[EN-A-10] 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 in order 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 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 as well as a high cost pressure by airlines, the provision of air navigation services (ANS) has recently drawn increasing attention from both the academic and the policy decision-makers perspective.

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. Changes in traffic demand and flow patterns have a direct influence on pre-tactical and strategical capacity planning [2]. 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 metric(s) in order to evaluate volatility in Air Traffic Management (ATM). Secondly, the influence of volatile traffic on ATM performance is analyzed, applying two different analysis methods.

For that, it is structured as follows: Section 2 deals with the current situation of volatile demand in Europe, as well as with recent publications. Section 3 introduces volatility definitions and metrics, the latter being also applied in several data sets. The influence of volatility on performance is determined in section 4 by analyzing demand and delay, on the one hand, and by presenting a Fuzzy Cognitive Mapping, on the other hand. Section 5 finishes with some conclusions and determines a way forward. Although the paper is primarily based on European data and procedures, the results might be applied to other airspaces.

2 Status quo and Literature Review

Today, Air Navigation Service Providers (ANSPs) represent one significant capacity restraining factor in commercial traffic, especially in regions with high traffic density. Long-term forecasts for 2050 predict an average annual traffic growth between 0.3% and 2.7% [3]. Moreover, the spatial distribution of demand is not evenly: the most frequented routes are within the core area of Europe, where seven large Hubs are located within a 1,000 km diameter [4]. In this context, ANSPs are faced with continuous challenges in capacity management.

An expansion of capacity requires investment in human resources and/or technology. However, an efficient resource planning is aggravated by insufficient prediction of actual traffic figures. The range and hence the uncertainty in the forecast for 2050 is about 15.6 million flights for Europe as a whole [3], but it does not determine the spatial distribution, respectively the growth rates for the individual ANSPs. In addition, the deviation between predicted and actual demand is often significant [5].

Volatility is rather a new field of research in 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 (see 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 2017, the Functional Airspace Block Europe Central (FABEC)[1] initiated a 'Volatility Taskforce' in order to identify volatility drivers, develop a metric for volatility and derive recommendations. As stated in the previous section, effects may contribute to volatility in multiple time periods and on several operational levels. The taskforce used a metric based on the share of unanticipated traffic, represented by the sum of intruder and extruder, in comparison to planned and actual traffic. Furthermore, they defined nine areas contributing to volatility, such as Geopolitics, ATFM or Weather [1,6] (see also annex, Figure 8). Although this study represented a first approach to the topic, the underlying metric might be seen as a way for measuring unpredictability, but not volatility. Furthermore it is not clear why the sum of intruder and extruder is used, since both effects partly compensate each other.

In May 2018, FABEC and the Baltic Functional Airspace Block (Baltic FAB)[2] 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 (see e.g. [7]).

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. yearly) and operational level e.g. Area Control Center (ACC) [8]. However, the measure proposed by EUROCONTROL has shortcomings: as only the highest and the average numbers are taken into account, the volatility in 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 to 10 years for investment cycles or during a week for shift planning purposes are not contemplated).

In summary one can state that the metrics introduced by EUROCONTROL and FABEC Volatility Taskforce provide a first approach to describe traffic demand fluctuations. Furthermore, spatial and temporal aspects were taken into account. However, even though it is commonly agreed that volatility has a high impact on performance [9], there is not a clear definition of the word itself within the ATM context nor are formulas available in order to quantify traffic demand volatility and its influence on delay and on other performance indicators. For all these reasons, a holistic approach including interdependencies between factors which cause or are influenced by volatility (cause and effect chain) is missing.

3 Volatility in ATM

3.1 Definition and Metrics

Volatility can be characterized as the 'width of the fluctuation', and thereby as a risk measure. In the context of air traffic and ANS provision, volatility describes the variability of a traffic flow along a specific unit within a given time period. For definitions and formulas, see [10–12]. According to financial measures, volatility σ denotes the (short-term) fluctuation of a time series by its mean or trend [13]. It is measured by the sum of standard deviation of change rates R_i between two or more periods (formula 3-1). The mean is indicated as μ, where n represents the number of observations.

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

3-1 Volatility Formula based on change rates

This metric measures the 'historic volatility' and is time invariant. It summarizes the probability of observing extreme values of traffic demand. The changes might be defined absolute, relative or logarithmic.

[1] It compromises the ANSPs of France, Germany, Switzerland, Luxembourg Belgium, Germany and the Netherlands as well as Maastricht Upper Airspace Control (MUAC).

[2] It is composed of the countries of Poland and Lithuania.

Formula 3-2 represents another alternative to approach volatility, by calculating the standard deviation based on the observed values *h* in period *t* (instead of the change rates). It is used in case of considering samples instead of the whole population.

$$\sigma = \sqrt{\sum_{t=1}^{T} \frac{\left(h_t - \bar{h}\right)^2}{T-1}}$$

3-2 Time Invariant Volatility Formula

Noting that the standard deviation is scale dependent, it is also worth computing the percentage coefficient of variation (CV), shown in formula 3-3.

$$CV = \frac{100}{\bar{h}} \sqrt{\sum_{t=1}^{T} \frac{\left(h_t - \bar{h}\right)^2}{T-1}}$$

3-3 Coefficient of Variation

Since the standard deviation and the coefficient of variation do not focus explicitly on the uncertainty aspect of volatility, it is also possible to use the Root Mean Square Percentage Error (RMSPE, formula 3-4) as a third measure, since it allows determining prediction errors.

$$RMSPE = 100 \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left(\frac{h_t - \hat{h}_t}{h_t}\right)^2}$$

3-4 Root Mean Square Percentage Error

Considering that the paper primarily focuses on finding a valid metric for ATM purposes, we focus on the application of formula 3-1 on different spatial and periodical scopes. Therefore, we use relative changes due to the heterogeneous size of the units.

3.2 Database

As stated in section 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, we use the World Bank Databases for long-term investigations and Performance Review Unit (PRU) for medium- and short-term analysis. We focus on ANSPs coordinated by EUROCONTROL.

At micro-level, we use data provided by Deutsche Flugsicherung GmbH (DFS), containing figures on sector group level for 'flights' and 'flight hours' (as demand), as well as 'ATCO-hours' (representing resources). The data is available for the ACCs Karlsruhe (UU), Munich (MM), Bremen (WW) and Langen (GG).

Annex Figure 9 emphasizes the necessity of considering multiple time periods. The graph shows the traffic movements per year worldwide. Furthermore, the overall (linear[3]) 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 volatilities.

The figure covers a very high aggregation level. Lowering the operational level, e.g. on ACC perspective, will probably increase volatility, since demand is expected to fluctuate more than in higher operational levels (see also Figure 2). Thus, it is expected that volatility grows with the disaggregation of data (law of large numbers).

Figure 1 shows the number of IFR-Flight hours, differentiated by sector groups. Despite the fact that all sector groups belong to the same ANSP, the scattering is high: UU_East flight hours are approximately seven times higher than the ones of GG_EBG02[4]. This divergence is caused by the different airspace characteristics: while Karlsruhe is only responsible for upper airspaces, Langen supervises lower airspaces and the corresponding sector group GG_EBG02 which is responsible for the southwestern area of Frankfurt airport, thereby controlling flights in the lower airspace, mostly with destination Frankfurt. As the traffic composition in the lower airspace is more heterogeneous, the capacity due to the complexity is lower and therefore comparatively less traffic is being controlled.

