Volatility in Air Traffic Management—How Changes in Traffic Patterns Affect Efficiency in Service Provision

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Abstract Air traffic demand and distribution fluctuates in long-, medium-, and short-term perspective. In order to ensure safe and efficient flight operations, air navigation service providers need to ensure that enough capacity is available for airspace users. For this purpose, reliable traffic forecasts are necessary to avoid capacity shortages or excesses and subsequently costs. However, the provision of air navigation services is hampered by several effects, i.e., unpredictable traffic patterns and trends. Despite awareness of such problem, there is not a common definition or metric yet to measure the so-called ‘volatility.’ The aim of this paper is twofold: to set out an approach addressing volatility measures for different spatial and periodical scopes, and to show the effects of demand fluctuations on the ATM system from a holistic point of view.

Keywords ATM · ANSP · Performance · Volatility · Fuzzy cognitive mapping

1 Motivation

Due to the growing number of flights and the high cost pressure on airlines, the provision of air navigation services (ANS) has recently drawn increasing attention from both the academic and the policy decision-makers perspectives. A major challenge regarding ANS provision is ‘planning under uncertainties’ as a result, for example, of a volatile traffic demand in terms of movement numbers and flow patterns, which significantly influence resource planning and allocation. Several factors could cause
or amplify volatility (i.e., weather phenomena, strikes, geopolitics, airline decisions or unexpected economic downturn [1]).

Volatile traffic affects ANS planning at multiple time-scales and operational levels [2]. Changes in traffic demand and flow patterns have a direct influence on pre-tactical and strategical capacity planning. Since airspace users tend to act more and more on a short-term basis, it seems reasonable to think that volatility has increased over the past years.

Against this backdrop, the paper focuses on two issues. Firstly, it provides a specific definition and derived metrics in order to evaluate volatility in air traffic management (ATM). Secondly, the influence of volatile traffic on ATM performance is analyzed, discussing two potential approaches.

For this purpose, the paper is structured as follows: Sect. 2 deals with the state of the art regarding volatility measurement as well as the underlying approaches published by authors with an operational or academic background. Section 3 introduces volatility definition and metrics, the latter also being applied to several data sets. In Chap. 4, we present the results for volatility on ANSP level and discuss potential effects on costs and resources. We also compare different volatility metrics and check applicability and meaningfulness.

Since there are several operational subdivisions of one ANSP, we calculate volatility scores for sector families in Chap. 5. The influence of volatility on performance is determined in Sect. 6. Key mechanisms within the ATM systems are analyzed by applying fuzzy cognitive mapping. Section 7 finishes with some conclusions and determines a way forward.

2 Current Situation and Literature Review

Volatility is a rather new field of research in the ATM context. The impact of volatility on performance has still neither been investigated by academic studies nor included in official EUROCONTROL benchmarking reports. As a result, volatility of air traffic is not considered in the policy decision-making process (e.g., the performance scheme of the SES Regulations). This may lead to insufficient collection and/or distribution of route charges in terms of an efficient demand-capacity-balancing.

In May 2018, FABEC and the Baltic Functional Airspace Block (Baltic FAB, composed of the countries of Poland and Lithuania) conducted the workshop ‘Volatility in Air Traffic and its impact on ATM Performance.’ The conference papers dealt primarily with unpredictability and capacity planning under uncertainties from an operational or an academic point of view (e.g., [3, 4]).

EUROCONTROL uses ‘traffic variability’ as a metric for demand fluctuations, by comparing the peak value with the corresponding average over a given time (e.g., annually) and operational level, e.g., area control center (ACC) [5]. However, the measure proposed by EUROCONTROL has shortcomings: as only the highest and the average numbers are taken into account, volatility during all other 10 months or 50 weeks is neglected. In addition, variability can be called ‘seasonality,’ since only
the whole year is considered. Trends for 5–10 years for investment cycles or during a week for shift planning purposes are not contemplated.

