High	1,43%	1,79%	1,91%	1,95%	1,97%	2,00%	2,02%

Figure A 21: Predicted KEA, FABCE

A10 Further Results of Environmental Costs

C02 costs (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	391,60	331,11	552,99	622,35	709,15	740,23	763,33
Low	394,61	605,57	695,36	763,37	848,98	875,52	902,93
Base	405,38	744,78	810,42	868,69	894,99	923,00	950,95
High	416,54	791,81	910,13	965,21	1000,61	1039,40	1068,74
Super High	425,02	824,60	966,95	1035,66	1084,18	1137,19	1180,58
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	391,68	333,16	555,05	624,53	710,99	742,09	765,27
Low	394,67	606,80	696,51	764,50	849,52	876,09	903,51
Base	405,38	744,78	810,42	868,69	894,99	923,00	950,95
High	416,47	791,28	908,85	963,92	999,17	1037,78	1067,08
Super High	424,90	823,66	964,82	1033,28	1081,40	1133,95	1177,02

Climate costs (CO2 + non-CO2) (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Lov	1152,01	974,04	1626,77	1830,81	2086,18	2177,59	2245,56
Low	1160,85	1781,45	2045,61	2245,66	2497,51	2575,59	2656,21
Base	1192,54	2190,98	2384,08	2555,49	2632,86	2715,26	2797,48
High	1225,36	2329,34	2677,40	2839,45	2943,59	3057,69	3144,01
Super Hig	1250,32	2425,79	2844,54	3046,69	3189,43	3345,37	3472,99
KEA	2021	2022	2023	2024	2025	2026	2027
Super Lov	1152,24	980,07	1632,85	1837,23	2091,58	2183,06	2251,25
Low	1161,04	1785,07	2048,98	2248,98	2499,10	2577,26	2657,91
Base	1192,54	2190,98	2384,08	2555,49	2632,86	2715,26	2797,48
High	1225,16	2327,76	2673,64	2835,65	2939,35	3052,91	3139,11
Super Hig	1249,95	2423,01	2838,30	3039,68	3181,25	3335,83	3462,54

Environmental costs (climate + local air pollution + noise + well to tank + habitat damage) (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	1824,24	1542,43	2576,05	2899,15	3303,53	3448,28	3555,91
Low	1838,24	2820,98	3239,28	3556,07	3954,89	4078,53	4206,19
Base	1888,42	3469,48	3775,27	4046,69	4169,22	4299,69	4429,89
High	1940,39	3688,58	4239,75	4496,35	4661,26	4841,95	4978,63
Super High	1979,92	3841,32	4504,42	4824,53	5050,56	5297,50	5499,59
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	1824,61	1551,97	2585,66	2909,31	3312,09	3456,94	3564,93
Low	1838,54	2826,72	3244,62	3561,34	3957,40	4081,16	4208,89
Base	1888,42	3469,48	3775,27	4046,69	4169,22	4299,69	4429,89
High	1940,07	3686,09	4233,79	4490,34	4654,55	4834,39	4970,88
Super High	1979,34	3836,92	4494,54	4813,43	5037,61	5282,39	5483,05

Figure 32. CO_2 costs, climate costs and environmental costs for DFS, 2021-2027

C02 costs (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	710,61	559,02	918,32	1022,87	1170,25	1226,47	1264,45
Low	725,55	1036,68	1158,56	1258,56	1405,25	1454,88	1500,13
Base	755,45	1295,92	1374,63	1473,46	1524,05	1576,39	1628,92
High	773,42	1385,39	1550,25	1650,59	1712,83	1781,13	1836,86
Super High	789,38	1443,95	1649,16	1773,89	1859,34	1952,90	2034,02
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	711,13	565,82	924,97	1030,06	1176,55	1232,90	1271,24
Low	725,91	1040,96	1162,47	1262,71	1407,75	1457,49	1502,93
Base	755,45	1295,92	1374,63	1473,46	1524,05	1576,39	1628,92
High	773,19	1383,46	1546,12	1646,24	1708,09	1775,88	1831,45
Super High	788,94	1440,65	1642,34	1766,02	1850,30	1942,43	2022,49