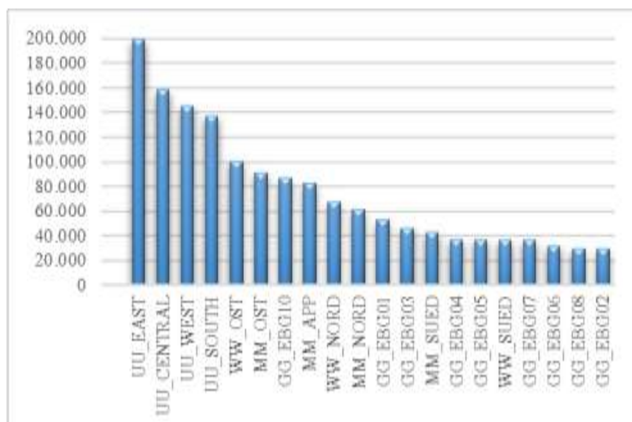

Figure 1: Flight Hours per Sector Group, 2017

Traffic figures may vary significantly over time. As an example, most airspace units experience traffic peaks in summer. Table 1 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 (Annex, Figure 10).

The largest number of flights occurs in summer, with the counter-peak in January or February. Karlsruhe UAC controls about three times more flights than Bremen ACC. However, the relative average is similar between all ACCs and all years (69%-75%).

[3] However, an exponential trend would fit better with the data

[4] EBG = Einsatzberechtigungsgruppe = Sector group

	Year	Sum	Min	Mean	Max
WW	2016	661,491	44,827	55,124	62,201
	2017	660,808	43,052	55,067	62,541
UU	2016	1,778,658	119,283	148,222	174,421
	2017	1,844,836	120,163	153,736	181,295
GG	2016	1,230,219	85,401	102,518	115,281
	2017	1,268,034	85,458	105,670	119,054
MM	2016	1,082,839	75,277	90,237	102,265
	2017	1,120,980	77,239	93,415	106,325

Table 1: Descriptive statistics of traffic movements (based on monthly counts)

Generally, more volatility could be expected at the micro-level, as sectors control less flights compared to sector groups, ACCs or ANSPs. The higher the amount of traffic the less volatility could be assumed, since one additional flight has a higher impact on lower operational levels.

3.3 Application at Macro-Level

As an example, Figure 2 shows the calculation of volatility for Belgium in a long-term perspective, by using Traffic movements. The graph shows the annual changes in air traffic (blue bars), the average change (red line) and the 66% confidence interval (green lines). Applying formula 3-1 on these figures results in a demand volatility of 17.5%. Using the same time period, Figure 3 shows the long-term volatility for a selection of countries. In long-term perspective, many influences may affect the distribution of traffic.

Volatility figures are characterized by a high scattering. Considering the complete database, Paraguay has the highest volatility (202%) in traffic demand, while United Kingdom has the lowest (4.1%). However, high volatility scores are not common. The worldwide median is 16.8%.

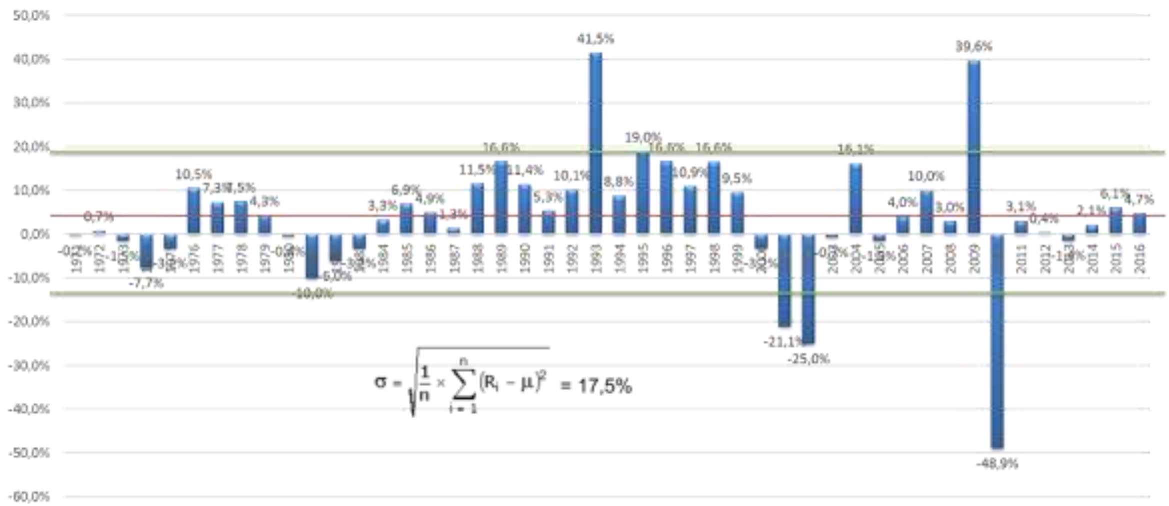

Figure 2: Volatility for Belgium, long-term, based on yearly traffic movements

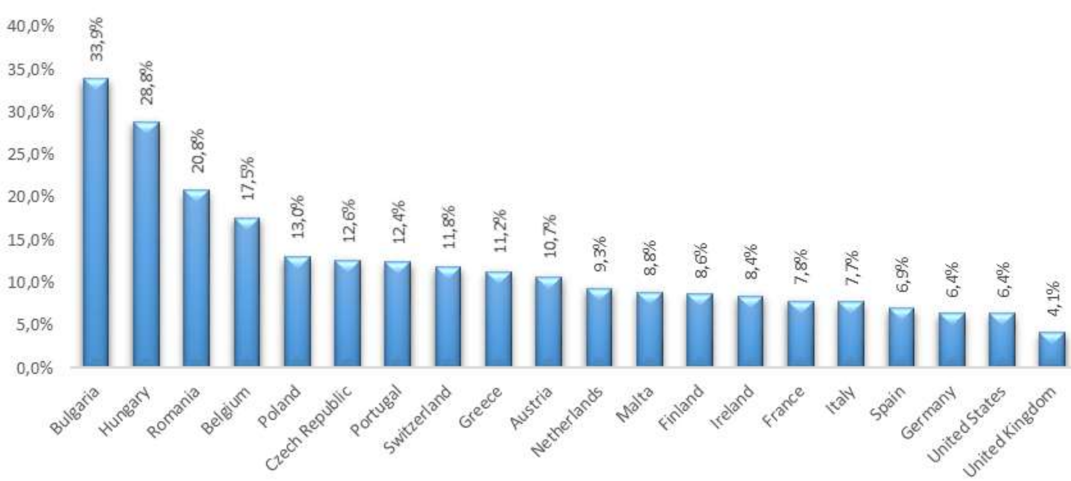

Figure 3: Long-term volatility in traffic movements for selected countries

The long-term view is important for ANSPs in order to enable an efficient resource planning. The implementation of systems usually takes 8 to 12 years. However, it might be even more important to consider medium- and short-term fluctuation. As an example, the training of new ATCOs takes approximately 5 years. It is beneficial to use time-based measures due to the possibility of subsumption [5] (time- or level based[6]).

Figure 11 (Annex) shows the volatility in traffic demand, represented by ‘IFR flight hours’, for EUROCONTROL ANSPs for a seven-year-period (2008-2014). Scores are similar to those based on ‘flights’, excepting for Malta Air Traffic Services (MATS) which is characterized by a deviation by about 6 percentage points. The volatility scores are lower than in long-term perspective for majority of ANSPs.

As a second aspect, we consider seasonal demand shifts. Therefore, we used 2018 data on daily basis to calculate a monthly and yearly volatility score for each ANSP. The underlying parameter is ‘flights’, since ‘flight hours’ were not provided by the database [14].

Figure 4 shows the volatility according to the corresponding ANSPs, differentiated to summer and winter season. Please note that, due to illustrational reasons, the ANSPs are represented by the corresponding countries and MUAC is missing in the figure. The monthly volatility scores are shown in Figure 5 for a selection of ANSPs. For data, see annex Table 3.