In summary, the currently available and applied metrics provide a first approach to describe traffic demand fluctuations. Furthermore, spatial and temporal aspects were considered. However, even though it is commonly agreed that volatility has a high impact on performance [2], there is neither a clear definition of the word itself within the ATM context nor are formulas available to quantify traffic demand volatility and its influence on delay and other performance indicators. For all these reasons, a holistic approach is missing which includes interdependencies between factors which cause or are influenced by volatility (cause and effect chain).

The current study aims to close this research gap by defining and comparing valid volatility metrics. The approaches used are applicable to multiple time horizons (long-, medium-, and short-term), and operational levels (ANSP, area control centers, sector families, etc.). Thus, this paper contributes significantly to the understanding of the extent and effects of traffic fluctuations.

3 Volatility Metrics

Volatility is a measure often used in finance, which enables a risk assessment. Approach, applications, and formulas are described comprehensively in [6–9]. In the context of air traffic and ANS provision, we define volatility as the variability of traffic flow along a specific unit within a given time period. In accordance with the financial metrics, traffic volatility \( \sigma \) denotes the (short-term) fluctuation of a time series by its mean or trend [10]. It is measured by the sum of standard deviation of change rates \( R_i \) (e.g., of flights) between two or more periods (1). The arithmetic mean is indicated as \( \mu \), and \( n \) represents the number of observations.

\[
\sigma = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n} (R_i - \mu)^2} \quad (1)
\]

This metric measure ‘historic volatility’ and is time-invariant. It summarizes the probability of observing extreme values of traffic demand. The changes might be defined as absolute, relative, or logarithmic terms. Formula (2) represents another alternative to approach volatility, by calculating the standard deviation based on the observed values \( h \) (e.g., for flights) in period \( t \) (instead of the change rates, \( \bar{h} \) stands for the arithmetic mean of \( h \)). It is used when samples are considered rather than the whole population.

\[
\sigma = \sqrt{\frac{\sum_{t=1}^{T} (h_t - \bar{h})^2}{T - 1}} \quad (2)
\]
Noting that the standard deviation is scale-dependent, it might be also worth computing the percentage coefficient of variation (CV), as shown in (3).

\[
CV = \frac{100}{\bar{h}} \sqrt{\frac{1}{T-1} \sum_{t=1}^{T} (h_t - \bar{h})^2}
\] (3)

The formulas (1)–(3) represent measures of variation. A second possibility to approach volatility, especially seasonal fluctuations, is represented by measures of uneven distribution. In scientific research, the most common economic metrics are GINI coefficient or Herfindahl-Hirschman-Index (HHI), see e.g., [11, 12]. GINI measures the relative concentration, e.g., of traffic demand over the year, based on the number of observations \(n\), the observation index (e.g., month) \(i\) and the corresponding demand \(x_i\) as shown in (4).

\[
\text{GINI} = \frac{2}{n \sum_{i=1}^{n} x_i} \left( \sum_{i=1}^{n} i \cdot x_i - \frac{n+1}{n} \sum_{i=1}^{n} x_i \right)
\] (4)

HHI is often used to calculate market shares of firms; however, it might be also transformed to shares of different time periods. The index represents the sum of the squared market shares of individual observations (5).

\[
\text{HHI} = \sum_{i=1}^{n} \left( \frac{x_i}{\sum_{i=1}^{n} x_i} \right)^2
\] (5)

The index is often normalized in a second step, fitting to an interval \([0, 1]\). The HHI is invariant regarding the number of observations. However, in our study, the number of observations is constant.

Considering that the paper primarily focuses on finding a valid metric for ATM purposes, we apply formula (1) on different spatial and periodical scopes first. Therefore, we use relative changes due to the heterogeneous size of the units, as well as absolute traffic figures in order to consider limitations in resource planning. In a second step, we will apply formulas (3)–(5) as well, compare the results, and discuss applicability and meaningfulness.

