PREDICTION OF AIRPORT DELAYS BASED ON NON-LINEAR CONSIDERATIONS OF AIRPORT SYSTEMS

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Abstract

Due to the high density of air traffic on major routes and around major cities, e.g. in Europe and the US, delays become an omnipresent problem that can no longer be solved during en-route flights. The turnaround of aircraft based on well defined processes becomes more and more important. Hence delay becomes a matter of airport management.
A new approach that considers airports as dynamic systems gives the key to predict airport delays in an innovative way and opens the channel to support activities around total airport management.
The paper introduces the idea how to apply methodologies of non-linear physics to data of airport processes to investigate the state of airports and characteristic points of bifurcation depending on the boundary conditions of airports.
Relevant delay-influencing parameters have been identified and their sensitiveness on the boundary conditions has been analyzed.
The knowledge of boundary conditions that result in turbulent or chaotic stages (measured by the Lyapunov Exponent) is essential for future airport management to prevent critical situations and has been investigated in this paper.
Based on assumptions of non-linear physics and knowledge of airport dynamic characteristics a method has been developed to predict off-block delays at airports based on boundary conditions. This method has been applied to several US airports.

1 Introduction

Today’s base of airport management are the operator’s experience and, in most cases, mobile phone technology. Major airports operate command and control centers to coordinate processes of airlines, airports, ground handlers, security staff, and police forces. The degree of coordination and cooperation between these different command and control centers depends on the airports size, the role of the airport in its environment and the operating parties. All varies from airport to airport.

Recent developments and research that supports airport management use airside simulation tools to predict off-block times for aircraft. A combined land- and airside simulation environment, e.g. described in [1], is currently the only instrument to predict and investigate infrastructural congestions based on process interactions. Properties of the system “airport” that result in congestions by its nature as a dynamic system are not yet known, and hence, not taken into account for airport management purposes. The interpretation of simulation-based results is problematic. It is difficult to decide whether properties of the applied simulation models or the nature of the system are responsible for the observed states (observed values e.g. delays) or variances of states. Hence, a new system based-approach is needed to investigate the dynamic system “airport”. This system approach or theory should be able to

- describe the evolution of the airport system,

- describe congestions within infrastructural elements of airports,
- predict future states of the system airport.

To develop that kind of theory, it is necessary to obtain a wider understanding of the airport system. A first step into that direction is provided by the present paper. The airport system is being analyzed by methods of non-linear physics to investigate airport-specific properties of causality. This opens the channel to predict future states and measurable parameters, e.g. delays. The investigations have further shown strong evidence that chaotic (non-predictable) states at airports exist.

2 Method

This chapter is dedicated to the introduction methods of non-linear physics to investigate the system airport.

2.1 Principles of causality

In physics, the relation between cause and effect are described by the principles of causality, explicitly specified in the Theory of Relativity [2]. In that theory, it is also mentioned that both cause and effect are linked together by the speed of light [2].

Generally, three cases of cause effect relations can be distinguished:

- equal results follow equal conditions – this is known as “weak principle of causality”
- similar results follow similar conditions – known as “strong principle of causality”

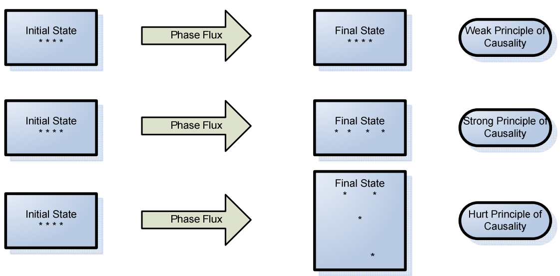

Figure 1: Principles of causality

- totally different results follow similar conditions – known as “hurt principle of causality”

The evolution of a system from the initial to its final state is given by another model of physics, the phase flux [3] as shown in Figure 1. This methodology is being adapted to airports in this paper.

The turnaround of aircraft at airports is a compilation of processes and process branches. It culminates at the moment of off-block, when all process branches (e.g. due to passengers, luggage, cargo) finish. The path through all processes as well as the interactions between processes can be considered as phase flux. The state of the system can be described by measurable parameters (e.g. delay) and derived parameters (e.g. delay change).

