

ATM SEMINAR 2007, BARCELONA, SPAIN

PREDICTION OF OPERATIONAL FAILURE STATES AT AIRPORTS BY MEANS OF STOCHASTIC TRANSITION MATRICES

Daniel Schaad, German Aerospace Center DLR, Braunschweig, Germany

Abstract

Airports are complex multivariate systems where large numbers of interdependent parameters contribute to the overall operational performance. Consisting of many structurally different subsystems, airports tend to lack functional transparency and thereby impede proper situational awareness for operational management. This is specifically critical in conditions where system malfunctions cause operational irregularities which require ad-hoc recovery action.

Transition matrices are a mathematical description of dynamic changes between system states. They can be generated from a given set of state observations to reflect the dynamic behavior of complex multivariate systems. In connection with airside process monitoring initiatives as part of the CDM (Collaborative Decision Making) concept, transition matrices can provide decision support to assess and predict critical failure states at airports. A decision support tool based on transition matrices may then be imbedded into other applications used for the operational management at airports.

The transition matrix methodology clearly represents a holistic approach to airport systems as it measures the status of global airport parameters and detects deviations from nominal states as failures. By constantly monitoring these system states, transition matrices are generated to statistically reflect functional dependencies and failure propagation within the system. After a certain "learning" phase, these matrices can then be used to predict failure states on the basis of a given status quo. This provides a basis to assess the criticality of a situation and to develop reactive strategies in a timely manner. Moreover, forecasts can be used to perform a "what-if probing" to analyze the expected outcome of planned corrective measures.

The transition matrix methodology has been described and applied to several test scenarios in order to demonstrate the matrix learning effect and its derived forecasting capability. The key elements of this methodology, its motivation and first results will be presented in this paper.

1 Introduction

Today's management at larger international hub airports deals with the complex task of providing interfaces between various subsystems of different organizational and operational structures. Examples of these subsystems are airlines, air traffic control facilities, ground handling companies, cargo services, and many more. Each of these subsystems, which are oftentimes referred to as "stakeholders", usually have a fairly high degree of intra-organizational efficiency which is the result of long-term optimization processes. However, it is the interaction between these stakeholders which oftentimes causes irregularities in airport operations. This may in part be due to the fact that interfaces between these stakeholders sometimes lack full compatibility to the inner structures of the subsystems.

Yet another major reason for suboptimal airport operations is the complexity of the global airport system as a synthesis of multiple heterogeneous subsystems. This complexity leads to a blurred view on functional dependencies which are critical to the understanding of failure propagation around the airport and reactive measures to counteract these irregularities. The number of crucial parameters in multivariate systems like airports is simply too high to be processed by human operators without decision support from data analysis tools. Moreover, a large number of parameters usually produces an even larger number of possible functional interdependences, which are hence totally unmanageable for humans. In many multivariate systems, human operators rely on "best practice" and experience-based patterns to cope with complex scenarios. This is, indeed, a justifiable approach and still today, most complex management tasks involve experience-based decision making, not only in airport operations. However, the danger involved in this practice is that an operator may deal with a "hidden" set of functional dependencies and thereby misinterpret situations by making false assumptions about failure propagation and the resulting development of events. It is obvious that certain functional links in an airport system are fully transparent and easily verifiable by observations. Other links, however, may not be as visible but also bear a considerable

statistical significance in failure propagation. Making these links visible and quantifiable is essential for a proper situational assessment and the projection of expected developments. The concept of transition matrices reveals these functional links by constantly observing malfunctions in the airport system as well and their propagation with time. The transition matrix thereby statistically “learns” from these observations and enables a human operator to predict failure states from a given operational condition.

The following paper will first present the motivation which has led to the development of a transition matrix methodology for airport management. Then, after presenting the concept, it will describe the research approach used for this development. Moreover, the paper will depict how transition matrices are “built” before summarizing first results of this ongoing research project with an additional outlook of further work to be done.

2 Motivation

Airports are highly complex systems with a large number of interacting subsystems. These subsystems or “stakeholders”, usually have their individual goals and functions. Moreover, they exchange information and resources between each other. As mentioned above, even with a high degree of process optimization within specialized subsystems, such as airlines, air traffic control facilities, ground handling/cargo handling organizations, airport operators, etc., it is their interaction which strongly determines an airport’s operational performance.

The goal of all CDM (Collaborative Decision Making) initiatives is therefore to facilitate and enhance air traffic performance (including punctuality, cost effectiveness, capacity, etc.) by establishing an information network that enables all stakeholders to exchange and monitor parameters which are relevant for their individual operations. This requires some kind of data pooling to ensure the principle of “common situational awareness”, i.e. the availability of equal information for all stakeholders at the same time and update rate. One can visualize the data pool as a centralized computer server which receives updated status and event information from any stakeholder who produces such data. At the same time, the server is accessible for airport stakeholders to monitor all data which is of operational interest to them [1].

Whilst this system-wide information sharing enables individual operators to enhance their performance through knowledge about the status of neighbouring subsystems, it can also be used for a global monitoring of the entire airport. This idea

has led to the Total Airport Management (TAM) concept.

An institutionalized form of TAM includes the implementation of centralized airport control stands (such as the Airport Operations Center – APOC) where stakeholder representatives sit together and constantly receive information about the airport’s operational status. In case of irregularities, these representatives can thus discuss and resolve problems on a tactical basis by direct communication. Their “common situational awareness” is provided by the system-wide information network [2].

