Some Spatio Temporal Characteristics of the Planning Error in European ATFM

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***Abstract*— There are numerous reasons, why the number of aircrafts entering a sector may differ from the anticipated number. They may be summed up as 'uncertain events' such as the non-respect of ground delays, weather conditions, flight plan incoherency and more. We apply simple statistical analysis tools in order to characterize these differences; how they behave and how they interact with each other. Our findings indicate that they follow simple laws over time and space and give first insights in how they may interact.**

I. Introduction

European Airspace is divided into a number of geographical sectors. Sectors have capacities limiting the number of aircrafts wishing to enter them at a given time. In order to respect capacities, aircrafts may be delayed or rerouted before take off. The decision which aircraft to delay and for how long is currently based on a deterministic model of the airspace [5] and constitutes a major task for Air Traffic Flow Management (ATFM). However, in reality, a number of uncertain events such as non-respect of ground delays, weather conditions, flight plan incoherency and more may lead to differences between planned and observed sector load [5].This has a direct impact on the controllers workload and thus on safety issues and on the optimal usage of available capacities. Unlike to analyzing the different uncertainty factors, such as [6], [5], we claim that these uncertainties, taken together, reveal interesting and simple properties. We are interested in finding relations in the interplay of these events in order to improve the planning procedure.

The report consists of two parts. In the first part, the data is described and the main analysis tools, correlation of random vectors and of stochastic processes are explained. In the second part, several experiments with data from single sectors and from neighboring sectors are carried out and interpreted.

II. Data

1) Data Structure: The data consists of the difference between the regulated demand (the number of aircrafts scheduled to enter a given sector in a given time interval) and the airborne demand (the number of aircrafts that really entered the sector in the same interval) of ATC sectors and is called the error E. For one day d and one sector S^i, one has $S^{i,d} = \begin{pmatrix} E_1^{i,d} \\ \vdots \\ E_p^{i,d} \end{pmatrix} \in \mathbb{Z}^p$where $E_k^{i,d}$ is the difference at time k in sector i at day d. For example, a sample interval of 5 minutes leads to $1 \leq k \leq 288$.

2) Independence and Traffic Seasons: Generally one is classifying traffic demand into weekday (Monday-Thursday), Friday and weekend (Saturday-Sunday) groups. Over the year, summer and winter traffic is distinguished [7]. Special events such as national holidays or strikes may form exceptions. In this report, we assume different days as being independent from one another. We use a total of 79 weekday data sets coming from the second half of the year 2003 from the four sectors EDBBUR1-4.

III. Correlations

Correlations are '(...) relations of (...) variables which tend to vary, be associated, or occur together in a way not expected on the basis of chance alone' [4].More formally, two random variables X and Y are correlated, when dependence in mean exists: for $X = x$ fixed, the mean $\bar{Y}$ is function of x [11].

A. Linear Correlations and Correlation Matrix

Variables are said to be positively linear correlated if high values of one variable tend to be associated with high values of the other and negatively if high values of the one tend to be associated with low values of the other. Depending on the type of the variables, different definitions of linear correlations exist [11].In this section we review correlations between vectors of random variables and between stationary processes and estimators for them. For real valued random variables, the linear correlation coefficient r is defined by $r = cov(X,Y)/\sigma_x\sigma_y$ where $cov(X,Y)$ is the covariance of X and Y and σ_i are their standard deviations. Given two vectors of random variables X, Y, the matrix $c_{ij} = cov(X_i, Y_j)$ designs the covariance matrix between X and Y. If each element c_{ij} is divided by $\sigma_i\sigma_j$,one obtains the correlation matrix.

B. Stochastic Processes and Cross-Correlation Function

Here, we consider $S^{i,d}$ as realizations of stationary stochastic processes, that is, as sequences of random events. Intuitively, stationarity means that the statistical properties of such a sequence do not vary over time. Thus, it seems easier to *mathematically* characterize a stationary process than an arbitrary one. We do not go into the details here (see e.g. [2], [3]), but we explain how a common analysis tool, the cross-correlation function, is to be interpreted. In the case of stationarity, the elements c_{ij} of the covariance matrix of two processes S^x, S^y are equivalent under the relation $\forall k, t \gamma_{S^x S^y}(k) = \mathbb{E}\{(S_t^x - \mu_{S^x})(S_{t+k}^y - \mu_{S^y})\}$. In general only $\gamma_{S^x S^y}(k) = \gamma_{S^y S^x}(-k)$ holds, since $\mathbb{E}\{(S_t^x - \mu_{S^x})(S_{t+k}^y - \mu_{S^y})\} = \mathbb{E}\{(S_t^y - \mu_{S^y})(S_{t-k}^x - \mu_{S^y})\}$. From this, it is possible to define a function, called the cross-correlation function, of the time difference k, called lag, to express the covariance of two processes. Similarly, the division by the product of the standard deviations leads to the cross-correlation function [2].