All processes during turnaround, including passenger processes, are well defined. The processes are mainly influenced by international and national regulators (security), airlines, airport, and aircraft manufactures (e.g. processes at the aircraft given by the aircraft manual e.g. [4] [5]). Uncertainties and congestions due to resource constrains (e.g. staff) can be induced by weather, missing infrastructures, and others. Hence, it could be expected that airports are systems, where equal initial states (and boundary conditions) result in equal or similar conditions. This is tested in the next section.

2.2 Test on equal conditions

The first step to test equal conditions at airports is to compare daily flight schedules (see Figure 2). The criteria that have to be tested are the scheduled times of arrival and departure of aircraft (the scheduled sequence). The assignment between arrival and departure is given by the aircraft tail number. The aircraft type is not taken into account in this paper. If two or more schedules are equal to each other, equal scheduled (and initial) conditions do exist.

This test has been performed for the airports of San Francisco (SFO), Boston (BOS), New York (JFK) based on [6]. The analysis of

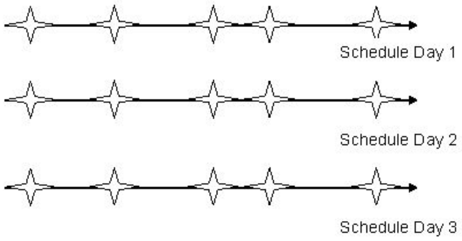

Figure 2: Equal daily flight schedules

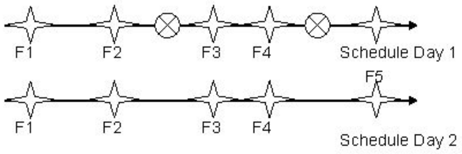

Figure 3: Additional flights (crossed circle) within daily schedules

daily arrival and departure schedules of these airports (based on data from 2010 [6]) show, that no equal sequence with equal scheduled times of arrival and departure could have been found. Flight schedules analyzed in this paper are limited to days of operation (between 0 and 24o'clock). Flight delays transferred into the next day are taken into account.

2.3 Test on similar conditions

To determine similar conditions the term similar has to be discussed. The meaning and the limits of “similar” usually depend on the considered problem [7].

A first assumption for the dynamic system airport is to allow additional flights within the flight schedule among frequently appearing flights as shown in Figure 3. The term “frequently appearing” has not been determined in the literature yet. In this paper, 80% of flights have to be found at the same position in each daily sequence. These flights are considered as frequently appearing.

A second assumption is, that the sequence of frequently appearing flights may change within a defined range of time. In this paper, a time frame of 15 minutes has been considered as shown in Figure 4.

Applying these assumptions to flight schedules of airports based on data for SFO, BOS and JFK [6], two clusters of similar flight schedules can be identified. Cluster one consists of flights between Monday and Friday, whereas

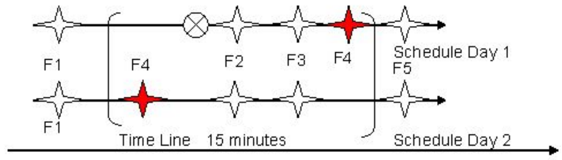

Figure 4: Additional flights (crossed circle) within daily schedules and changed scheduled flights (red stars)

cluster two consists of flights of weekends and public holydays.

Based on the available data [6], approximately five percent of days (depending on the airport) can not be classified. The reason is a high percentage of unscheduled and charter flights.

2.4 Test on chaos

Based on the data given in [6] and the assumption made in this paper, the airport is a system that consists of similar initial conditions.

However, recent publications report “chaos at airports” [8] [9]. This section is dedicated to describe how to find out whether chaos at airports exists or not.