Both CDM and TAM bear considerable potential when it comes to the optimized interaction between stakeholders at airports. Yet, the vast amount of parameters which interact in these multivariate systems can barely be understood and processed by human operators without the help of some computer-based analysis tool. Such a tool will have to guide a human operator through the complex structure of parametric linkage within an airport system. Based on a given situation, it will have to unveil the most relevant cause-and-effect chains to provide a guideline for possible corrective actions, especially in critical situations. Beyond streamlined operations, this will certainly provide higher safety levels and thus expand existing airport safety standards [3].

In order to fulfil global operational management tasks at airports, it is of utmost importance to understand the effects of decisions taken by some centralized control entity. Moreover, the concept of “common situational awareness” has to be extended beyond the mere monitoring of current statuses and include projections of the most likely future events.

All of this calls for a methodology to detect functional links in an airport system and use these to assess operational conditions and their expected changes. Considerable research has been done about failure propagation in coupled systems [4]. This research focuses mostly on crisis situations in complex large-scale systems, such as nuclear power plants, for instance [5]. Failure propagation in airport systems, however, still remains a fairly undiscovered issue despite intensive research activity in new ATM concepts [6]. It can be assumed that a better understanding of failure propagation at airports can help to improve tactical as well as strategic airport management and enhance an airport’s operational performance.

To meet this goal, a methodology has been developed from the concept of state transition matrices, which can be used to record state changes and calculate transition probabilities to anticipate future operational conditions. The idea of using

transition probabilities to calculate expected state changes has found wide acclaim in the concept of Markov-Chains [7]. However, the mathematical concept used here is somewhat different as it allows multiple interconnected state changes to occur in parallel.

The methodology focuses on failures (i.e. non-nominal parameters) and their propagation throughout the airport system. It is deeply imbedded in the CDM concept as it requires a comprehensive parametric monitoring of airport processes and resources. The monitoring is used to produce an “average transition matrix” which statistically reflects transition probabilities on the basis of an airport’s operational data history. This can be seen as the analytical part of the methodology as it reveals common linkage between distributed parameters in an airport system. Moreover, the approach features a forecasting capability based on the average transition matrix which can be used to calculate future state probabilities from a given parametric condition.

The methodology is intended to serve as a theoretical basis for future CDM/TAM tools supplying operational analyses and forecasts at airports to support global decision-making processes. Such tools may become elements of centralized airport control facilities and assist mainly in tactical tasks of the operational management. In addition to a large number of dedicated tools built upon CDM data sharing, such as Arrival/Departure Management Systems (AMAN/DMAN), Turnaround Management Systems (TMAN), Surface Management Systems (SMAN), Gate and Stand Allocation Systems, etc., these tools may provide a better global view on airport operations by analysing system structures, assessing the operational status quo and predicting imminent system state changes.

3 The Concept of Decision Support Based on Transition Matrices

Statistical data gathered by observing failure state transitions in airport systems is “stored” in the transition matrix, thus providing various opportunities for the use as support data in operational decision making processes. There are four main types of decision support granted by the transition matrix methodology:

Probabilistic Forecasting

The airport’s global failure status is recorded in constant time intervals by status sensors in airside processes (esp. turnaround processes), airport infrastructure and resources, reports (e.g.

NOTAMs, METARs, ATIS, etc.), as well as direct input through operators. Thus, a large number of critical parameters that contribute to the functioning of an airport and its various subsystems are monitored and the recorded data can be used for a statistical analysis of failure state transitions. The relative frequency of occurrence of a “failed” parameter j in step t following a failure in i at $t-1$, as well as the average “responsibility” of failure i (which depends on the number of other failures at $t-1$) is stored as t_{ij} in the so called “average transition matrix T_{avg} ”. The term “average” indicates that the matrix does not refer to a single state transition but reflects a mean transition after recording multiple state changes. The data used to build T_{avg} is data from the “learning phase” of the matrix. This learning phase can, of course, be permanent so that the matrix constantly gains statistic “solidity”.

Once the matrix is sufficiently “solid” (i.e. converges into a stable condition), it serves as a database for probabilistic failure forecasts based on the latest measured status (i.e. the status quo). The statistical coupling of failures will then show its effect in iterative calculations with the average transition matrix. Starting from the current failure state of the airport, the human operator can project the expected failure distribution after k time steps and thus obtain a better idea of events to come.

The forecast of expected critical failure states then directs human attention to relevant parameters and can hence provide vital decision support functions. A forecast may, for instance, lead to the bundling of resources to prevent or counteract a certain development. Probabilistic forecasting is therefore one of the main assets of the transition matrix methodology.

Situational Assessment

Situational assessment functions provided by transition matrices are based on their forecasting capability. The underlying idea is that a situation can be assessed by looking at the most probable failure events it will trigger in the future. Thus, considerable knowledge about the airport’s dynamic condition can be derived. One measure is the propagated failure strength from the status-quo situation to a given time-step in the future. It can be directly calculated from the matrix and the current failure state (expressed by a state vector) and yields the average number and fractional responsibility of failures triggering other failures. The propagated failure strength can be regarded as a global indicator for the criticality of a situation, since it shows how strongly current failures are amplified or attenuated as they propagate through the airport system with time.

