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ComplexWorld

Mastering Complex Systems Safely

SESAR WP-E Research Network

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1 INTRODUCTION

ComplexWorld is the SESAR Workpackage E Research Network for the theme 'Mastering Complex Systems Safely'.

ComplexWorld brings together researchers from academia, research establishments, industry and SMEs that share common interests and expertise in the field of ATM Complexity Management, providing them with a structured way and a stable forum for the development, exchange, and dissemination of research knowledge.

The purpose of the present document is to define the high-level, strategic scientific vision for the Complex World Network and to provide an orderly and consistent scientific framework for the WP-E Complexity theme.

1.1 The SESAR Programme

The **SESAR (Single European Sky ATM Research)** programme is one of the most ambitious research and development projects ever launched by the European Community. The programme is the technological and operational dimension of the Single European Sky initiative to meet future capacity and air safety needs.

The SESAR vision is to have an affordable, seamless European ATM system, enabling all categories of airspace users to conduct their operation with minimum restrictions and maximum flexibility. The **SESAR Concept of Operations** (ConOps) describes the ATM operation envisaged in Europe in 2020 and beyond in order to achieve this vision. The SESAR ConOps covers the complete ATM process from early planning through flight execution to post flight activities. The ConOps builds on ICAO Global Air Traffic Management Operational Concept, endorsed by the ICAO Eleventh Air Navigation Conference in 2003, which establishes a globally harmonized set of concepts and international requirements for the future ATM system, thus constituting a key input for all major ATM development programmes. The SESAR ConOps represents a specific application of the global concept, adapted and interpreted for Europe with due regard to the need for global interoperability.

The main features of the SESAR ConOps are summarized below:

- **Performance-orientation**: the concepts are driven by a performance-based approach. The ConOps has been built on a Service Orientated Performance Partnership (ATMPP), based on the participation and buy-in from the different stakeholders (Civil Airspace Users, Military, Air Navigation Service Providers, Airports, Supply Industry and Social Partners). An ATM performance based approach is considered essential to express the general expectations about the future ATM system in terms of precise performance targets. ICAO defines the Performance Based Approach as being based on the following three principles:
  - Strong focus on desired/required results.
  - Informed decision making, driven by the desired/required results.
  - Reliance on facts and data for decision-making.

  The SESAR performance framework will:
  - translate the expectations of the ATM stakeholders into a shared set of values and priorities;

  - define operational requirements in performance terms rather than specific technology/equipment;
  - be the basis for impact assessment and trade-off analysis for decision-making.

- **Trajectory-based Operations (TBO)**: the ConOps is centered on the TBO paradigm, which aims to ensure that the Airspace User flies its trajectory as close as possible to its intent, safely and cost efficiently, within the infrastructure and environmental constraints. In highly congested areas, however, it is foreseen the possibility of establishing route structures, if required to enable the required capacity (trade-off between flight efficiency and capacity).

  The trajectory is owned by the airspace user. Trajectories will be expressed in all 4 dimensions (4D) and will be flown with much higher precision than today. 4D precision data will be shared throughout the system, increasing predictability and improving decision making. A major requirement is therefore to change the current ICAO Flight Plan into a 4D Trajectory with a common definition and exchange format.

  The Business/Mission Trajectory evolves out of a layered planning process. The different development phases of the trajectory are the:

  - Business Development Trajectory (BDT).
  - Shared Business Trajectory (SBT).
  - Reference Business Trajectory (RBT).

- **Flexible and dynamic airspace organization**. In managed airspace a separation service will be provided but the role of the separator may be delegated to the flight crew. In unmanaged airspace the separation task lies solely with the pilot.

- **Automation support**, together with **new ground and airborne separation modes**, will be used to provide additional capacity. Procedures will change significantly and future situational awareness needs will differ from today.

- **Integrated airport operations**. Airports will be fully integrated into the system, with particular emphasis being placed on turn around management, runway throughput and improved environmental performance.