The test on chaos of dynamic systems is a very complex challenge. In general, the test on chaos is divided in more steps [10]. In step one, time series data are analyzed by Fourier analysis. The scope of this analysis is to find periodic behaviour of the dynamic system. Each function that describes the time dependent evolution of a dynamic system can be described by a function of harmonics as shown in Equation (1).

$$s_n = \frac{a_0}{2} + a_1 \cos \varpi x + \ldots + a_n \cos n \varpi x + b_1 \sin \varpi x + \ldots + b_n \sin n \varpi x \qquad (1)$$

The coefficients can be derived from the Euler equation (Equation (2) and (3) [3] [7]). A common method to picture these coefficients is the so-called power spectrum [3] [7] as shown in Figure 6 in Section 3.

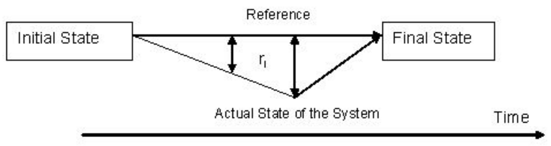

Figure 5: Distance of actual system trajectory compared to reference trajectory

$$a_n = \frac{2}{T}\int_0^T f(x)\cos n\varpi x dx \qquad (2)$$

$$b_n = \frac{2}{T}\int_0^T f(x)\sin n\varpi x dx \qquad (3)$$

In step two of this investigation, the Lyapunov exponents [7] based on the system's trajectory can be determined. The Lyapunov exponent is a measure of the distance between a reference and an observed trajectory [7] as shown in Figure 6. The trajectory is represented by data points that are determined by parameters representing the state of the system. One component of this vector is the delay, usually divided into arrival and departure delay. For cancelled flights, the departure delay is assumed to be 1440 minutes. That limits the calculated Lyaponov exponent based on Equation (4).

The Lyapunov exponent [7] can be determined by equation (4).

$$\lambda_i = \lim_{N\to\infty}\frac{1}{N}\ln\frac{r_i^{(N)}}{r_K} \qquad (4)$$

If the Lyapunov exponent equals zero all the time, the system is conservative and remains stable. A negative Lyapunov exponent indicates a fix point (fixed final state) for the evolution of the system. A positive Lyaponov exponent is an indicator for non-predictable future states. In case of chaos, the Lyapunov exponent grows rapidly to infinity.

3 Results

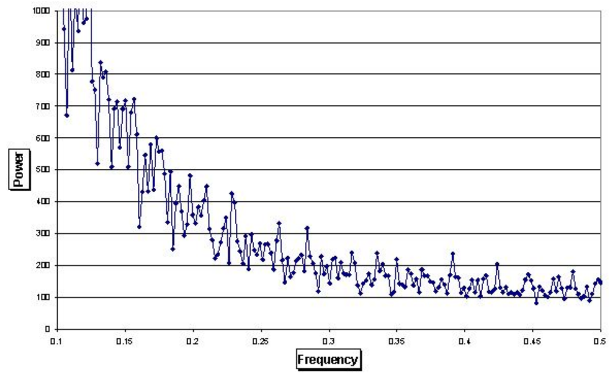

Figure 6: Power spectrum example of delayed A320 flights (January 1-8 2004)

Based on the described method, first results of the performed analysis are presented in this section.

A representative power spectrum as a result of the Fourier analysis of the data [6] is shown in Figure 6. No clear peaks can be found. That indicates that within the considered time frame no periodic events (e.g. periodically delayed flights) can be found within the data.

To determine the behaviour (the states as part of the evolution) of airports, described by Lyapunov exponents, data of San Francisco (SFO), Boston (BOS) and JFK New York of 2010 [6] have been used and analyzed. Lyapunov exponents (equation (4)) have been calculated for individual days.

Figure 7 provides an overview on Lyapunov exponents of randomly selected days at SFO. The reference trajectory of each of the shown tracks is the individual daily schedule.