Another concept for situational assessment are “diversion vectors”. If \bar{s}_t is the failure state vector at t and \bar{s}_{t-1} its predecessor, the diversion vector is $\bar{s}_{div} = \bar{s}_t - \bar{s}_{t-1}$. Forecasting the development of these diversion vectors (and especially their magnitude) shows the “drift” tendency of the current situation and can be interpreted as a dynamic index of situational criticality.

A third measure is the mathematical divergence (*div*) of the transition matrix T_{avg} itself. Since the matrix represents a linear function in this context, $div(T_{avg})$ is not very spectacular but provides a measure of how sensitively the forecast changes with variations in the current state. On one hand, this can be seen as a measure of forecast reliability, since it shows how “wrong” a forecast will be with false data. On the other hand, it gives a human operator some indication of how effective an interference with the system is expected to be. This may provide some interesting decision support for ad-hoc strategies to limit failure propagation in critical system states.

Diagnosis

The transition matrix methodology even provides a diagnostic function with the matrices applied in reverse time order. This can be done to trace back potential failure origins if events have not been recorded, for instance. The concept behind this is analogous to the forecasting function. In “diagnosis mode”, the probabilistic transition matrix is build in reverse order from a set of recorded failure state changes. It is then applied iteratively to look at the most probable “root causes” for other failure state scenarios where there may be no recorded data available. Even if recordings exist, however, it can be very revealing to identify the statistically most probable root causes and compare them against the recorded ones to find out if events follow a known pattern. Identifying known event patterns may then point directly to pre-defined action plans whereas new event sequences call for ad-hoc strategies. Thus, the diagnostic function can play a major role in decision making processes as human operators need “reverse reference” to asses their current situation and develop strategies accordingly. Dealing with large multivariate systems like airports can sometimes cause situations where human operators are overwhelmed by incoming event data and where they tend to act as if they had just been introduced to the scenario. In these critical situations, two very fundamental questions serve as guidelines for any managerial task: “What has -most probably- happened?” and “What will -most probably- happen with and without corrective actions?”. Both questions can be answered with the

help of transition matrices and their forecasting and diagnostic capability.

What-if Probing

Failure scenarios at airports oftentimes trigger corrective actions from human operators. Finding the proper strategy, however, can be difficult in multivariate systems like airports, as failures interact strongly during their propagation throughout the system. Thus, if a specific failure shall be resolved, it is mostly insufficient to address this failure directly. In fact, all failures have to be addressed that contribute to the occurrence of the specific failure. Once the most probable cause failures have been identified through diagnostic analyses (or data records) it is the task of operational management to develop a strategy which counteracts the specific failure. The effect of a selected strategy obviously determines its quality. Thus, the effects of operational decisions have to be studied in order to identify an appropriate failure response strategy. A real-world airport scenario, however, cannot be addressed by means of “trial-and-error”, as this would have a disastrous impact on the operational environment. Effects therefore have to be anticipated which can be done by “what-if probing” with the help of transition matrices.

The underlying principle of “what-if-probing” is a forecast of expected events based upon a variable starting point. Thus, an average transition matrix can be used in just the same way as for failure projections. The only difference is that the initial condition is no measured failure state but a hypothetical situation created by some response strategy. In most multiple failure scenarios, operational management has to deal with limited resources so that only a certain number of existing failures can be addressed at once. By means of “what-if probing”, all possible variations of instantly addressed failures can be analysed in their expected propagation and result. This reveals how and at what expense they affect a specific failure after a given period of time. The “expense” is the amount of other expected failures which may develop in a strategy that succeeds to “wipe out” a specific failure in focus.

In connection with certain pre-defined “cost factors” (for instance, the overall number of failures at a given time t , or additional “weight”-factors for the occurrence of individual failures) a combinational projection of these initial conditions can be used to create a priority list of failures that should be directly addressed as part of a response strategy. “What-if probing” can thus be a vital decision support tool in critical operational conditions, as it directs the focus of human operators to relevant parameters which ought to be addressed instantly to prevent further escalation.

In addition to that, the “what-if probing” approach based on transition matrices can be used to perform system studies by simulating scenarios and their event progression. This can be a vital research tool for the analysis of a complex airport system. Since the average transition matrices statistically reflect an actual airport they can be used to identify critical system structures and thus be a guideline for system optimization.

4 Research Approach

Following the conceptual development of transition matrices for the use in airport systems, the main focus of research has been on their application to actual airport scenarios. This was done in order to demonstrate the functionality of transition matrices and go beyond a purely theoretical development of this concept. One basic requirement for the testing of this methodology was a model airport system to which it could be applied.

The Generic Airport Model

For the sake of simplification and generalization it was decided to develop a generic airport model (Figure 1) which reflects a typical airport structure by defining a hierarchic order of airport subsystems as well as their individual determinants. These determinants are input parameters which, if disturbed, impede the full functionality of a subsystem and the airport itself. Summarizing all subsystem parameters in so-called “state vectors” thereby creates a mathematical basis for the description of operational conditions at the airport. Even though the generic airport is designed as a simplified model, most realistic situations can indeed be “translated” into state vectors with the help of parameters derived from subsystem functions.

After investigations into adequate mapping functions for the conversion of events or (sub)system states into state vectors, a very simple approach has been chosen, which is the binary representation of parameters. Thus, any parameter which is “undisturbed” is shown as a “zero” whilst disturbed parameters change to “one”. At first glance, this approach appears fairly rough, yet it could be shown that the parameters receive their “weight” statistically as a result of their relative frequency. A major advantage of the binary approach is its straightforward conversion of observations into parametric values. Binary mapping functions are also known to be specifically suitable for computer processing. Moreover, binary measurements appear in a format which is highly compatible with probabilistic calculations.