- **Collaborative Decision Making (CDM)** will allow members of the ATM community to participate in the decision-making process and lead to high-quality decisions.

- **System Wide Information Management (SWIM)**. Information sharing in a secure environment is an essential enabler of the foreseen concepts. The current information management, based on fixed network connection and custom, point-to-point, application-level data interfaces, will be replaced by a net-centric operation where the ATM network is considered as a series of nodes, including the aircraft, providing or consuming information. SWIM will provide an open, flexible, secure, service-oriented architecture that will allow for easier addition of new systems and connections. SWIM will support CDM processes using efficient end-user applications to exploit the power of shared information.

- **Interoperability between civil and military systems** will be a key enabler to enhance the overall performance of the ATM network. Mutual consideration and full integration of both civil and military needs in planning of operations will ensure the overall efficiency of the ATM network. The ConOps aims at safeguarding military requirements regarding the access to and the flexible use of airspace.

In order to plan a stepped approach for creating the future ATM system, increasing levels of ATM capability have been defined. The **ATM Master Plan** provides a plan for implementing these capabilities addressing deployment and R&D planning in terms of roadmaps for Operational Evolutions, Enabler Development & Deployment, and Supporting Aspects. The European ATM Master Plan is a "rolling" plan that will be regularly updated, while continuous performance monitoring will be undertaken to ensure that the future ATM activities will deliver the agreed benefits defined within an agreed performance framework.

After the completion of SESAR Definition Phase, the ATM Master Plan was handed over to the **SESAR Joint Undertaking (SJU)**, who is responsible for its execution and updates for the coming years. The SJU was created under European Community law on 27 February 2007, with EUROCONTROL and the European Community as founding members, in order to manage and supervise all projects and activities to be undertaken during the SESAR Development Phase, as defined in the **SESAR Programme**.

The SJU is responsible for "carrying out specific activities aimed at modernizing the European air traffic management system by coordinating and concentrating all relevant research and development efforts in the Community". This includes **long-term and innovative research**.

1.2 WorkPackage E – SESAR Long Term and Innovative Research

It is commonly agreed, and clearly reflected into the Lisbon Agenda and other EU declarations and treaties, that knowledge development and innovation shall be two of the cornerstones of the European economy. A strong collaboration between business, research centers, universities, and the public sector is acknowledged as a key requirement for a successful research and innovation strategy. These principles are also true for ATM: to remain competitive in the global market, long-term research and innovation are as vital for the European ATM industry as they are for any other industry.

Taking into account that ATM innovation cycles are typically between 15 and 20 years, the ATM community must look for "quick wins" that take advantage of already existing concepts and technologies, but also keep an eye on long-term, high-risk, potentially disruptive research that may bring the concepts and technologies that will be implemented 20 years from now.

As indicated in the previous section, all European-funded ATM research and development is now consolidated into SESAR. Whilst most of the SESAR programme is devoted to developing and putting in place the concepts outlined in the SESAR Concept of Operations, in most cases making use of technologies that are already (or almost) ready for implementation, the SESAR Programme also includes a work package specifically devoted to **long-term and innovative research: WorkPackage E (WP-E)**.

The key contribution from WP-E will be twofold:

- Firstly, it will be a **catalyst** to create a healthy European research capability for ATM and related CNS that will persist beyond the lifetime of the current SESAR development programme. To achieve this goal, WP-E will have to stimulate creativity and innovation, develop new scientific and technical challenges beyond those currently identified, facilitate the sustainable development of ATM research capabilities, and promote ATM and air transport as a serious and challenging topic for study, encouraging graduates to seek careers in the discipline.
- Secondly, it will make provision and provide **funding for research activities** that are not currently planned within the 'mainstream' SESAR development work packages. Such research will address applications to become operational beyond the current SESAR timeframe (nominally 2020), as well as innovation that may have application in the nearer term and provide 'quick wins' for SESAR.