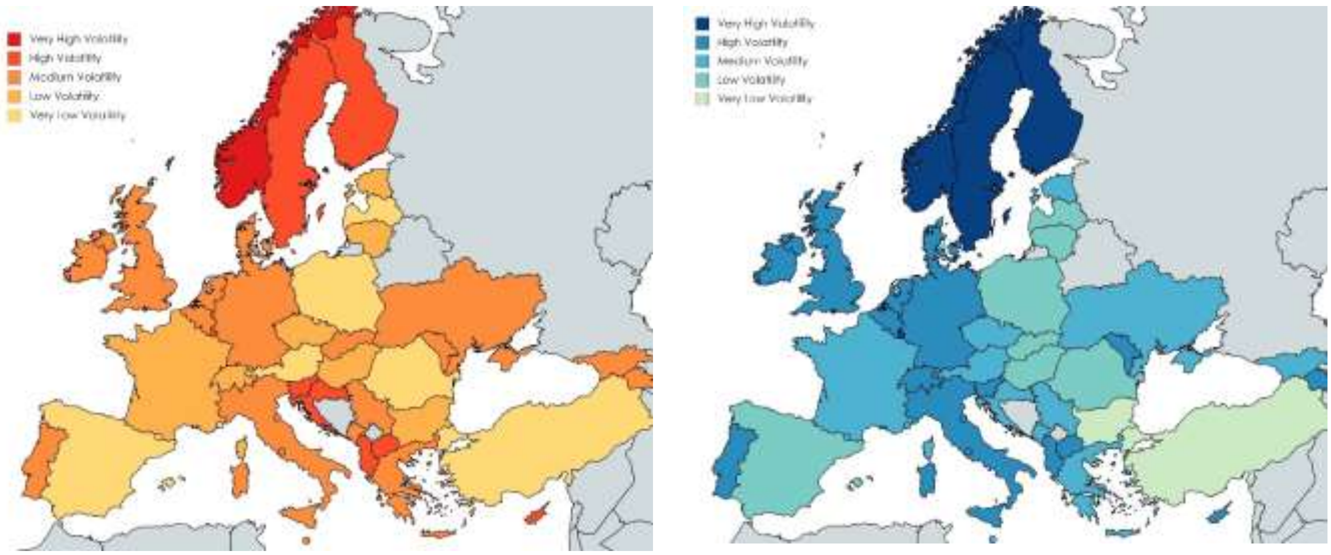

Figure 4: Volatility Score for summer (left) and winter (right), 2018

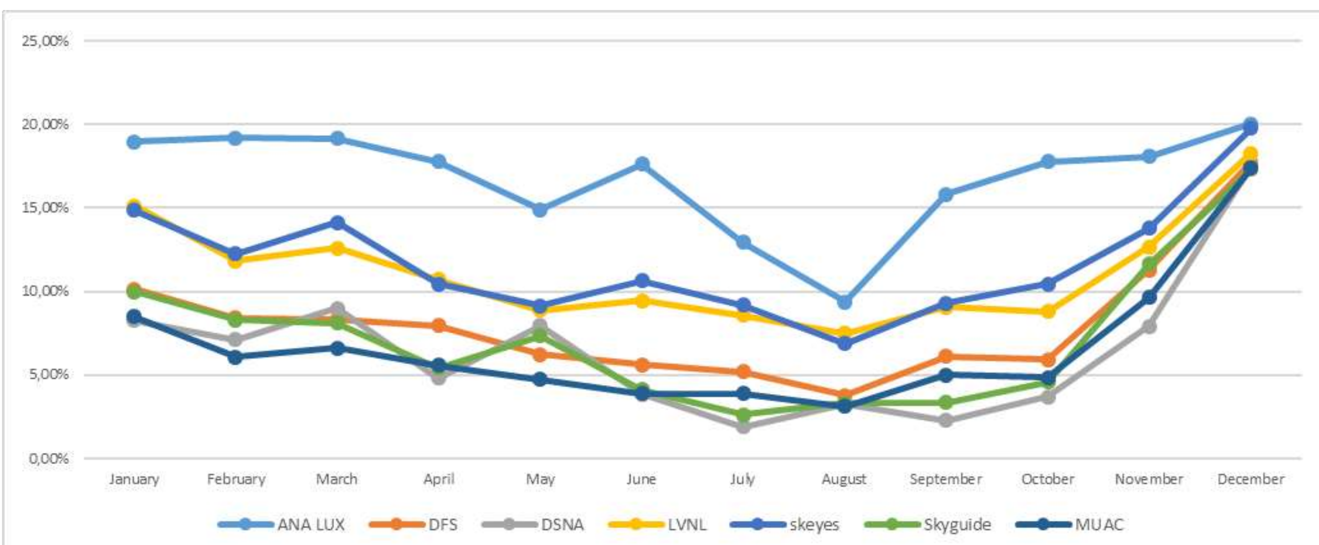

Figure 5: Monthly Volatility scores for ANSPs based on daily flights, 2018

[5] It is not possible for flights due to double-counting

[6] Aggregation of data regarding operational level

Both 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 whole Scandinavia for 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 at Christmas time and New Year's Eve: on December 24th, 25th and 31st, demand figures are significantly lower.

3.4 Application at Micro-Level

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 appropriately changes in traffic flows. 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 the demand, sectors can be splitted or merged. Volatile traffic hampers the efficient planning of these capacity enhancing measures significantly. However, sector data were not available for the study, so we apply the methodology on sector group data in order to calculate volatility. In this way we use 'flight hours' for demand.

Traffic demand fluctuates considerably over the year, as shown in Figure **12** (annex). The upper peak represents three times more flight hours than the lower peak, depending on the considered sector group. Furthermore, weekly and seasonal effects are visible in the graph.

According to Figure 6, volatility metrics differ quite substantially between the sector groups. On the one hand, the highest scores are visible for Bremen sectors north and south. On the other hand, three out of four sector groups are assigned to Karlsruhe UAC. Comparing Figure 6 with Figure 1, there is no clear dependency between total overall demand and volatility score. Nevertheless, small units tend to be characterized by a higher volatility. Further reasons may be the amount of military aircrafts being controlled in the different areas, which seems to be less volatile, and the areas of responsibility that control flows to smaller airports, which tend to service low-cost carriers. They are more likely to be volatile.

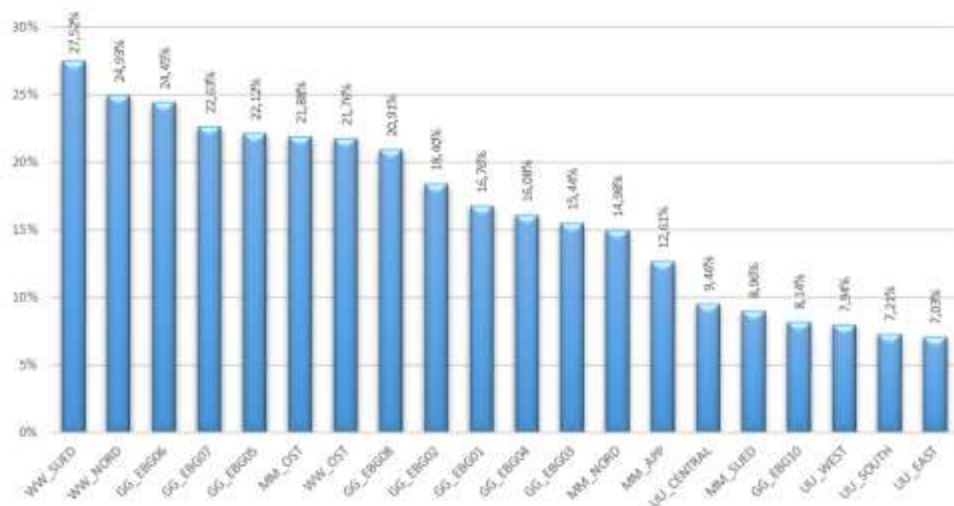

Figure 6: Volatility of German sector groups, monthly basis, 2017

4 INFLUENCE ON PERFORMANCE

4.1 Dependency of Traffic Volatility and Delay

In order to determine the impact of volatility on performance, the interdependence between flights and delays is illustrated in Figure 13 and Figure 14 (annex). The green and blue dots represent winter traffic, and the yellow and red are the corresponding ones for summer. It has to be considered that volatility primarily affects airspaces that operate at the capacity limit and/or have no possibility for airspace adjustments (e.g. by splitting a sector).