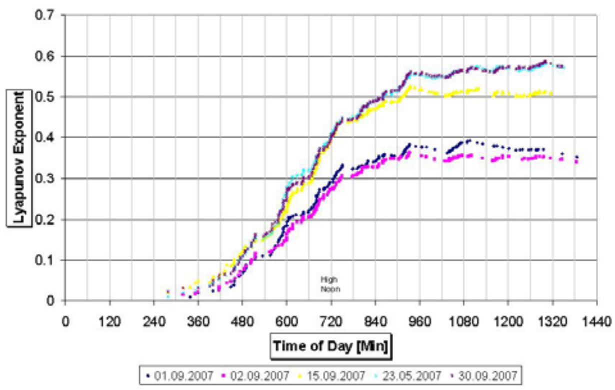

Figure 7: Lyapunov exponents of randomly selected days (in September 2007) of San Francisco International Airport; the difference between weekends and regular weekdays is clearly indicated.

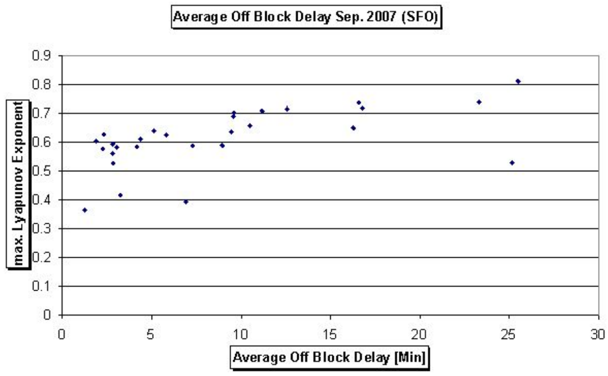

Figure 8: Max. Lyapunov exponents as function of average off-block delay

Widely-spread off-block delays (transfer of arrival delay to departure delay of the same aircraft) can be observed (reactionary delays). Reasons for the observed distribution are disruptions of operations (at previous airports, flight operations and disruptions during the turnaround process) Hence, the values of the calculated Lyapunov exponents increase with progressing time. At the end of each day the Lyapunov exponent decreases. This is a result of a lower dependency between flights in the evening. Hence, a relaxation of the system can be observed.

Figure 7 indicates a difference between weekdays (upper curves) and weekends/public holydays (lower curves). Airports presented in this paper show clear differences in demand as a function of weekdays and weekends. Hence, the number of possible disruptions (based on interactions between aircraft and required infrastructure) is much lower on weekends/public holidays compared to regular weekdays.

Based on the individual Lyapunov exponents of each day, the daily maximum value can be derived. A cross correlation between average daily delay and the maximum Lyapunov exponents observed in September 2007 in San Francisco (SFO) is shown in Figure 8. This Figure is representative for all considered airports in this paper. In general, the average daily delay increases with increasing maximum Lyapunov exponent. However, a clear correlation can not be found. Hence, the Lyapunov exponent is an indicator for huge

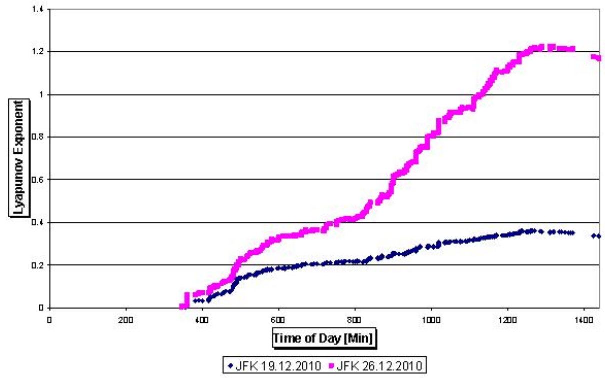

Figure 9: Comparison of a regular day of operations (December 19th 2010) and a chaotic day of operations (December26th 2010) at JFK airport

average delays, but does not refer to expectable delay values.

Figures 7 and 8 give an impression of the regular behaviour of airports. No significant system disruptions occurred. The evolution of individual Lyapunov exponents of chaotic days is significantly different. The evolution can be described by the gradient of the exponents and respectively the calculated values as presented in Figure 9. On days of regular traffic operations the value of Lyapunov exponents (based on the applied calculation method) is usually clearly below the value one. The value one results from a scaling effect of the used data. Figure 9 compares exemplarily a regular day and a chaotic day at JFK Airport based on data given in [6]. The maximum value of the calculated Lyapunov exponents exceeds the value one significantly as well as the calculated gradients. The same result has been found for Boston International Airport (BOS) at the same day.