WP-E makes use of two main instruments:

- **Research networks** provide a structured way to build research knowledge, competence and capability, through a stable forum allowing the development, exchange and dissemination of knowledge among multidisciplinary groups of organisations (academia, industry, research establishments...) that share a common interest in a relevant domain.
- **Research projects** will explore new ideas falling outside the other SJU work packages. These will be mainly long-term, high-risk and/or high-potential research ideas, but there may be also room for innovative projects with application in the shorter term.

The number of WP-E research themes is initially limited to four. These research themes were defined following broad consultation with experts from academia, industries and various research organisations, the SESAR Scientific Committee and the European Commission. WP-E networks and projects are expected to address the following research themes:

- Legal Aspects of Paradigm Shift;
- Towards Higher Levels of Automation in ATM;
- Mastering Complex Systems Safely; and
- Economics and Performance.

ComplexWorld is the Research Network for the theme 'Mastering Complex Systems Safely'.

1.3 ComplexWorld Research Network - Mastering Complex Systems Safely

Complex Systems Science is one of a number of names given to the study of Complex Systems, also known as Complexity Theory, Complex Systems Theory or Complexity Science. This kind of systems can be defined as the collection of a high number of parts (elements, individuals, agents...) that interact with and adapt to each other, such that the system exhibits behaviours at the system-wide level that emerge from the combined actions of individuals (emergent behaviour) and cannot be understood only from the information stored at the individual level. Understanding how these interactions create the collective emerging behavior is not a trivial task, as emergence carries with it the additional implication that these phenomena typically cannot be predicted by examining the individuals' behaviour alone.

Complexity Science is not a single theory, but it is highly **interdisciplinary** and encompasses a set of ideas, methodologies and tools from different fields, such as nonlinear dynamics, statistical physics, artificial intelligence, or numerical simulation, among others.

Complexity Science has been applied with success to the study of physical (e.g. turbulent fluids) and biological phenomena (e.g. the interactions of the components of living cells) [Har99, And79]. More recently, the insights gained from the study of complex physical systems have begun to be applied to complex sociotechnical systems [Man05, Axe81, Bor03].

ATM system exhibits some characteristics that make it suitable to be analysed from a Complexity Science approach. Let us enumerate the most relevant:

- large number of components;
- heterogeneous components: airports, regulations, flights, natural conditions, etc.;
- multiple temporal and spatial scales;

- highly structured system: there is an airport network structure, on the one side, and many different layers (commercial, regulation, passengers, traffic) on the other;
- complex structure of the interactions between pairs or groups of different components;
- adaptive to the changing external environment;
- system of systems, i.e. single components as airports may also exhibit complex features;
- self-organization;
- non-determinism.

All these characteristics together give rise to emergent behaviours, a fingerprint of complex systems. However, most effort done so far in air traffic modelling has not taken into account this paradigm. The WP-E research theme 'Mastering Complex Systems Safely' will explore how Complexity Science can contribute to understand, model, and ultimately drive and optimise the behaviour and the evolution of the ATM system that emerges from the complex relationships between its different elements.

The **ComplexWorld Network** is an open partnership between universities, research centers, and industry, aiming at:

- fostering the interaction and cross-fertilization between the Air Transport and the Complex Systems research communities;
- identifying the state-of-the-art in the relevant disciplines;
- defining and describing the main research challenges and their potential benefits for the ATM system, in order to set direction for future research and create a momentum of research in the field;
- attracting talented Complex Systems researchers towards ATM; and
- defining, developing and maintaining a clear roadmap for establishing and consolidating a research community at the intersection of Complexity and ATM of clear added value for the European ATM sector.