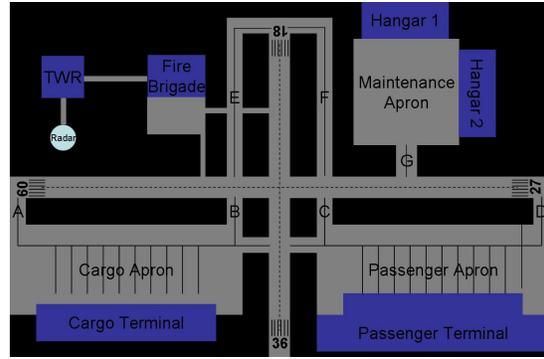


Figure 1: layout of the generic airport model (Generica International Airport)

The set-up of the generic airport model and its corresponding state vector parameters was done on the basis of standard airport functions and resources [8],[9]. The individual determinants could thus be derived from known subsystem functions and requirements (Figures 2,3). Following a generic approach, a high level of simplification could be achieved as the model was only built to demonstrate the meaningful use of transition matrices. This led to the selection of $n = 185$ parameters to describe the global airport system state. It is obvious that these parameters are an arbitrary selection which can always be altered, expanded or reduced, as long as it matches the airport system observed.

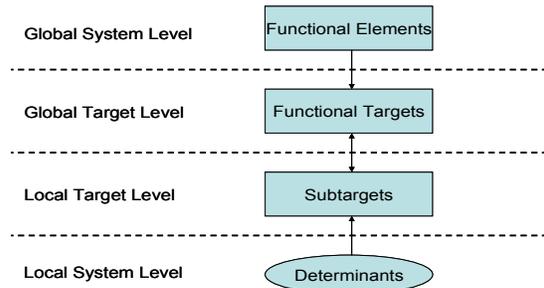


Figure 2: system structure used to derive failure parameters from functional determinants

With the simplified (yet useful) assumption that if disturbed, all parameters can act as both input and output failures (e.g. cause and effect), any resulting transition matrix is square with $\dim(T) = n \times n$. The corresponding state vectors are of $\dim(\vec{s}) = n \times 1$. Those parameters that are known to always remain unaffected by other airport parameters can be disregarded in probabilistic calculations as their probability values have no real

meaning. Good examples of such “input-only” variables are all weather-related parameters.

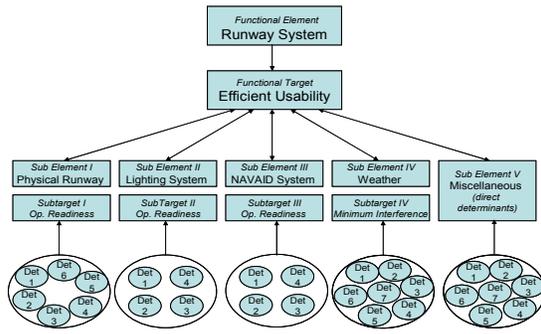


Figure 3: example of a functional subsystem tree for the runway system

Airport Scenarios

Once the generic airport model was set up, a first goal was to demonstrate the generation of average transition matrices on the basis of actual airport scenarios. These airport scenarios had to be developed to match the existing airport model and eventually covered a period of 10 days. Each of the nine first days featured a specific operational failure case ranging from smaller operational disturbances as a result of turnaround irregularities to larger incidents like emergency landings and security breaches. Every scenario had a dominant failure source in one of the following categories: weather, airport infrastructure, turnaround, security, traffic flow, airspace, emergency situations, visibility and strike. The tenth day provided a scenario of miscellaneous failures with no specific emphasis on a particular category.

All airport scenarios have been developed as a time-tagged sequence of non-mathematical event descriptions. These descriptions could then be manually translated into binary state vectors. All state recordings were referred to a standard time interval of one minute which appears to be a reasonable choice for airport operations. For a longer interval between two events, the previous state vector was assumed to remain constant. Since all one-day scenarios covered airport operations from 6:00 to 24:00 (which equals 1080 minutes), each scenario created a set of 1080 sequential state vectors.

The Learning Phase

After implementing the matrix generation code into Matlab®-scripts, the scenarios were used to build ten different average transition matrices, one for each day. By visualizing them, first qualitative checks could be performed to test if these matrices reflect failure linkage in the affected

subsystems as expected. With positive results in these checks, a “global” nine-day matrix was generated to incorporate all events described in the first nine scenarios. The tenth scenario was then used to test the forecasting capability of the average transition matrix which had “learned” from 9 other scenarios.

Forecasting

The ability to forecast failure probabilities can be tested by comparison of failure event projections against real failure events. This is done by using recorded events to generate a failure event matrix E_{fail} of a specific time span (e.g. k time-steps) which -having observed n parameters- yields a $k \times n$ matrix.

In a second step, the initial failure state of this event sequence is used together with the average transition matrix to calculate k successive failure states, which are also summarized in a $k \times n$ matrix – the forecast matrix F_{fail} . Overlaying the two matrices can already give a visual impression of how “close” the forecast would have been relative to the actual event progression. Mathematically, $F_{fail} - E_{fail}$ yields the difference between forecast and actual failure state for each parameter and in every time step.