Both figures show a positive correlation between delay and demand. This observation is consistent among all ACCs in FABEC. Depending on the different demand situation (see sections 3a and 3b), the functional correlations depend on the ACC coordinated traffic. These different relationships are shown in the figures by the functions for Average Delay Minutes (ADM).

One major difference between the ACCs is the spread of the data points. For Karlsruhe, there is a higher scattering in demand for the winter flights, while delay figures are higher in summer. This might lead to the conclusion that volatility and delay are correlated negatively. However, looking into the figures of Marseille, the effect is the other way around. In summer, traffic is characterized by a higher scattering and also by higher delay figures.

The observed interdependencies allow several statements to be made. As an example the saturation of airspace is important. As soon as the capacity limit is reached, volatility has a higher impact on delay than in unsaturated airspaces. Since the demand is higher in the summer, the delay also increases because the associated sectors are working at the capacity limit, thereby not being able to increase capacity due to operational or organizational reasons.

However, the effect of saturation is not provable by analyses based only on the graphics. The different correlations between scattering in demand and delay suggest that there are multiple, possibly interacting, effects that affect the delay. Therefore, it is necessary to follow an approach considering the whole system.

4.2 Fuzzy Cognitive Mapping

Humans commonly tend to think that only direct causal relations between two concepts exist. Nevertheless, thanks to the understanding of complex systems[7], we know that changes in one variable may have influence on variables which were not initially identified, or that one variable may generate an unexpected chain of events. With this idea in mind, this work is intended to better understand what and how volatility may affect or be affected by ATM. To that end, a Fuzzy Cognitive Map is developed.

Cognitive Maps consist of a set of concepts and linkages which express cause-effect networks [15,16]. However, causes are often uncertain, usually fuzzy. The notion of fuzziness was introduced into cognitive maps, giving rise to Fuzzy Cognitive Maps (FCM) [17].

FCM is a participatory, semi-quantitative method that allows the integration of views from different experts and the construction of a graph structure that can be used to analyse scenarios [18]. 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 analyse. Furthermore it permits the simulation of scenarios according to which policy makers may analyze how the system may behave under certain impacts.

Every concept (C) is defined at a discrete time, so its state may change over time (Figure 7). They 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 negatively). Linkages are labelled by weights (W_{26}), reflecting the strengths of the relationships between two concepts (C_2 and C_6). Weights are represented by a numerical scale from 0 to 1. Once the map has been built-up, we can identify the cascading effects: in our case, the effects occurring in a specific part of the system when there is a volatility problem.

FCM is applied in five steps:

1. Make a list of concepts/parameters/factors
2. Connect concepts through arrows
3. Determine whether the connection is positive or negative
4. Weight the connection (between 0 and 1)
5. Identify the impacts

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 (see annex, Figure 15). It enabled us to show the relationships between them and to determine causes and effects of volatility that are usually not discernible to the naked eye.

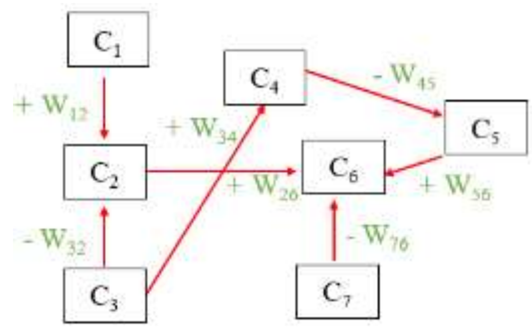

Figure 7: Fuzzy Cognitive Map

According to the 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 denotes the individual importance of a concept, so '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. Finally, FCM also allows us to analyze how a change in one concept may affect the whole system (step 5). Results indicate that, irrespective of the concept we change, almost always the same variables are affected, i.e. Airport charges, Airspace charges and ATFM Regulation needs (see Table 2).

[7] Systems in which the many parts that comprise it interact with each other and with their environment and whose links give rise to new behaviors that could not be explained by analyzing each element separately.

In short, these variables should be taken into consideration when talking about volatility. They will be the most sensitive and problematic aspects in case of external shocks. Moreover, being aware of their central position may help stakeholders act accordingly, since they may decide whether or not to adequate current buffers or to add a few new (see, for example, the case of overload for controllers).

	Out	In	Centr.
Economic Activity	2.50	0.00	2.50
Passenger Demand	1.00	3.50	4.50
Airline Demand	1.00	4.25	5.25
Flight ticket price	1.25	1.00	2.25
ATFM Regulation	1.00	2.50	3.50
Quality of service	0.50	2.75	3.25
Air traffic flow	1.00	4.25	5.25
Flexibility (Ops)	1.00	2.00	3.00
Complexity	3.50	4.00	7.50
Overload	0.50	1.75	2.25
Predictability	4.25	3.50	7.75

Table 2: Results of Fuzzy Cognitive Mapping

5 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 level to European airspace on the scope axis. The paper shows that volatility scores are sensitive to both factors. In addition, the highest volatility is observable in December. Rather, unexpected are the low volatility scores for summer.

However, as it is not yet clear which effects are responsible for amplification or attenuation of volatility, the paper provides an analysis to determine the effect on delay. In addition, a FCM is applied to enable a holistic consideration of the whole system. In this way, it is possible to show which elements are sensitive regarding volatility, e.g. caused by external shocks. A quantification, e.g. by regression analysis, might be a subject of further research.

The calculation method represents one potential approach, since only one formula was applied, expecting to match ATM requirements most. In further studies, it should be checked whether the formula have to be adapted or substituted by other formulas, partly proposed in section 3.1. Therefore, a useful applicability on short-, medium- and long-term problems is mandatory to be proven in further studies. Quantifying the impact on the performance of ANSPs might be another research focus with respect to cost effectiveness. In addition, it might be beneficial to include sectors, sector groups and ACCs of other ANSPs. It would enable the consideration of particularly strong, unforeseen traffic fluctuations to be incorporated into regulatory measures, respectively policy decision making.