1.4 The Complex ATM White Paper

The **Complex ATM White Paper** is the common research vehicle that defines the high-level, strategic scientific vision for the Complex World Network. The specific objectives of the White Paper are to:

- analyze the **state-of-the-art** within the different research areas relevant to the Network, identifying the major accomplishments and providing a comprehensive set of references, including the main publications and research projects;
- include a complete list of **tools and techniques** from the field of Complex Systems, a list of application topics, and an analysis of which techniques are best suited to each one of those applications;
- identify and perform an in-depth analysis of the most promising research avenues and the **major research challenges** lying at the junction of ATM and Complex Systems domains, with particular attention to their **impact** and potential benefits for the ATM community;
- develop an **indicative roadmap** on how those research challenges should be tackled;
- identify **areas of common interest and synergies with other SESAR activities**, with special attention to the research topics covered by other WP-E networks.

2 STRUCTURE OF THE DOCUMENT

In the elaboration of this White Paper, three different levels are envisaged: foundations, modelling and applications (the scope of these notions is explained below), as sketched in the following figure:

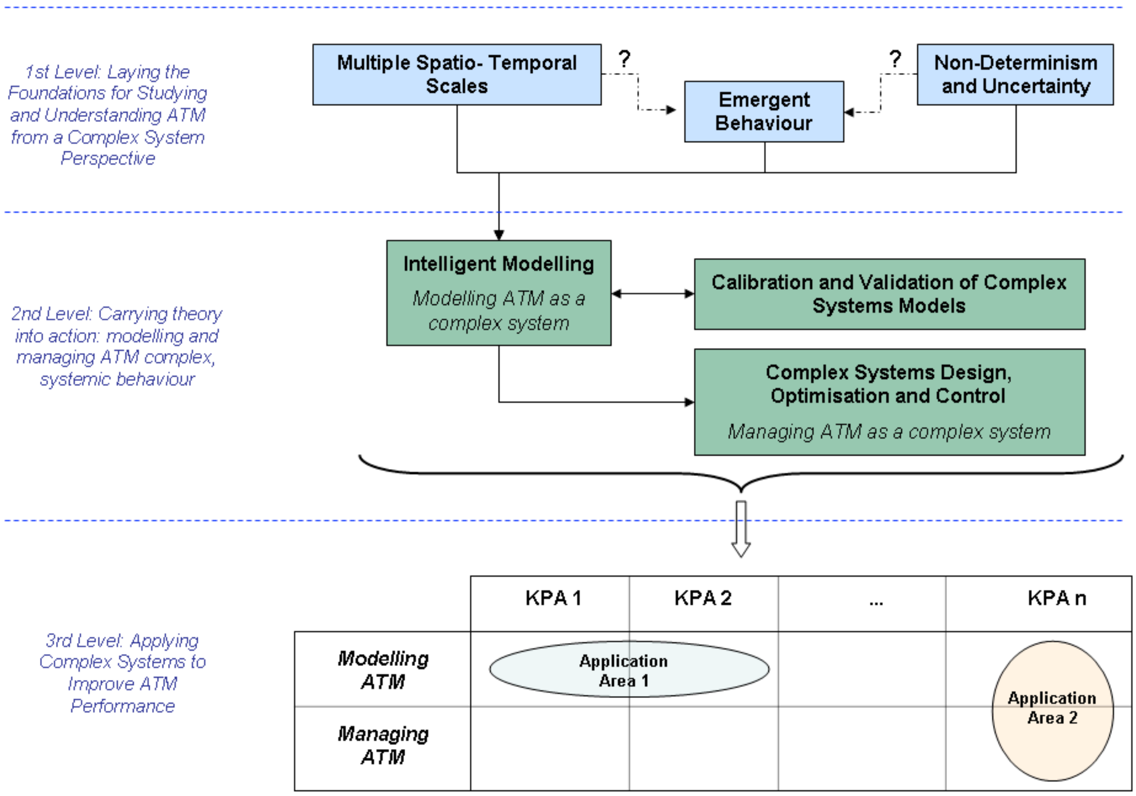

Figure 1. Complex White Paper Structure

These three levels will define the three main parts of the White Paper. The first part (foundations) is formed by Section 3, entitled "Foundations for studying and understanding ATM from a Complex Systems perspective". In this section the characteristics of Complex Systems that can be found in ATM are analyzed; among others, the following: multiple spatio-temporal scales (sub-section 3.1), non-determinism and uncertainty (sub-section 3.2), and emergent behaviour (sub-section 3.3).