4 Application on Macro-level

4.1 Database

As stated in Sect. 2, volatility may be computed over various time periods and operational levels. Since environment and objectives differ between these levels, we follow a macroscopic and a microscopic approach. At ‘macro-level’ (ANSPs), we use
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Fig. 1 Development of flight movements worldwide, 1971–2016 (Worldbank)

the Worldbank database for long-term investigations and data from the performance review unit (PRU) for medium- and short-term analysis [13–15]. We focus on ANSPs coordinated by EUROCONTROL.

Figure 1 shows the annual traffic movements between 1970 and 2016, based on Worldbank data. It emphasizes the need to consider multiple time periods: the overall (linear) trend is represented by the dotted line. Considering other time periods will result in another trend and, according to the definition in the previous section, in other volatility scores.

4.2 Long- and Medium-Term Analysis

As a first example, (1) was applied to the number of annual flights in European countries. The data was provided by Worldbank. $R_i$ thus represents the change rate of flights in relation to the year before. A calculation example for Belgium is provided in Fig. 2. The red line shows the arithmetic mean $\mu$, the green lines delimit the 66% confidence interval.

Since the calculation is based on growth rates, the relative differences $R_i$ are available between 1971 and 2016. Applying formula (1) leads to a volatility score of $\sigma = 17.5\%$ for Belgium.

Figure 3 shows the long-term volatility scores for a selection of European countries. Bulgaria has the highest volatility score (33.9%) in traffic demand, while the United Kingdom has the lowest (4.1%). In general, (worldwide) volatility scores are characterized by a high level of scattering. However, high volatility scores are not common: The worldwide median is 16.8% in a long-term perspective. Since formula (1) is scale-dependent, countries with a relatively high traffic demand show low volatility scores. In contrast, countries such as Bulgaria and Hungary benefit from higher demands (and subsequently positive growth rates) due to the end of
the political conflicts after 1990. Furthermore, growing traffic between the Arabic countries and Europe and/or America contributes to changes in growth rates.

High volatility scores may inhibit the resource planning of ANSPs. Fluctuations with high amplitudes, which is expressed by the volatility score, lead to high contingency costs. This is due to the necessity to provide staff and infrastructure for the case of maximum demand. However, the implementation of systems usually takes between 8 and 12 years.

It might be even more important to consider medium- and short-term fluctuation. A main cost driver of ANSPs is represented by human resources. The training of new controllers requires approximately five years and contingency costs might be higher than for infrastructure (hard and software) due to the annual costs per Air Traffic Control Officer (ATCO) or ATCO-hour. The medium-term analysis is based on PRU data, which is available for the years 2008–2017. It is beneficial to use time-based measures due to the possibility of subsumption.
The medium-term perspective also enables the possibility to consider ANSPs instead of countries. Formula (1) was applied on EUROCONTROL ANSPs for a seven-year period (2008–2014). Figure 4 shows the medium-term volatility scores based on the change rates of ‘IFR flight hours’ \( R_i \). Scores are similar to those based on ‘flights,’ except for Malta Air Traffic Services (MATS) which is characterized by a deviation of about 6 percentage points. Volatility scores are lower than in the long-term perspective for majority of ANSPs.

### 4.3 Seasonality

As a further aspect, we consider seasonal demand shifts. The key underlying rationale is the same as for the long- and medium-term perspective: high fluctuations lead to high contingency costs. In order to calculate seasonal volatility, we used 2018 data provided by PRU dashboard (monthly flights). The data is available on daily basis. Formula (1) was applied on ‘flights,’ since ‘flight hours’ were not provided by the database [16].

Figure 5 shows the volatility according to the corresponding ANSPs, differentiated by summer and winter season. Since the scores differ between both seasons, classification is also different. The thresholds are shown in Table 1.