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Copyright Statement

ANNEX

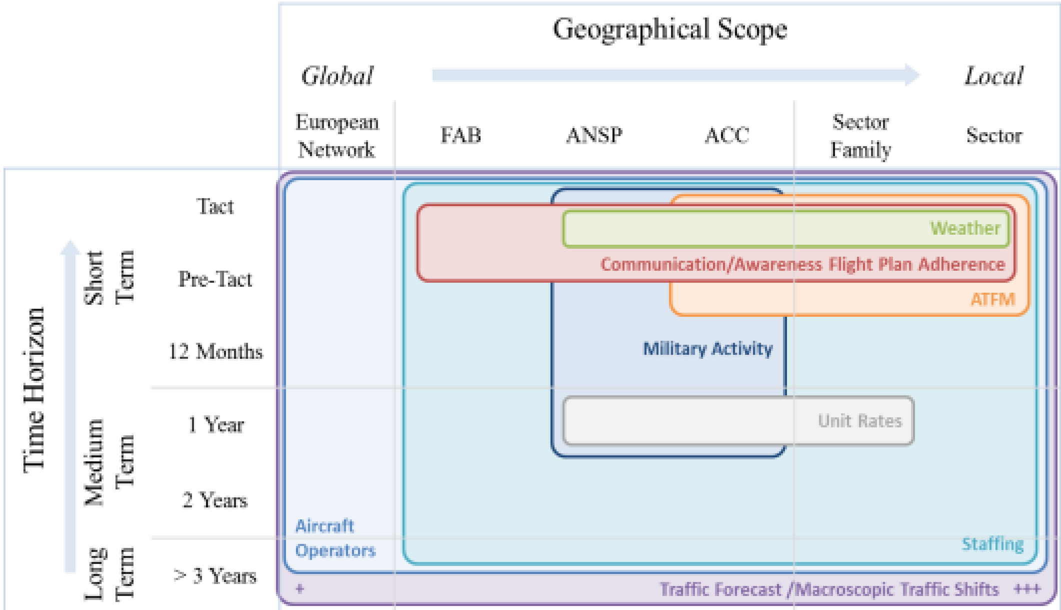

Figure 8: Elements affecting volatility in traffic demand and flow, according to volatility taskforce

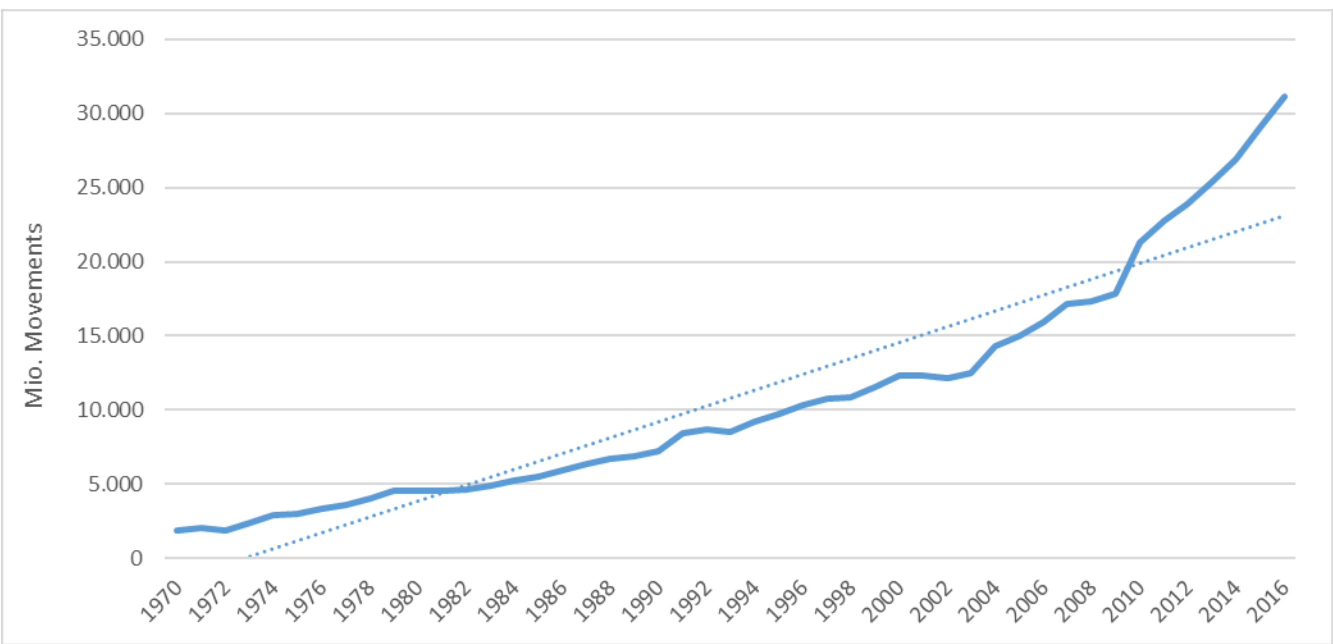

Figure 9: Development of Flight Movements worldwide, 1971-2016 (World Bank)