Heavy snow storms at the east coast of the United States were responsible for that chaotic behaviour. However, a slight relaxation can be observed at the end of the day.

4 Prediction of Airport Delay

The (usually) good nature of airport systems opens the channel to predict off-block delays of flights within a certain range and a certain probability as shown in Figure 10.

One of these methods, presented in this paper, is based on multi-dimensional regression.

The state of an aircraft can be understood and represented as a vector. This vector can be projected in a coordinate system called phase space [11]. The vector can consist of the following components:

- Number of departing passengers
- Number of arriving passengers
- On-block delay
- Demand (during turnaround services)
- Aircraft type
- Destination
- Airline
- Scheduled turnaround time

A 2D- or 3D projection of these vectors in a phase space (if two or three parameters respectively are taken into account) give a first visual impression on the distribution of data points and the quality of the aspired regression function. In the next step, the regression coefficients have to be determined. Using these coefficients, multi-dimensional regression can be applied to calculate (or better to recalculate) off-block delays based on boundary conditions (expressed by the vector). In most cases, linear equations like equation (5) are sufficient to determine delays. The quality of the derived delays can be increased significantly, if noisy data can be extracted from the data set [12] [13].

$$\text{Delay} = a + \sum b_j x_{ij} + E_i \qquad (5)$$

a and b_j = Coefficients resulting from regression
x_{ij} =components of state vector

Based on linear multidimensional regression and data for the airports of Phoenix, Charlotte, Washington, San Francisco and Philadelphia [6], regression coefficients were derived (shown in Table 1). The vector of state was given by the on block delay and scheduled turnaround time.
Based on Equation (5) and the derived coefficients, off-block delays were calculated

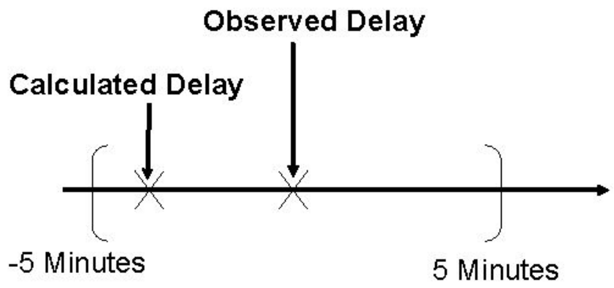

Figure 10: Range of permitted deviation between calculated and observed off-block delays

	A	B_1	B_2	PROBA-BILITY [%]
Phoenix	1,310	0,078	-0,002	68,9
Charlotte	-0,520	0,098	0,002	71,2
Washing-ton	-1,406	0,159	-0,002	74,4
Pittsburgh	-1,277	0,155	0.003	70,8
San Francisco	-1,588	0,067	-0,002	75,2
Philadel-phia	1,400	0,121	0,003	54,8

Table 1: Regression coefficients based on linear multidimensional regression and probability to find an observed off-block delay within a range of plus or minus five minutes

and compared to observed off-block delays of the same flights (flights of the year 2007). If calculated and observed values were in a certain range (see Figure 10), a positive event was counted. The ratio of positive events and the number of all flights (of one airport in one year) represent the quality of the regression. This value (named probability) is given in table 1 as well.

5 Relation to airport management

If an airport function (regression curve) and regression coefficients are known, off-block delays can be calculated for each boundary condition within the range of the underlying data. Hence, an operator can be informed about the risk of delay for each flight, based on the conditions of an individual flight as well as the state of the airport and its history (day of operation). This information can be used to reschedule processes (e.g. turnaround or passenger processes), hence these information can be used for airline and airport management.

6 Next Steps

To apply this method successfully, the stability and the properties of change of the calculated regression coefficients (the changes within the airport due to changes of procedures and processes) have to be investigated in more detail.

This paper has shown that chaotic states at airports exist. One upcoming task is to identify the boundary conditions that lead to chaos. Points of bifurcation have to be identified and a mathematical formulation of the problem (and the solution) has to be developed in order to have a future indicator for problematic situations at airports.

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