C. Estimation

The quantities are estimated with corresponding functions in the language for statistical computing 'R' [10].

D. Non Linear Correlations

Different visualization techniques such as scatter-plots and 3D-surface plots are applied for the identification of non linear relationships.

IV. Results

The experiments are carried out for single sectors and for pairs of two adjacent sectors.

A. One Sector

In these experiments the behavior of the data inside a single sector is investigated.

1) Nature of the Data: The histograms in figure 2 suggest a normal distribution as a possible source for the data. The variables, however, take discrete values. Accordingly, a normality test has to be rejected on the 1 % level. From this, we draw several conclusions:

If the data is interpreted as having been arisen from a continuous distribution, it should be interpreted as being 'binned'. Moment estimation and other statistics of the data should then take into account the binnings. The data can be interpreted as qualitative, too: it is possible to define meaningful ordinal scales such as negative difference, no difference, positive difference or others. Nominal scales such as weekday or airac cycle can be interesting in reasoning over groups of similar data.

2) Stationarity: The mean values and standard deviations fluctuate around constant values between time slots 50 and 240 (figure 1). Moreover, the empirical autocorrelation function cuts off very quickly (around lag 4). From this, we have arguments that the data can be considered as stationary in time[1]. However, in the remainder we will keep on comparing results with and without stationarity hypothesis.

3) Daily Stationarity: The overall distributions have a similar shape in the four different sectors: their x-extension seems to be correlated with the traffic volume. The frequency of 'no error' is very high.

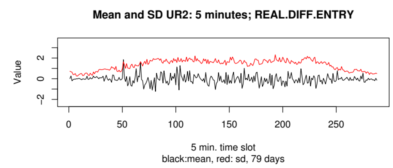

Fig. 1. Error Mean and Standard Deviation in UR2 (5 minutes) On the x-axis, you see the time in 5 minutes intervals. On the y-axis the value is displayed.

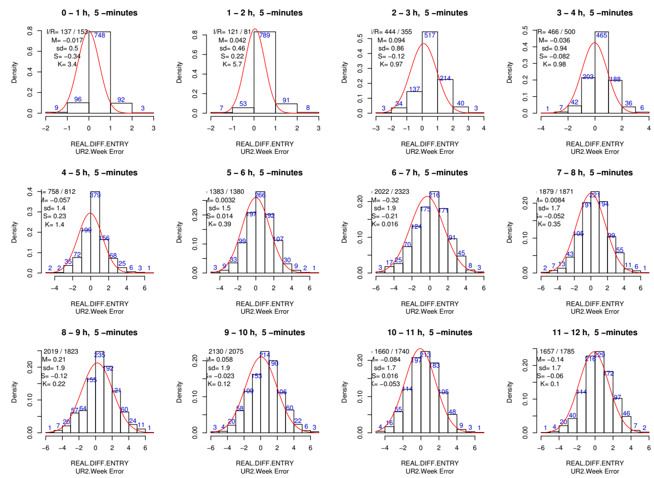

Fig. 2. Distribution of the error in the morning and corresponding normal distribution

4) Hourly Stationarity: The error histograms for each full hour over the day are evaluated. 79 days * (60 minutes/5 minutes) = 948 observation underly every histogram (figure 2). In the morning and night hours there is low traffic volume. Between 5 h and 20h, the shape of the distributions are symmetric, normal-like distributions with extensions proportional to the traffic volume. The hypothesis, that the different samples could have been arisen from the same distribution has to be rejected at the 1 % level.

5) No Stationarity: Similar shapes of the distribution as in the stationary case are observed.

6) Same Underlying Distribution Study: With the hourly stationary data, we tested the hypothesis of a same underlying distribution between6h and 18h with a chi-square technique [1]. The results are that the hypothesis has to be rejected on the 1 % level when the whole data (from june to december) is taken into account. Testing in monthly intervals, however lets maintain the hypothsis in most of the cases. To answer the question whether the results arise from the data volume or from meaningful differences in the data, we may describe the potential region boundaries by classification methods.

B. Two Sectors

Relations between two adjacent sectors are sought.