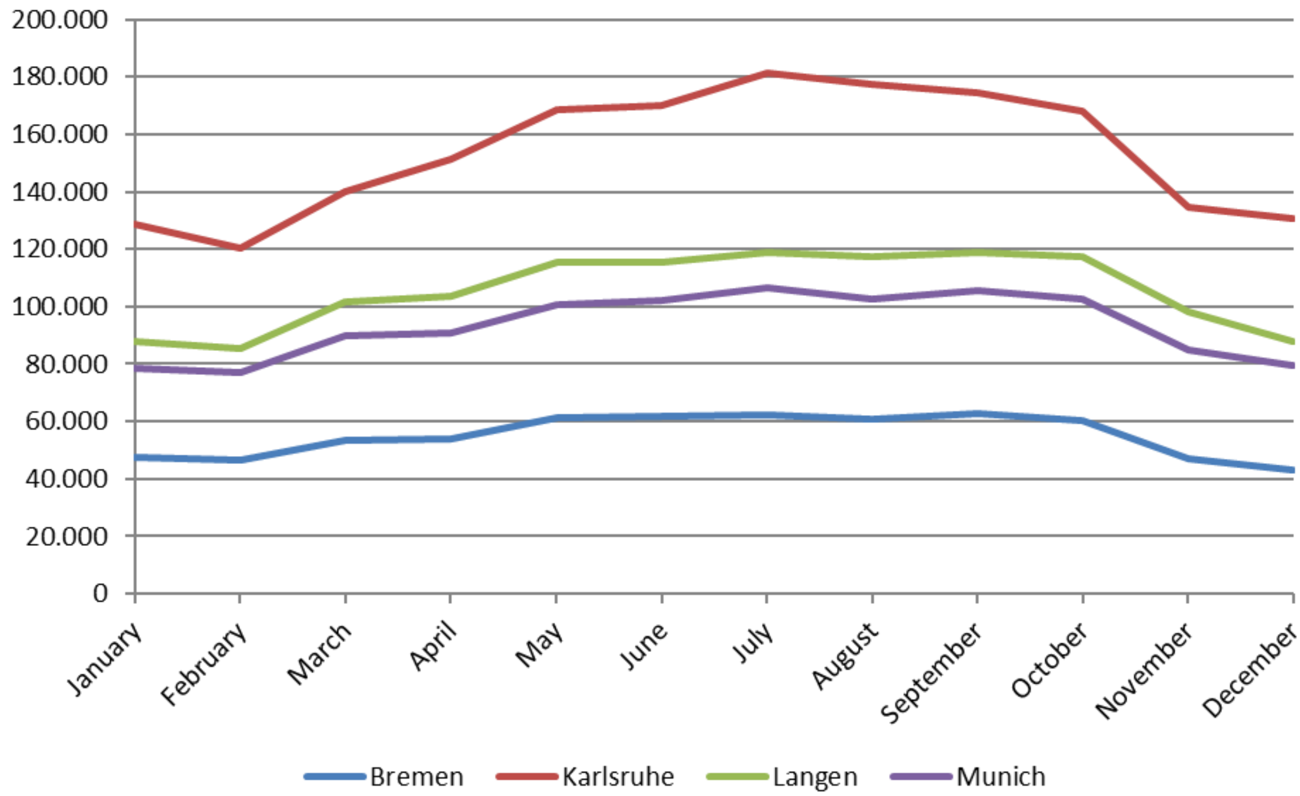

Figure 10: Monthly Traffic Movements for DFS ACCs, 2017

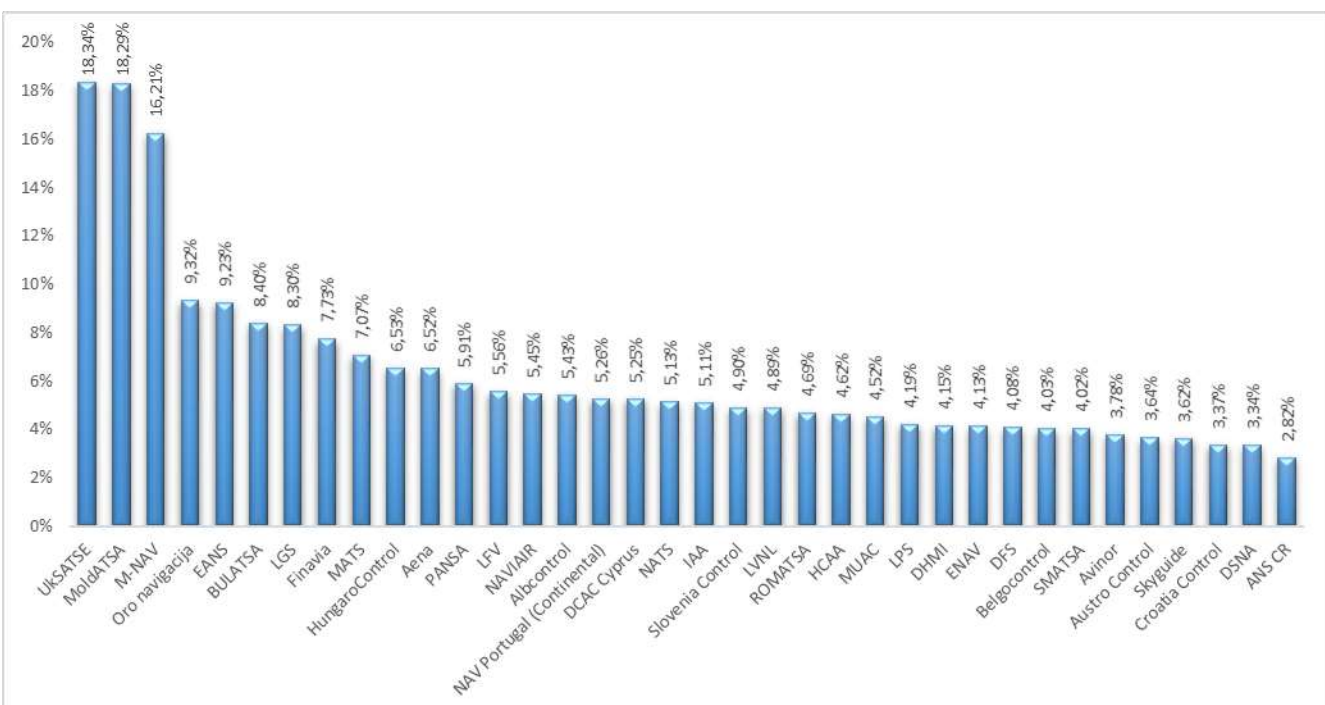

Figure 11: Medium-term volatility in Flight Hours (PRU Data)

ANSP	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Albcontrol	10.47%	10.3%	11.7%	14.6%	17.0%	15.1%	13.0%	12.3%	14.9%	15.2%	12.8%	17.5%
ANA LUX	18.94%	19.2%	19.1%	17.8%	14.9%	17.6%	12.9%	9.4%	15.8%	17.8%	18.1%	20.0%
ANS CR	9.84%	7.9%	7.2%	7.3%	5.4%	3.3%	4.0%	2.8%	3.9%	5.9%	10.5%	16.2%
ANS Finland	14.83%	12.9%	13.2%	14.0%	12.6%	10.9%	7.3%	8.6%	12.5%	11.6%	16.5%	31.7%
ARMATS	18.42%	11.5%	12.0%	10.0%	7.8%	8.2%	6.5%	8.0%	11.2%	10.8%	13.1%	9.7%
Austro Control	7.33%	5.9%	5.2%	5.2%	4.3%	3.6%	2.5%	4.2%	3.2%	4.1%	8.3%	14.7%
Avinor	26.05%	27.9%	27.5%	30.7%	27.0%	23.7%	17.6%	20.8%	26.0%	24.4%	29.8%	55.2%
BULATSA	5.27%	4.9%	4.3%	6.0%	6.1%	4.8%	3.0%	3.3%	4.6%	5.2%	5.3%	7.8%
Croatia Control	8.46%	7.5%	8.0%	10.2%	11.3%	10.8%	8.1%	8.8%	11.1%	11.1%	8.1%	15.0%
DCAC Cyprus	11.29%	12.0%	12.0%	11.9%	10.8%	11.5%	9.9%	8.3%	16.4%	10.7%	13.3%	15.5%
DFS	10.14%	8.4%	8.3%	7.9%	6.2%	5.6%	5.2%	3.8%	6.1%	5.9%	11.3%	17.7%
DHMI	3.53%	3.7%	3.4%	3.6%	3.4%	3.2%	2.4%	2.2%	3.1%	3.6%	3.9%	5.7%
DSNA	8.26%	7.1%	9.0%	4.8%	7.9%	3.9%	1.9%	3.2%	2.3%	3.7%	7.9%	17.5%
EANS	7.13%	7.7%	6.6%	5.5%	5.1%	4.9%	3.0%	5.7%	4.6%	7.6%	11.1%	12.7%
ENAIRE	7.04%	5.5%	5.2%	2.9%	4.3%	2.7%	2.3%	2.9%	2.8%	3.6%	4.8%	15.1%
ENAV	8.49%	8.3%	8.6%	3.9%	9.5%	5.4%	3.6%	4.4%	4.2%	4.2%	9.5%	21.4%
HCAA	8.62%	7.7%	6.7%	8.2%	8.4%	7.0%	5.3%	5.5%	7.3%	7.9%	7.4%	13.6%
HungaroControl (EC)	6.11%	5.7%	4.8%	4.3%	5.2%	4.4%	3.0%	2.9%	4.0%	4.7%	5.0%	11.8%
IAA	10.13%	10.2%	13.7%	5.4%	7.2%	7.3%	5.9%	5.3%	8.0%	8.3%	9.5%	25.8%
LFV	19.05%	16.7%	16.9%	18.3%	14.0%	12.7%	8.4%	9.4%	13.6%	14.7%	19.9%	27.7%
LGS	6.30%	5.3%	5.2%	5.1%	3.8%	3.1%	2.8%	3.1%	4.3%	5.7%	8.7%	10.3%
LPS	6.99%	5.8%	4.9%	5.2%	7.3%	5.6%	4.1%	4.0%	5.4%	5.4%	5.3%	12.8%
LVNL	15.12%	11.8%	12.6%	10.7%	8.9%	9.4%	8.6%	7.5%	9.1%	8.8%	12.7%	18.3%
MATS	11.00%	7.4%	6.6%	6.8%	7.9%	9.9%	9.5%	8.7%	11.5%	7.6%	8.0%	15.0%
M-NAV	10.22%	9.2%	7.2%	13.1%	11.2%	10.4%	7.8%	9.9%	11.5%	11.9%	8.4%	16.3%
MOLDATSA	15.47%	10.8%	10.5%	9.8%	7.3%	11.1%	11.5%	10.9%	8.2%	7.0%	11.6%	17.2%
MUAC	8.47%	6.1%	6.6%	5.6%	4.7%	3.9%	3.9%	3.1%	5.0%	4.9%	9.6%	17.4%
NATS (Continental)	11.42%	9.7%	10.6%	7.8%	7.2%	6.5%	5.4%	5.1%	7.1%	6.7%	11.7%	39.4%
NAV Portugal	10.46%	10.2%	10.0%	7.5%	6.3%	5.0%	4.3%	5.2%	6.1%	6.7%	9.0%	15.8%
NAVIAIR	12.51%	9.0%	10.1%	10.5%	8.3%	8.6%	5.2%	6.2%	9.4%	8.8%	14.9%	24.8%
Oro Navigacija	6.16%	5.1%	5.0%	6.4%	5.7%	5.1%	2.9%	4.0%	5.0%	5.3%	5.3%	10.9%
PANSA	7.24%	4.7%	4.7%	4.8%	4.3%	3.7%	2.4%	2.4%	3.0%	3.8%	6.5%	14.3%
ROMATSA	6.90%	5.6%	4.7%	4.0%	4.0%	3.7%	3.3%	3.2%	3.4%	3.9%	4.1%	10.7%
Sakaeronavigatsia	9.70%	10.0%	8.2%	5.6%	7.6%	8.9%	7.3%	7.6%	8.4%	6.8%	7.5%	7.5%
skeyes	14.86%	12.2%	14.1%	10.5%	9.1%	10.6%	9.2%	6.9%	9.3%	10.4%	13.8%	19.8%
Skyguide	10.00%	8.3%	8.1%	5.4%	7.3%	4.1%	2.6%	3.3%	3.3%	4.6%	11.6%	17.3%
Slovenia Control	10.93%	8.5%	10.6%	12.0%	10.6%	9.6%	8.8%	9.3%	9.9%	10.1%	11.6%	15.4%
SMATSA	8.65%	6.7%	6.6%	8.0%	8.5%	7.1%	4.1%	4.8%	6.5%	8.4%	8.5%	13.3%
UkSATSE	10.10%	7.2%	5.9%	5.2%	8.8%	5.5%	5.0%	6.0%	5.8%	5.3%	8.2%	11.2%