This matrix difference is the basis for any attempt to answer the crucial question if the transition matrix methodology helps to predict certain failure events at airports from a set of previous data recordings.

To be stochastically meaningful, however, any validation technique has to ensure that recorded events used for the learning phase of the transition matrix are not used again for a comparison against failure forecasts as this would not prove any predictive quality of the transition matrix, whatsoever. Thus, the tenth scenario was used to perform forecasting tests with the average transition matrix developed from the nine other scenarios. For further validation, however, more real-world scenarios are needed to assess the predictive power of the methodology. Such validation is scheduled for the first half of 2007 and will be supported by two European airports.

As shown in the following paragraph, an analogous validation technique can be applied to test the diagnostic capability of transition matrices.

Diagnosis

The diagnostic feature of transition matrices is their ability to “retrace” failure events by reversely looking at their propagation throughout the system up to a given failure state. This yields probability

distributions of previous states which can be interpreted as “failure cause” probabilities. Validating this diagnostic capability requires a comparison of real events leading to a certain state and the corresponding diagnosis provided by some average transition matrix. Again, the recorded data used for this purpose must not be the same as the “learning data” processed to build an average transition matrix, since this would create a self-referential system with no diagnostic value.

The validation of a diagnostic use of transition matrices in airport systems has to show whether or not this approach sufficiently supports the detection of failure cause in actual airport scenarios. First trials with test scenarios have already shown very promising results, yet further validation will include more real-world data from two European airports.

5 Transition Matrix Building

The idea behind the average transition matrix is to mathematically formulate a “mean” transition between consecutive system states, which, in the context of this work are limited to failure states. This concept is somewhat related to Discrete Markov Chains [7], yet different as it allows parallel state transitions with stochastic interaction. These failure states are expressed by vectors which incorporate parameters that can either be “disturbed” or “undisturbed”. Thus, these failure parameters only take on binary values with “zeros” representing undisturbed parameters and “ones” indicating disturbed parameters. Failure states have to be observed in constant time intervals Δt in order to be used for discrete time transitions developed here.

Generally speaking, a single transition matrix $T_{t,t+1}$ between two consecutive states \vec{s}_t and \vec{s}_{t+1} has to fulfil the equation $\vec{s}_{t+1} = T_{t,t+1}\vec{s}_t$. Supposing $\dim(\vec{s}_t) = n \times 1$ for all t , the matrix $T_{t,t+1}$ is square with $\dim(T_{t,t+1}) = n \times n$. With two given consecutive failure states, there is obviously no unique solution for the transition matrix entries. This can be easily understood by looking at the problem as a system of n equations with $n \times n$ unknowns (i.e. the matrix entries). The system is hence strongly underdetermined.

In analogy to the idea of finding regression curves to describe functional dependencies in a set of measured values, the transition problem tries to determine functional linkage (given by transition matrices) between measured system states. Like in regression problems, certain assumptions have to be made to narrow the problem down to a level where the remaining number of unknowns can be determined following a “best fit” strategy. This certainly always implies the risk of pre-

determination by the model builder, yet is necessary to master an underdetermined system.

The following assumptions are made when building a single transition matrix between two states: With a given failure in element j of \vec{s}_{t+1} , (i.e. $s_{j,t+1} = 1$, with $s_{j,t+1} \in \vec{s}_{t+1}$) all failures in \vec{s}_t are assumed to have an influence on $s_{j,t+1}$. The only remaining question is their individual weight which can be assigned in a very simple manner by assuming an equally shared “responsibility” of all input failures for any consecutive output failure. For instance, if three input parameters are disturbed (i.e. $\|\vec{s}_t\|_1 = 3$), all $s_{j,t+1}$ for which $s_{j,t+1} = 1$ are equally triggered by the three disturbed $s_{i,t}$ and each of them assumes on third of the “cause responsibility” for a triggered failure. In formal notation this yields the matrix entries $t_{ji} \in T_{t,t+1}$ as follows:

$$t_{ji} = \begin{cases} \left(\sum_n s_{i,t} \right)^{-1} & | s_{i,t} = 1 \wedge s_{j,t+1} = 1 \\ 0 & | s_{i,t} = 0 \vee s_{j,t+1} = 0 \end{cases}$$

Building an average transition matrix from m given states (i.e. $m-1$ single transitions) could simply be done by calculating

$$T_{avg} = \frac{1}{m-1} \sum_{t=1}^{m-1} T_{t,t+1}$$

This, however, would take the absolute frequency of occurred linkage between $s_{i,t}$ and $s_{j,t+1}$ into account, which is not as meaningful as their relative frequency, i.e. the percentage of failures triggered in $s_{j,t+1}$ by $s_{i,t}$ based on the total number of failed $s_{i,t}$. This yields an average transition matrix of the following appearance:

$$T_{avg} = T_{sum} M \quad \text{with} \quad T_{sum} = \sum_{t=1}^{m-1} T_{t,t+1} \quad \text{and}$$

$$M = \begin{pmatrix} \left(\sum_{t=1}^{m-1} s_{1,t} \right)^{-1} & 0 & \dots & 0 \\ 0 & \left(\sum_{t=1}^{m-1} s_{2,t} \right)^{-1} & 0 & \vdots \\ \vdots & 0 & \dots & 0 \\ 0 & \dots & 0 & \left(\sum_{t=1}^{m-1} s_{n,t} \right)^{-1} \end{pmatrix}$$