Climate costs (CO2 + non-CO2) (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Lov	2090,45	1644,50	2701,48	3009,07	3442,62	3608,01	3719,73
Low	2134,42	3049,68	3408,23	3702,41	4133,93	4279,94	4413,05
Base	2222,36	3812,32	4043,85	4334,58	4483,42	4637,38	4791,92
High	2275,22	4075,50	4560,49	4855,68	5038,76	5239,69	5403,64
Super Hig	2322,17	4247,78	4851,47	5218,40	5469,77	5745,00	5983,64
KEA	2021	2022	2023	2024	2025	2026	2027
Super Lov	2091,97	1664,53	2721,06	3030,20	3461,16	3626,92	3739,72
Low	2135,45	3062,27	3419,72	3714,60	4141,28	4287,60	4421,29
Base	2222,36	3812,32	4043,85	4334,58	4483,42	4637,38	4791,92
High	2274,56	4069,84	4548,34	4842,86	5024,82	5224,24	5387,71
Super Hig	2320,90	4238,06	4831,41	5195,24	5443,17	5714,19	5949,71

Environmental costs (climate + local air pollution + noise + well to tank + habitat damage) (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	3310,30	2604,12	4277,88	4764,95	5451,49	5713,40	5890,31
Low	3379,92	4829,27	5397,04	5862,89	6546,20	6777,42	6988,20
Base	3519,17	6036,92	6403,56	6863,95	7099,63	7343,44	7588,15
High	3602,88	6453,68	7221,67	7689,11	7979,03	8297,22	8556,83
Super High	3677,23	6726,49	7682,45	8263,50	8661,55	9097,39	9475,28
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	3312,71	2635,84	4308,89	4798,41	5480,86	5743,33	5921,96
Low	3381,56	4849,20	5415,23	5882,19	6557,84	6789,55	7001,26
Base	3519,17	6036,92	6403,56	6863,95	7099,63	7343,44	7588,15
High	3601,84	6444,72	7202,44	7668,82	7956,96	8272,74	8531,60
Super High	3675,21	6711,10	7650,69	8226,83	8619,42	9048,60	9421,55

Figure 33. CO_2 costs, climate costs and environmental costs for DSNA, 2021-2027

CO2 costs (Mill €)

KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	24,43	19,55	31,42	35,44	40,19	42,04	43,34
Low	24,78	34,84	39,70	43,67	48,33	49,93	51,49
Base	25,66	44,02	47,23	50,77	52,41	54,16	55,85
High	26,33	47,18	53,35	56,32	58,58	61,05	62,97
Super High	26,87	49,19	56,78	60,57	63,64	67,00	69,80
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	24,44	19,82	31,69	35,73	40,44	42,30	43,62
Low	24,79	35,01	39,86	43,83	48,43	50,04	51,60
Base	25,66	44,02	47,23	50,77	52,41	54,16	55,85
High	26,32	47,10	53,18	56,17	58,40	60,85	62,76
Super High	26,86	49,06	56,51	60,27	63,29	66,59	69,34

Climate costs (CO2 + non-CO2) (Mill €)

KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	71,86	57,51	92,43	104,26	118,23	123,67	127,51
Low	72,89	102,49	116,79	128,47	142,17	146,89	151,47
Base	75,50	129,51	138,95	149,36	154,19	159,32	164,31
High	77,45	138,79	156,93	165,69	172,33	179,61	185,25
Super Higl	79,06	144,71	167,04	178,19	187,22	197,10	205,34
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	71,90	58,31	93,22	105,10	118,98	124,43	128,31
Low	72,93	103,00	117,25	128,95	142,46	147,20	151,80
Base	75,50	129,51	138,95	149,36	154,19	159,32	164,31
High	77,42	138,56	156,44	165,23	171,80	179,00	184,62
Super Higl	79,00	144,32	166,23	177,31	186,19	195,88	203,99

Environmental costs (climate + local air pollution + noise + well to tank + habitat damage) (Mill €)

KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	113,79	91,07	146,37	165,09	187,22	195,83	201,91
Low	115,42	162,29	184,93	203,44	225,13	232,60	239,86
Base	119,55	205,08	220,03	236,52	244,16	252,29	260,19
High	122,65	219,78	248,51	262,38	272,89	284,41	293,35
Super High	125,19	229,15	264,51	282,16	296,46	312,12	325,16
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	113,86	92,33	147,62	166,44	188,40	197,04	203,18
Low	115,48	163,10	185,67	204,19	225,59	233,10	240,38
Base	119,55	205,08	220,03	236,52	244,16	252,29	260,19
High	122,60	219,42	247,73	261,65	272,06	283,45	292,35
Super High	125,10	228,53	263,23	280,78	294,83	310,19	323,02

Figure 34. CO_2 costs, climate costs and environmental costs for Skeyes, 2021-2027

C02 costs (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	1729,99	1298,97	2216,09	2474,77	2759,29	2891,07	2980,88
Low	1760,91	2423,45	2781,17	3029,97	3297,69	3414,10	3520,49
Base	1819,87	2900,20	3176,42	3382,22	3498,36	3622,04	3746,41
High	1864,10	3068,28	3492,42	3686,55	3832,76	3996,78	4134,44
Super High	1901,87	3194,13	3708,53	3953,39	4150,41	4370,26	4564,50
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	1730,15	1301,04	2218,03	2476,72	2760,98	2892,76	2982,65
Low	1761,02	2424,51	2782,11	3030,84	3298,20	3414,63	3521,06
Base	1819,87	2900,20	3176,42	3382,22	3498,36	3622,04	3746,41
High	1864,01	3067,84	3491,55	3685,72	3831,85	3995,77	4133,39
Super High	1901,71	3193,33	3707,04	3951,80	4148,60	4368,20	4562,27

Climate costs (CO2 + non-CO2) (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	5089,25	3821,29	6519,26	7280,23	8117,23	8504,88	8769,08
Low	5180,22	7129,24	8181,58	8913,51	9701,07	10043,54	10356,49
Base	5353,66	8531,76	9344,33	9949,74	10291,41	10655,24	11021,13
High	5483,77	9026,21	10273,92	10845,02	11275,12	11757,64	12162,60
Super High	5594,89	9396,42	10909,67	11630,00	12209,58	12856,34	13427,74
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	5089,72	3827,37	6524,97	7285,95	8122,19	8509,85	8774,29
Low	5180,53	7132,38	8184,36	8916,06	9702,57	10045,09	10358,18
Base	5353,66	8531,76	9344,33	9949,74	10291,41	10655,24	11021,13
High	5483,52	9024,90	10271,37	10842,59	11272,45	11754,66	12159,53
Super High	5594,42	9394,08	10905,28	11625,33	12204,26	12850,28	13421,20

Environmental costs (climate + local air pollution + noise + well to tank + habitat damage) (Mill €)							
KEP	2021	2022	2023	2024	2025	2026	2027
Super Low	8058,98	6051,14	10323,46	11528,47	12853,89	13467,75	13886,11
Low	8203,04	11289,38	12955,79	14114,82	15361,95	15904,25	16399,83
Base	8477,68	13510,30	14797,03	15755,73	16296,76	16872,91	17452,30
High	8683,72	14293,29	16269,07	17173,43	17854,51	18618,60	19259,85
Super High	8859,68	14879,52	17275,80	18416,47	19334,25	20358,42	21263,25
KEA	2021	2022	2023	2024	2025	2026	2027
Super Low	8059,73	6060,76	10332,49	11537,54	12861,74	13475,61	13894,37
Low	8203,54	11294,35	12960,20	14118,86	15364,32	15906,72	16402,50
Base	8477,68	13510,30	14797,03	15755,73	16296,76	16872,91	17452,30
High	8683,32	14291,22	16265,04	17169,58	17850,28	18613,87	19254,99
Super High	8858,94	14875,82	17268,85	18409,07	19325,83	20348,83	21252,89

Figure 35. CO_2 costs, climate costs and environmental costs for Europe, 2021-2027