Table 3: Monthly Volatility scores for EUROCONTROL ANSPs, 2018

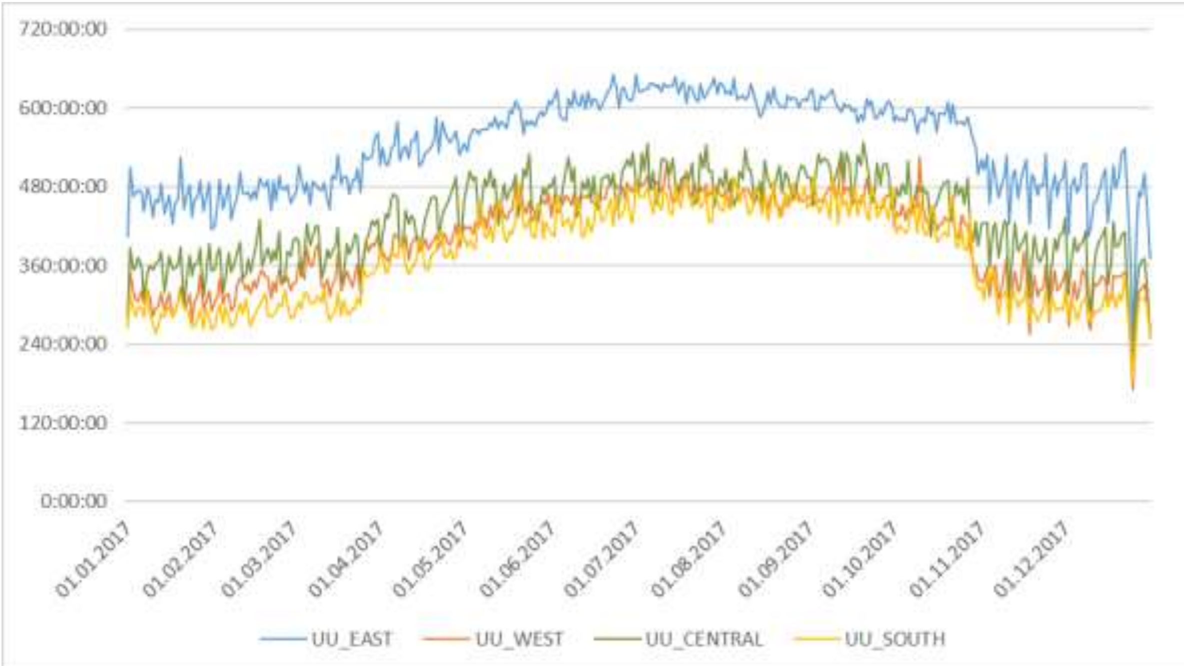

Figure 12**: Daily Flight hours, 2017, Sector Groups of Karlsruhe Upper Airspace Control**