This average transition matrix reflects two observations which make its entries interpretable as transition probabilities. These observations are the relative frequency of occurred linkage between two parameters as well as the fractional “responsibility” of an input failure for the failed output, which depends on the individual sum of failed inputs. These two combined can be seen as the transition probability between two parameters:

$$p_{trans,ji} = \frac{\sum_{t=1}^{m-1} t_{ji}}{\sum_{t=1}^{m-1} S_{i,t}} \text{ with } p_{trans,ji} \in T_{avg} .$$

It should be noted that the fractional responsibility is already implied in the definition of t_{ji} itself, whilst the relative frequency of occurrence is obtained by dividing the expression with

$$\sum_{t=1}^{m-1} S_{i,t} .$$

This concludes the process of matrix building from a set of m consecutively observed system states. One can refer to this process as the “learning phase” of the matrix. The resulting average transition matrix is a stochastic matrix which, on the basis of aforementioned assumptions, reflects probabilities for individual failure transitions (Figure 4). This matrix can now be used for the prediction of failure probabilities resulting from any given state. With state vector observations made in constant time intervals Δt , transition probabilities reflected by the matrix logically refer to this specific Δt only, which has to be taken into consideration when using the matrix for state predictions.

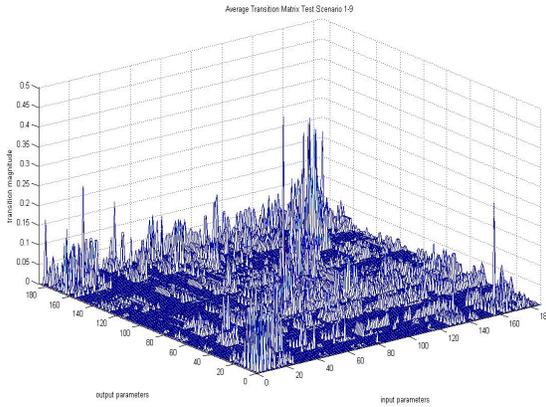


Figure 4: graphical representation of an average transition matrix

The following paragraph shows how T_{avg} can be used for failure state predictions.

Calculating failure probabilities

Starting from a given initial failure state, the average transition matrix can be used to calculate a probability vector showing the probability of occurrence for each failure after k time-steps. With a state \vec{s}_t at t , the probability of a failure in element j after one time step is given by

$$s_{j,t+1} = 1 - \prod_{i=1}^n (1 - p_{trans,ji} S_{i,t}) .$$

It shall be noted, that \vec{s}_t can now either be the measured state at present or a probability vector at some future point in time. With a given Δt and a currently measured state vector \vec{s}_0 , k iterations of the aforementioned loop therefore provide \vec{s}_k , which is the failure probability vector after $t = k\Delta t$.

The “probability tree” concept behind the loop formula is shown in Figure 5.

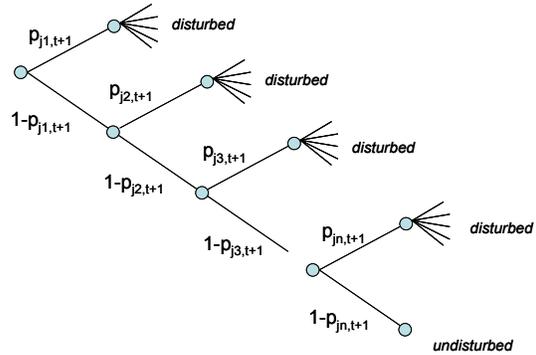


Figure 5: the probability tree concept used for failure prediction

The concept of permeability

It is obvious that the calculation of failure probabilities shown above does not apply the usual method of vector transformation through matrices, which is the matrix-vector multiplication. This is unfortunate as a vast amount of analytic concepts have been developed in linear algebra to study this type of vector transformation [10],[11]. A famous example is the eigenvector concept which appears rather useful for the analysis of dynamic systems and failure propagation. Thus, it is worth searching for operations in linear algebra which produce meaningful results when applied to the average transition matrix.

This incentive has led to the concept of permeability which is based on the idea that the average number of failure states which permeate from an initial state \vec{s}_0 to a specific failure $S_{j,k} \in \vec{s}_k$ after k time-steps is a useful index for the “gravity” of this failure. After k steps, the permeability vector \vec{v}_k^{perm} is given by $\vec{v}_k^{perm} = T_{avg}^k \vec{s}_0$. With $|\vec{s}_0|$ being the sum of initial failures, \vec{v}_k^{perm} yields a distribution showing the average number of input failures which “permeate” to each output failure after k time-steps. Thus, the average number of failures that make it through the k -step propagation to trigger failure j is given by

$$v_{j,k}^{perm} = \left(\sum_{i=1}^n p_{trans,ij} \right)^{k-2} \left(\sum_{i=1}^n p_{trans,ij} s_{0,i} \right) = \left(T_{avg}^k \vec{s}_0 \right)_j$$

\vec{v}_k^{perm} shall henceforth be called “expected failure strength (EFS)”.

One could visualize this concept by thinking of several cannons firing simultaneously at many targets. Following a statistical distribution, the cannonballs of these cannons usually split up into smaller shrapnels. Each simultaneous firing equals one transition. The targets themselves are connected to cannons which in the next round fire a cannonball of the size and weight of all material hitting the target in the previous round. This process repeats itself $k-1$ times. In each firing every cannon hits a specific target with a certain probability but since its cannonballs split up, it is - in average - only a certain fraction of the cannonball which strikes the target once a hit occurs.