The applied volatility score is still based on growth rates. The figures show that volatility is higher in winter for the majority of ANSPs. There are some extreme values, represented by Norway for both periods, and the whole of Scandinavia for the winter season. The same effect is visible for FABEC-ANSPs: volatility decreases in summer and increases in winter. ANA LUX is confronted with the highest volatility in demand. This might be due to the overall smaller demand figures in winter (and
for ANA Lux). Subsequently, there is a higher (relative) change rate for a similar (total) shift in summer. For December, the high volatility can be explained by a demand fluctuation during Christmas time and New Year’s Eve, given that demand figures are significantly lower on December 24th, 25th, and 31st. Due to illustrational reasons, the ANSPs are represented by the corresponding countries and MUAC is not included in the figures.

The results show some expected and some rather unexpected results. Especially the higher fluctuation of large-scale ANSPs might not be comprehensively covered by the relative measure of formula (1). Since ATCOs are licensed for a predefined number of sectors only, it is not possible to shift resources arbitrarily. Subsequently, it might be doubtful whether a metric based on formula (1) leads to meaningful results for seasonal volatility.

There are two possibilities to adjust the calculation of the score in order to improve the metrics. First, it is possible to use actual traffic figures instead of growth rates, but still apply formula (1). Second, as discussed in Chap. 3, there are potential alternatives, e.g., formulas (3)–(5).

These formulas were applied to PRU data [14]. The volatility scores are based on actual monthly flights in 2019. Furthermore, we calculated a peak load share (PLS). The metric divides the number of flights during the three most frequented months by the total number of flights in the whole year. Table 2 shows the results of all five indicators.

| Class          | Winter (%) | Summer (%) |
|----------------|------------|------------|
| Very high      | >6         | >15        |
| High           | 10–16      | 10–15      |
| Medium         | 7–10       | 5–10       |
| Low            | 6–7        | 4–5        |
| Very low       | <6         | <4         |
Table 2  Seasonal volatility metrics for a selection of ANSPs, 2019

| ANSP        | $\sigma$ | CV (%) | HHI (%) | GINI (%) | PLS (%) |
|-------------|----------|--------|---------|----------|---------|
| ANA LUX     | 596      | 9.0    | 8.4     | 4.7      | 27.1    |
| Avinor      | 3.856    | 7.8    | 8.4     | 4.2      | 27.1    |
| BULATSA     | 16.830   | 23.0   | 8.7     | 12.4     | 32.5    |
| DFS         | 33.153   | 12.8   | 8.5     | 6.8      | 28.3    |
| DSNA        | 48.413   | 17.6   | 8.6     | 9.5      | 30.0    |
| ENAIRE      | 31.069   | 17.3   | 8.6     | 9.4      | 30.0    |
| ENAV        | 36.114   | 23.7   | 8.8     | 12.9     | 32.6    |
| IAA         | 7.869    | 14.6   | 8.5     | 7.9      | 29.0    |
| LVNL        | 5.130    | 9.7    | 8.4     | 5.1      | 27.3    |
| MUAC        | 16.045   | 10.3   | 8.4     | 5.6      | 27.8    |
| NATS        | 28.649   | 13.6   | 8.5     | 7.3      | 28.8    |
| Skyeyes     | 6.670    | 12.5   | 8.5     | 6.7      | 28.3    |
| Skyguide    | 18.067   | 16.5   | 8.5     | 8.9      | 29.6    |

The volatility score based on formula (1), $\sigma$, is scale-dependent and subsequently grows with the size of the corresponding unit. However, this might reflect the challenges of volatility more precisely. GINI and CV are highly correlated. These relative measures might be multiplied by the actual demand or resource figures to calculate effects on the input- and output side. HHI seems to be unsuitable to compare volatility between single ANSPs. The peak load share might be of special interest for some ANSPs, e.g., if airspaces are primarily used in the summer or winter season. However, it gives no holistic description of the trend during a whole year. Subsequently, we suggest to use the CV or GINI coefficient.