[1] with the categories "negative", "zero" and "positive"

1) Correlation Matrix: In order to have a base not using the stationarity hypothesis, we estimate the correlation matrix of two vectors S^{UR2} and S^{UR3}. High values near the diagonal may be seen. They correspond to the average traveling time between sector one and two. Apart from this, no systematic patterns may be seen.

2) Cross-Correlation Study: In order to better interpreter the results of the previous experiment, we estimated the cross-correlation function for each pair of adjacent sectors S_i,S_j in our data. Only those aircrafts traveling between the sectors S_i and S_j were selected. An illustrative example is shown in figure 3. In the upper part, the data from sector UR2 is plotted in black and the data from UR3 in blue.The curves are quite similar but shifted by some time. Correspondingly, the maximum of the cross correlation function is at lag 2. This corresponds to the diagonal in the correlation matrix above. The correlation is not equal to 1 as one might expect since the speed of the different aircrafts varies. All other values are nearly 0.

3) Stationary Lag Plot and Shape Plot Study: From the above, we know that the absence of a (linear) correlation does not imply the independence of the variables. In order to better understand the relationships between the two processes, we plot the values of the first process against the time shifted values of the second, independently of time (figure 4). We choose the first five lags (from 0 to 4) as an illustrative example. The signs of the correlation coefficients are visible in all plots, the linear correlation is particularly visible for lag = 2. However, the correlations are very weak and no trivial non linear relationship is visible. Note that the range of the values (between -3and 3) compared to the number of observations (79 days * 288 values) is very small. Therefore, we investigate the frequencies of the occurring values (figures5,6). On the x axis you see the values taken by the process in UR2 and on the y axis those by the lagged version of UR3. On the z axis we display the number of occurrences of the tuples[2]. For example, the maximum of this curve, the tuple (0,0) is occurring 7 times, whereas the combination (-3,-2) (left lower corner) is only occurring once.

4) Independence Study: A chi-square test of independence [3] results in dependency in 20 minutes windows around time lags of 50 (about 4 hours) and 240 (about 20 hours). For all other time lags, the independence hypothesis can be rejected at the 1 % level. The meaning of the 'dependency peaks' still has to be investigated. More knowledge of the form of dependency has to be aquired, for example with decision trees or other nonlinear regression or classification methods.

V. Conclusions and Future Work

This report presents a statistical description of the error in the current European Air Traffic Flow Management system and its propagation to neighboring sectors.

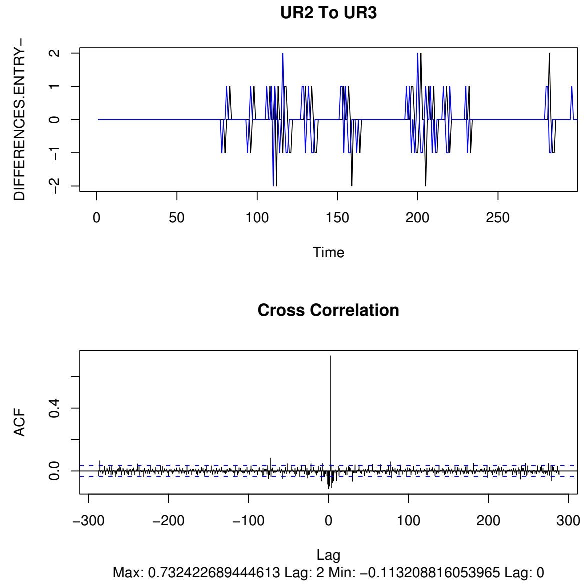

Fig. 3. Cross Correlation Function UR2-UR3

The main result from the one sector analysis is that there is evidence to accept a stationarity hypothesis on the data. Based on this we found that the shape of the distribution of this error is very simple.Operationally this may be interpreted by the fact that the sources of uncertainty are independent from each other. Depending on the time of the the year, the observations may be considered as arising from a same underlying distribution. A more detailed analysis of the different regions in observation space may be helpful here.