The whole propagation of hits from the initial round of firing to a final strike of target j after k time-steps can be regarded as a filter between the initial firing and the final hit. The “strength” of the final hit indicates how permeable the system is for the initial firing to propagate its effect on target j . A simplified representation of a 5-step “propagation filter” (which only shows relevant linkage) is given in Figure 6. Please note that the transition probability between individual parameter pairs remains constant in every transition.

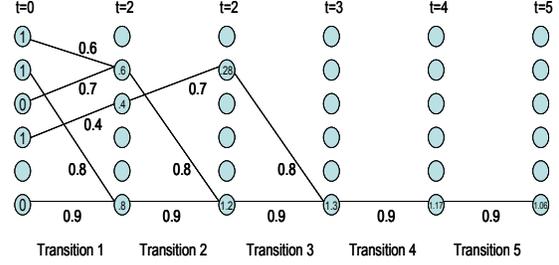


Figure 6: the concept of permeability

The example clearly shows that the propagation filter can both amplify and attenuate the EFS in each step. In order to understand the overall tendency of a propagation process, it is useful to define a “decay factor” $d_{s_0}^k$ which can be defined as

$$d_{s_0}^k = \frac{|\vec{v}_k^{perm}|}{|\vec{s}_0|}$$

With $d_{s_0}^k < 1$, the propagation is “self-containing” and has the tendency to decay. $d_{s_0}^k = 1$, however, indicates a stable propagation which neither grows nor decays, whilst $d_{s_0}^k > 1$ clearly shows a growing propagation which has the tendency to create more failures in the system. It shall be noted that

$$d_{s_0}^k = f(k, s_0),$$

so that a propagation process can, for instance, grow for a while and then become self-containing, or vice versa. In other cases, $d_{s_0}^k$ may even oscillate around $d_{s_0}^k = 1$. Hence, it is always important to specify for which initial state s_0 and time-step k the decay factor is calculated.

Alongside “failure probability”, the “expected failure strength (EFS)” is a useful indicator in failure state predictions with the help of an average transition matrix. Based upon the concept of permeability it adds an important aspect to a purely binary understanding of failures: The concept follows the idea that with output failures triggered by more input failures than others (and by a higher probability), these output failures themselves usually trigger subsequent failures more strongly than others.

6 Results

In applying the transition matrix methodology to various test scenarios, it has been shown that a matrix can “learn” from statistical observations and thereby reflect probabilities of state transitions in future events. The whole process of generating an average transition matrix has been described, tested and optimized for the use in probabilistic forecasts. The forecasting functionality itself has then been applied to a composed test scenario and shown promising results inasmuch as the tendency of events was very much in line with occurrences described in the test scenario. However, a complete validation process requires the use of more real-world data which can only be obtained from airports themselves. Thus, a cooperation has been formed between the author and two European airports to test the forecasting methodology with data from airport operational databases (AODBs), weather services, traffic management systems, etc..

Figure 7 shows the propagation of failure probabilities over 30 minutes from a given starting condition (i.e. a measured failure state). The underlying average transition matrix was generated from nine test scenarios, whilst the initial condition is a measured state in the tenth scenario.

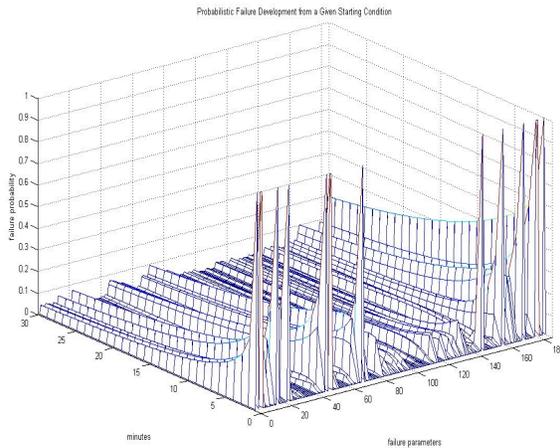


Figure 7: 30 minute failure probability projection from a given starting condition

The example of a failure probability projection shown in Fig.7 shall be “de-ciphered” verbally to illustrate the forecasting capability of transition matrices.

A condensed read-out of the initial failure state vector shows that the starting condition describes a situation with

- reduced visibility at the airport
- construction/restoration activity on/near the runway

- debris/object on/near the runway
- delays with aircraft waiting on the taxiway.

With the average transition matrix calculated from nine days, a 30-minute projection produces the following results which are read out from the 30-minute probability vector (limited to parameters with $p > 6\%$):

30 minutes after the measured starting condition, there is a

- a 19% probability of delayed operations
- a 9,5% probability of an unusually high traffic volume (per unit of time)
- a 9% probability of non-nominal apron occupancy times
- an 8.5% probability of reduced operational readiness of the runway
- a 7.2% probability of non-nominal gate occupancy times
- a 7.1% probability of TMA airspace restrictions due to operational irregularities
- a 6.8% probability of disturbed traffic exchange between runways and taxiways
- a 6.3% probability of non-nominal taxiway occupancy times

In analogy to the forecasting capability, the diagnostic function has shown very satisfactory results in retracing failure origins, which is very helpful when it comes to failure analysis after critical events. The question, however, which is the suitable timespan for a meaningful diagnosis, still has to be answered by further validation.