Worldbank and PRU data allow only a very high aggregation level. Changing the perspective on lower operational levels will probably increase volatility since demand is expected to fluctuate more than in higher operational levels (law of large numbers). The application on a disaggregated level is discussed in section 0.

5 Application on Micro-level

Chapter 4 dealt with potential metrics to calculate volatility on the ANSP level. Most of the European ANSPs operate multiple area control centers (ACCs), dividing the corresponding national airspaces horizontally and/or vertically. The smallest structural unit is formed by the sectors, which can be combined or divided (‘split’) according to traffic demand. The possibility of combination, however, depends on the licensing of the air traffic controllers. Therefore, the sectors are allocated to sector families (SF). This operational level is defined as ‘micro-level.’ For volatility calculation, we use data provided by Deutsche Flugsicherung GmbH (DFS), containing
figures on sector family level for ‘flights’ and ‘flight hours’ (as demand), as well as ‘ATCO-hours’ (representing resources). The data is available for the ACCs Karlsruhe (ACC1), Bremen (ACC2), Langen (ACC3), and Munich (ACC4).

Figure 6 shows the number of IFR flight hours per year, differentiated by sector families. Due to the sensitivity of the data, the corresponding units are anonymized. Even though all sector families belong to the same ANSP, scattering is high: ACC1 SF1 flight hours are approximately seven times higher than the ones of ACC3 SF2. This divergence is caused by the different airspace characteristics: while some sector families are only responsible for upper airspaces, others supervise lower airspaces. The sector family ACC3 SF2 covers the southwestern area of Frankfurt airport, thereby controlling flights in the lower airspace, mostly with Frankfurt as their destination. As traffic composition in the lower airspace is more heterogeneous, capacity is lower due to the complexity and therefore comparatively less traffic is being controlled.

Traffic figures may vary significantly over time. As an example, most airspace units experience traffic peaks in summer. Table 3 shows the number of flights for each ACC for the years 2016 and 2017, as well as the mean, minimum, and maximum. The underlying annual shape of the demand curve is similar for all 4 ACCs.

![Fig. 6](image)

**Table 3** Descriptive statistics of traffic movements (based on monthly counts)

| ACC  | Year | Sum     | Min  | Mean  | Max    |
|------|------|---------|------|-------|--------|
| ACC1 | 2016 | 1,778,658 | 119,283 | 148,222 | 174,421 |
|      | 2017 | 1,844,836 | 120,163 | 153,736 | 181,295 |
| ACC2 | 2016 | 661,491  | 44,827 | 55,124 | 62,201 |
|      | 2017 | 660,808  | 43,052 | 55,067 | 62,541 |
| ACC3 | 2016 | 1,230,219 | 85,401 | 102,518 | 115,281 |
|      | 2017 | 1,268,034 | 85,458 | 105,670 | 119,054 |
| ACC4 | 2016 | 1,082,839 | 75,277 | 90,237 | 102,265 |
|      | 2017 | 1,120,980 | 77,239 | 93,415 | 106,325 |
The largest number of flights occurs in summer, with the counter-peak in January or February. Karlsruhe controls about three times more flights than Bremen. However, the relative average is similar between all ACCs and all years (69–75%). Generally, higher volatility scores could be expected at the micro-level, as sectors control less flights compared to sector families, ACCs or ANSPs. The higher the amount of traffic the less volatility could be assumed, as one additional flight has a higher impact on lower operational levels.

The analysis on ANSP level demonstrated that fluctuations in traffic demand occur differently. In addition, pure demand figures on this operational level might not reflect changes in traffic flows appropriately. Therefore, it is useful to disaggregate the analysis by sectors, since capacity is basically provided within this smallest entity of the airspace.

Airspace structure is characterized by dynamic subdivisions. According to demand, sectors can be splitted or merged. Volatile traffic hampers efficient planning of these capacity enhancing measures significantly. However, sector data were not available for this research, so we applied the methodology on sector family data in order to calculate volatility. In this way we use ‘flight hours’ for demand.