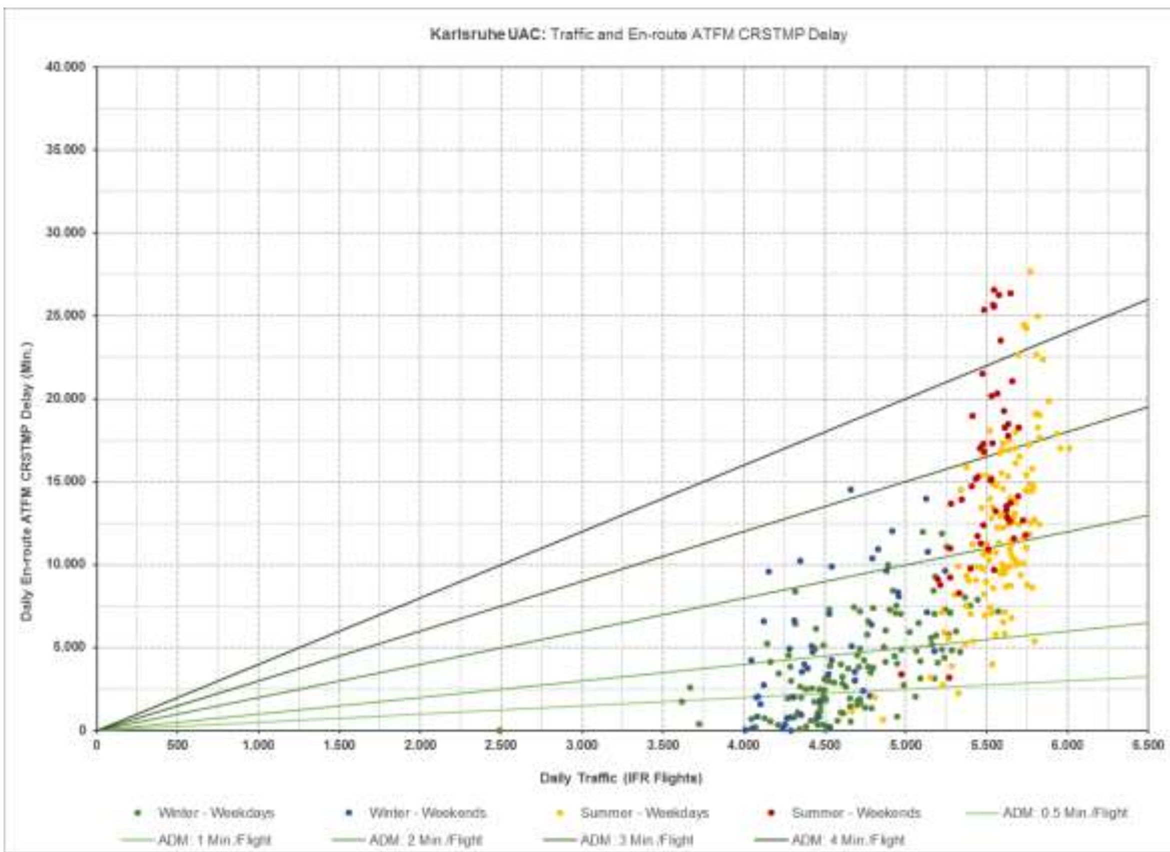

Figure 13: Demand versus Delay, Karlsruhe, 2018

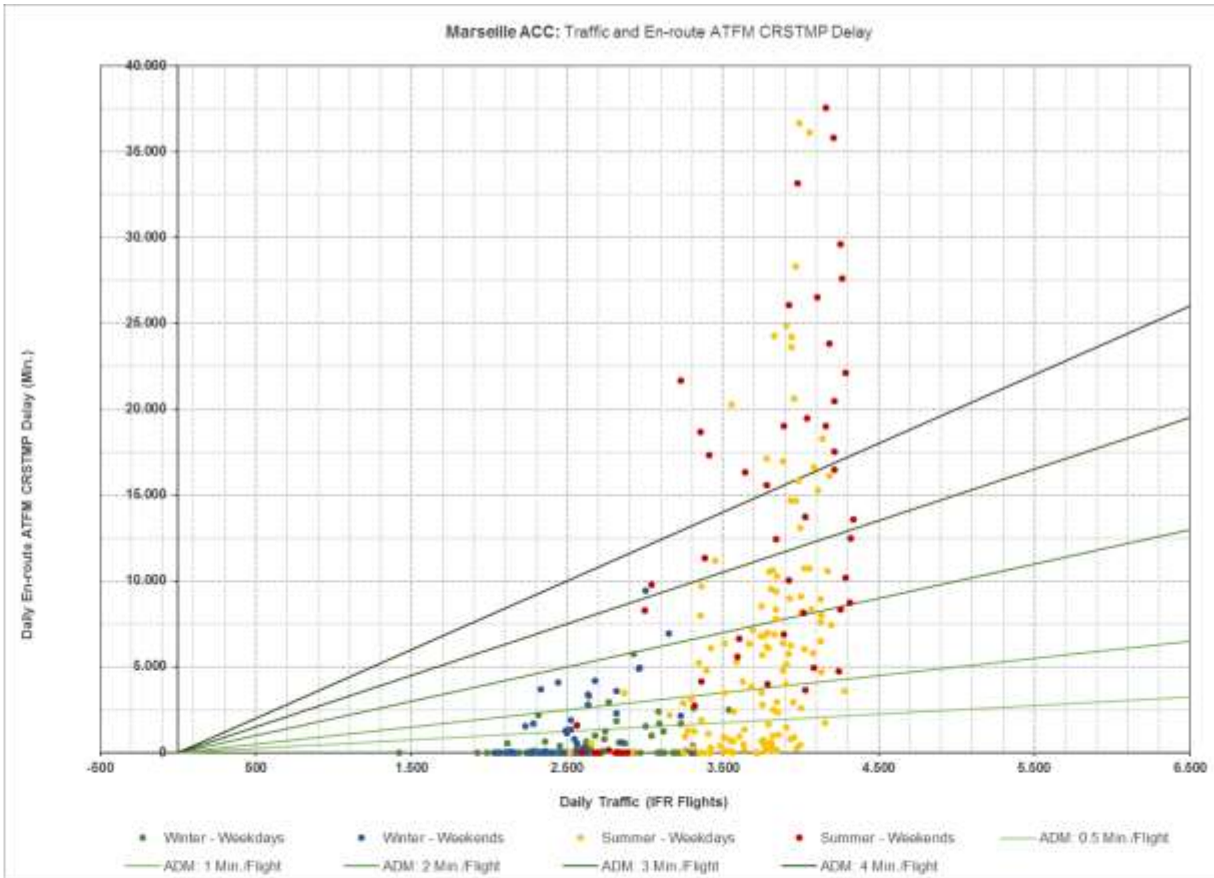

Figure 14: Demand versus Delay, Marseille, 2018

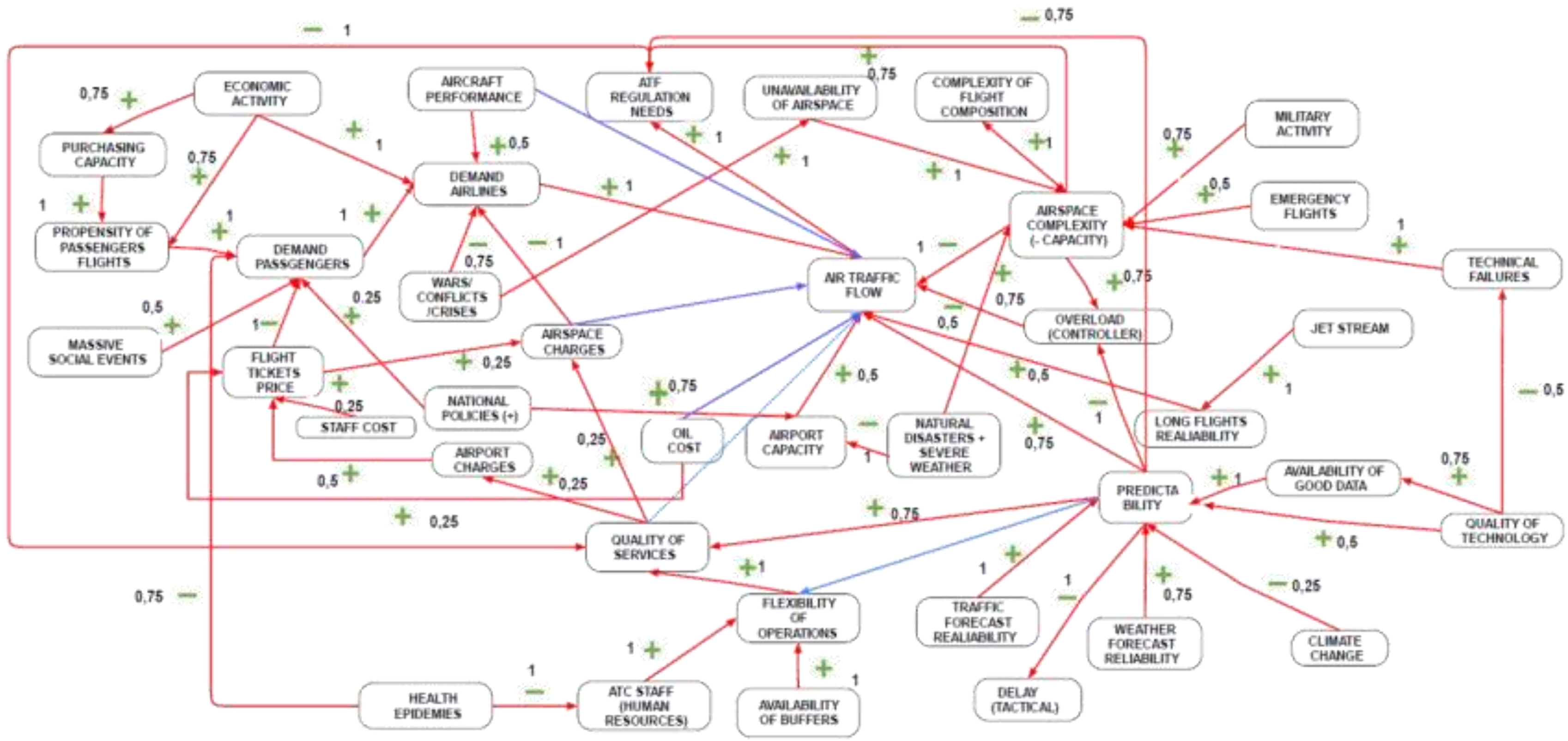

Figure 15: Fuzzy Cognitive Map