Alongside forecasting and diagnostic functions, the use of classic linear algebra has led to the concept of permeability, which provides a better view on the operational structure of an airport by showing the “permeation” of failures throughout the system with time. This concept has been applied to the test scenarios in connection with event forecasts and thereby proven an added value for the structural understanding of an airport system.

7 Conclusions and Outlook

To sum up, the transition matrix methodology has shown very promising results in both its situational assessment functionality and its capacity to support global airport system analysis independent of specific situations. Even in very large-scale systems, its mathematical background is suitable for on-line calculations as the computational power required remains constant for each time step and is limited to the generation of a single transition matrix (namely for the last

transition) with the subsequent calculation of the new average transition matrix.

The application of transition matrices to airport systems has proven to be a promising methodology for the structural and situational analysis of airport airside processes. Its potential to reflect failure event probabilities makes it a highly interesting approach for both reactive and anticipative management strategies at airports. Particularly interesting is the forecasting capability which can provide a vital decision support functionality in critical operational conditions and therefore serve as the basis for IT-tools in Total Airport Management (TAM). Thus, further research will focus specifically on the validation of forecasts based upon probabilistic transition matrices. As mentioned above, this will be done in cooperation with European airports in order to show the applicability of this concept to a real-world environment. A further step will then have to be the development of a test tool which can be used by human operators to validate their improved situation awareness.

In addition to the aforementioned elements,, further research will have to focus on the testing of situational assessment tools based upon the average transition matrix, such as “what-if probing” and the development of failure containment strategies. In multiple-failure scenarios and limited corrective resources, “what-if” forecasts will have to be calculated and adapted to human operators in order to support them in finding appropriate reactive strategies. Whilst the matrix generation and most forecasting calculations remain well within the limits of on-line computational power, the combinational problem of selecting k failures out of n and forecasting their future development can imply a high computational effort which may require the optimization of algorithms for on-line calculations.

Finally, the transition matrix concept fits perfectly into ongoing research efforts at the German Aerospace Center DLR, which aim at combining different TAM tools into a real APOC to test their interaction and applicability with human operators. Building and integrating a situational awareness tool based on transition matrices could certainly add to these efforts and pave the way for an integrated management of airport operations.

8 References

- [1] Eurocontrol Doc., 2006, *Airport CDM Implementation*, Eurocontrol, Brussels, Belgium
- [2] Günther, Y.; Inard, A.; Werther, B.; et.al., 2006, *Total Airport Management – Operational*

Concept & Logical Architecture, Eurocontrol/DLR, Brussels, Belgium, Braunschweig, Germany

[3] ICAO Doc. 9859 (AN/460), 2006, *Safety Management Manual (SMM)*, First Edition, International Civil Aviation Organization, Montreal, Canada

[4] Casti, John L., 1979, *Connectivity, complexity, and catastrophe in large-scale systems*, Wiley, Chichester/United Kingdom

[5] Perrow, Charles, 1992, *Normal Accidents: Living with High-Risk Technologies, 1999*, Princeton University, Princeton, USA

[6] Bianco, Lucio; Dell’Olmo, Paolo; Odoni, Amadeo R.,(Ed.), 2001, *New Concepts and Methods in Air Traffic Management*, Springer, Heidelberg, Germany

[7] Romanovskij, Vsevolod I., 1970, *Discrete Markov Chains*, Wolters-Noordhoff, Groningen, Netherlands

[8] Ashford, Norman; Stanton, Martin H.P.; Moore, Clifton A., 1997, *Airport Operations*, McGraw-Hill, New York, USA

[9] Wells, Alexander T., Young, Seth B., 2003, *Airport Planning & Management*, Fifth Edition, McGraw-Hill, New York, USA

[10] Valentiner, Siegfried, 1967, *Vektoren und Matrizen*, de Gruyter, Berlin, Germany

[11] Hogben, Leslie (Ed.), 2006, *Handbook of Linear Algebra*, Chapman & Hall/CRC, Boca Raton/USA

9 Abbreviations

AMAN	Arrival Management System
AODB	Airport Operational Database
APOC	Airport Operations Center
ATIS	Automated Terminal Information System
ATM	Air Traffic Management
CDM	Collaborative Decision Making
DLR	Deutsches Zentrum für Luft- und Raumfahrt
DMAN	Departure Management System
EFS	Expected Failure Strength
ICAO	International Civil Aviation Organization
METAR	Meteorological Aviation Routine Weather Report

NOTAM	Notice to Airmen
SMAN	Surface Management System
TAF	Terminal Area Forecast
TAM	Total Airport Management
TMA	Terminal Area
TMAN	Turnaround Management System

10 Biography

Daniel Schaad is a doctorate researcher at the German Aerospace Center DLR in Braunschweig, Germany. He earned his Masters degree in Aeronautical Engineering from the Technical University of Berlin in 2004. In his diploma project, he set out a concept to integrate hydrogen applications into airport operations. The project was supported by Airbus Industries and Frankfurt Airport operator Fraport. Daniel Schaad then worked as a young graduate engineer on a weather satellite mission (MSG-2) for the European Space Agency before joining DLR as a doctorate researcher. He spent one year at Arizona State University in Tempe/AZ and worked as a student consultant for aerospace projects in Slovakia, Norway and Greenland.