Traffic demand fluctuates considerably over the year. The upper peak represents three times more flight hours than the lower peak, depending on the considered sector family. Furthermore, the data also reveal weekly and seasonal effects are also visible in the data.

According to Fig. 7, volatility metrics differ quite substantially between the sector families. On the one hand, the highest scores are shown for ACC2 sector families 1 and 3. On the other side, all three sector families with the lowest score are assigned to ACC1.

Comparing Fig. 6 with Fig. 7, there is no clear dependence between total overall demand and the volatility score. As a tendency, small units are characterized by a higher volatility (such as ACC 2). Further reasons might be the amount of military aircraft being controlled in different areas, which seems to lead to less volatility. In addition, the upper airspace (e.g., ACC 1 handling only traffic in the upper airspace)

**Fig. 7** Volatility of German sector families, monthly basis, 2017
and areas with a higher share of homogenous traffic (such as Approach Units of large Hubs like ACC3_SF9 and ACC4_SF1) seem to have a lower volatility, whereas the areas of responsibility that control flows to smaller airports, which tend to service low-cost carriers, are characterized by higher volatility.

In order to test the influence of volatility on performance, there are several analytical tools, such as regression analysis. This methodology enables the consideration of the interaction of several effects. Regression analysis is purely quantitative and thus does not require a priori assumptions. However, within this paper, we focus on the semi-quantitative approach of fuzzy cognitive mapping (FCM, Chap. 6). Furthermore, besides the analytical approaches, there is also the possibility of fast- or real-time traffic simulations (Chap. 7).

6 Fuzzy Cognitive Mapping

6.1 Approach and Methodology

Humans commonly tend to think that only direct causal relations exist between two concepts. Nevertheless, thanks to the understanding of complex systems we know that changes in one variable may influence variables which were not initially identified, or that one variable may generate an unexpected chain of events (commonly referred to as cascading effects). With this idea in mind, this paper is intended to better understand what and how volatility may affect or be affected by ATM. A fuzzy cognitive map is developed to this end.

Cognitive maps consist of a set of concepts and linkages which express cause-effect networks [17, 18]. However, causes are often uncertain, usually fuzzy. The notion of fuzziness was introduced into cognitive maps, giving rise to fuzzy cognitive maps [19].

FCM is a participatory, semi-quantitative method in which the experience, knowledge, and perceptions of the system of different experts on the topic (in our case, three air traffic controllers, two engineers specialized in performance management, one engineer with a focus on operational performance and two economists with specific knowledge of the European aviation sector) give rise to the construction of a graph structure that can be later used to simulate scenarios according to which policymakers may analyze how the system may behave under certain impacts [20]. In this way, these maps encourage systematic causal propagation (forward and backward chaining), helping to identify cascading effects and interdependencies across elements (including unexpected trade-offs and synergies) that otherwise would be difficult to analyze.

The approach is illustrated in Fig. 8. First, every concept (C) is defined at a discrete time, so its state may change over time. In a second step, all concepts are related to each other through directed arrows that indicate both the direction of the causality and the degree of influence one concept (C_2) can have on another (C_6) (positively or...
Linkages are later labeled by weights ($W_{26}$), reflecting the strengths of the relationships between two concepts ($C_2$ and $C_6$). The weights are represented by a numerical scale from 0 to 1. Finally, once the map has been built-up, we can, on the one hand, perform scenario analysis to identify the cascading effects (in our case, the effects occurring in the whole system when there is a volatility problem in one part of it) and, on the other hand, estimate the following three indicators: Out-degree of a concept (a measure of the strength of the influence of one concept on other concepts in the network), In-degree of a concept (a measure of the dependency of a concept on other concepts in the network), and centrality (it denotes the individual importance of a concept).