As far as the cross-sector analysis is concerned, we found no linear correlations apart the trivial ones with time lags corresponding to the sector crossing time. A comparison between the correlation matrix and the cross correlation function leads us to the same conclusions. Independence between the variables can be found only in small time windows around lags of 4 hours and 20 hours which is counter intuitive and has to be investigated in more detail.However, structure is found in terms of simple shapes of joint distributions of two variables.From this we strengthen the hypothesis, that there are no linear long term effects [4] of the error propagation. Comparing stationarity with non stationarity hypotheses generally leads us to similar results. We will keep in mind this hypothesis when investigating predictability of the ATFM error. As next steps, we will test the hypothesis of linear long term effects against multiple linear correlations. Moreover classification of observations into meaningful groups, such as geographical areas or seasons days of the week may help to strengthen spatio and temporal stationarity hypotheses and thus to simplify the problem. In this context, sampling intervals larger than 5

[2]we transform it to its fourth square in order to scale the range

[3]with the categories "negative", "zero" and "positive"

[4]e.g. morning - afternoon effects

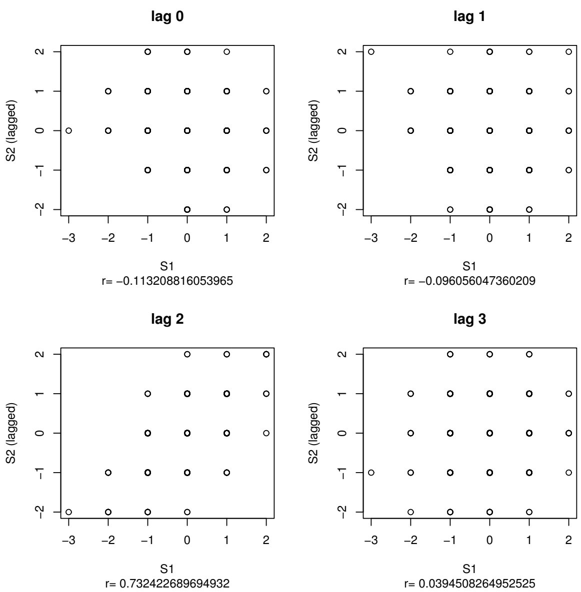

Fig. 4. Stationary Lag Plot

minutes and neighborhoods more general than geographical neighborhood will be studied.

VI. Acknowledgments

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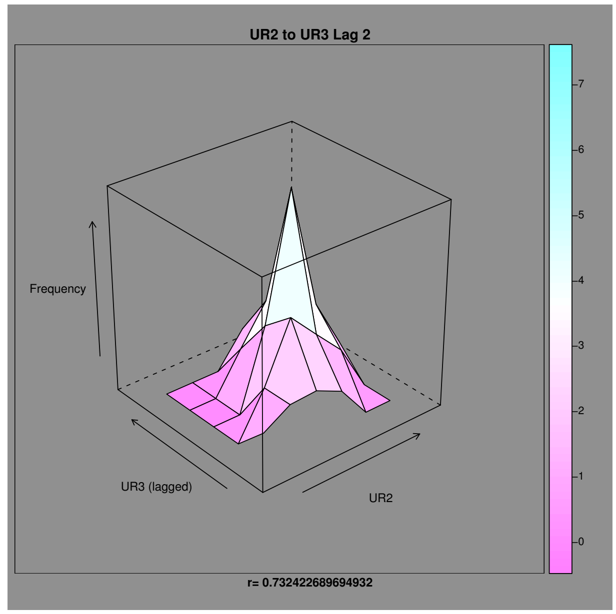

Fig. 5. Stationary Shape Plot Lag=2

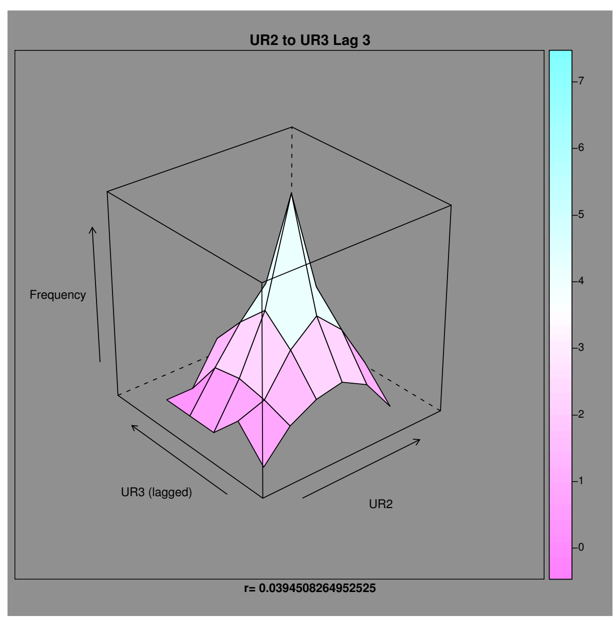

Fig. 6. Stationary Shape Plot Lag=3