6.2 Results

The eight experts found 39 concepts, such as ticket prices, wars/conflicts/crises, oil cost or airspace charges, among others. A complex map with these 39 concepts was built (Fig. 9), enabling us to show the relationships between them and to determine causes and effects of volatility that are usually not discernible at first sight.

According to our FCM, the concepts with the highest capacity to influence other variables or concepts (Out-degree) are ‘predictability,’ ‘airspace complexity,’ and ‘economic activity.’ By contrast, the concepts with the highest capacity for being influenced by the remainder (in-degree) are ‘air traffic flow,’ ‘demand from airlines,’ ‘airspace complexity,’ ‘demand from passengers,’ and ‘predictability.’ Centrality allows us to conclude that ‘predictability’ and ‘airspace complexity’ are the key variables to be considered when deciding certain policies or actions to reduce volatility by airlines and air navigation service providers.

When it comes to the scenario analysis, it involves examining what would happen in the whole system if there were a change in one of the concepts (e.g., a pandemic, like the COVID-19, or an increase of staff costs, among others). With this idea in mind, and after estimating a weight function and conducting the analysis with the software FCmapper [21], a common trend can be observed: the system reacts in a negatively).
similar way, irrespective of the fact in which concept a change (or shock) occurs. In other words, whether there is a change in one or another concept, the same variables are almost always the most affected by these changes. This means that these variables (in our case, ‘airport charges,’ ‘airspace charges,’ ‘ATFM regulation needs,’ ‘demand from passengers,’ ‘demand from airlines,’ ‘flight ticket price,’ ‘air traffic flow,’ ‘quality of services,’ ‘overload (controller),’ ‘airspace complexity,’ and ‘complexity of flight composition’) are the most sensitive in the case of external shocks, whatever they may be, so they should be taken into consideration by policymakers and air traffic managers when facing volatility in the performance and operation of the air system. This will help them to act accordingly, since they may decide whether or not to current buffers are appropriate or not or whether it is necessary to add some new buffers (see, for example, the case of overload for controllers).

In short, FCM is a very useful tool for understanding volatility, as it implies a high degree of complexity. It not only depends on certain obvious variables affecting it directly, but also on other variables that are indirectly relevant and that had not been identified if were not for the construction of this complex system. Thus, the whole map should be seen in the context to prevent global consequences, as the impact of one variable may influence others in unexpected ways.

Moreover, despite being constructed by experts, the fact that it is easily to understand for the general public is what makes FCMs a very interesting alternative to be considered in policymaking.

7 Conclusion and Way Forward

The present paper develops a general definition to describe volatility of air traffic demand for a wide span of reference time periods, as well as for geographical scopes. Based on macro- and micro-level data, the method was applied on various examples
ranging from a 1 year to a >50-year period along the time axis and from sector family level to European airspace on the scope axis. The paper shows that volatility scores are sensitive to both factors. In addition, the highest volatility can be observed in December. By contrast, the low volatility scores for summer are rather unexpected. However, this picture changes when using a scale-dependent calculation basis, which might be more useful due to the nature of ANSP staff planning.

In addition, an FCM is applied to enable a holistic consideration of the whole system. In this way, it is possible to show which elements are sensitive to volatility, e.g., caused by external shocks. A quantification, e.g., by regression analysis, might be a subject for further research. Furthermore, the approach to simulate different traffic scenarios and their influence on sector configurations will lead to further insights with regards to resource planning.

The applied calculation methods represent one potential approach. Standard deviation and GINI coefficient are expected to match ATM requirements most. In further studies, it should be checked whether the formula must be adapted or substituted in order to calculate volatility based other time periods (e.g., day and night time differences).

Quantifying the impact on the performance of ANSPs (e.g., regarding cost effectiveness) might be another research focus. The simulation, which is currently work in progress, will represent a fundamental contribution. In addition, it might be beneficial to include sectors, sector families, and ACCs of other ANSPs. This would enable the consideration of particularly strong, unforeseen traffic fluctuations into regulatory measures, respectively, policy decision making.

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