The second part (modelling) is formed by Section 4 entitled "Modelling and managing ATM complex, systemic behaviour", in which it is described how the tools and techniques identified in section 3 can be put together to model the ATM system (sub-section 4.1), how these models can be calibrated and validated (sub-section 4.2), and used for the design, control and optimization of the system (sub-section 4.3). A section on information management and decision making is also included (sub-section 4.4). Additional material for this part has been included (provisionally) in Annex 2, called "Resilience and system stability".

As indicated, sections 3 and 4 are divided into sub-sections, according to the different research themes being analyzed. Each sub-section includes a review of the state of the art (definitions and concepts, tools and techniques, gaps, challenges, and barriers), and an identification of related research lines.

With respect to the third part (applications), the objective is to apply the tools described in sections 3 and 4 to tackle specific problems of the ATM system, aiming at the final goal of improving its performance. This part is still at a preliminary stage, and will be completed during the lifetime of the Network (as well as the White Paper itself). At this stage, all the material related to applications is collected into Annex 3, called "Potential applications for complexity science in ATM", in which a total of ten potential applications are described.

One of the objectives of the White Paper is the identification of open research questions linked to complexity applications. A list of such questions, related to the potential applications presented in annex 3, is given in Section 5, called "Open research questions".

The document ends with a final section, Section 6: Conclusions, and with several annexes: Annex 1: Glossary; Annexes 2 and 3, already described; Annex 4: Data Requirements, with a technical description of the data necessary for the identified research threads that are currently missing; and Annex 5: References.

3 LAYING THE FOUNDATIONS FOR STUDYING AND UNDERSTANDING ATM FROM A COMPLEX SYSTEMS PERSPECTIVE

As explained in section 1.3, the ATM system exhibits some characteristic features of complex systems (large number of heterogeneous components, complex structure of interactions...). The purpose of this section is to discuss more in depth some of these properties, in particular multiple-scales, non-determinism, and emergent behaviours.

3.1 Multiple Spatio-Temporal Scales

3.1.1 State of the Art

3.1.1.1 Definition and Concepts

The ATM system exhibits different regimes of operation. The relevant temporal and spatial scales vary depending on the phenomenon within the ATM one is interested in.

For example, regarding the spatial scaling one finds different needs of granularity: European network level, to study phenomena such as network congestion or ATFM algorithms; FABs or National airspace level, e.g. for benchmarking on cost efficiency of different ANSPs; airport level, e.g. to study runway delay. Moreover, there are some events which are space-independent, like adopting regulations or more generally policy making.

In the same way, one identifies different temporal scales. Indeed, conflict resolution takes place within flight times, adaptations of the network to external conditions such as volcanic ash or pilots' strikes occurs over a scale of weeks, and (airport) slot assignment happens twice a year, at the IATA Schedules Conferences (see also Section 3.2).

Modelling systems at a microscopic level may demand huge amounts of computational resources. Given that no every single aspect turns out to be crucial for the study of a given problem, one can gain in efficiency by using a multi-scale approach, in which every question is addressed within the proper level of detail.

There are some basic concepts associated to the problem of having multiple scales. The most relevant among them are the following:

- **Multiscale Modeling** is the fact of solving problems which show important features at several scales.
- **Granularity** is the extent to which a system is broken down into pieces for its observation or modelization.
- **Coarse-graining** is the process of reducing the granularity of a system, lessening the number of degrees of freedom of the system by grouping elements together and losing microscopic detail.
- **Slow and fast variables** refer to those variables of the problem which vary at slow or fast rates, respectively.

The problem of having multiple scales in a system has already been tackled in other disciplines, mainly in physics or biology. To address multiple spatial scales different levels of coarse-graining have been applied. The quantum properties of the atomic nucleus are considered in particle physics, but approximated as a single structure if the object of research is at the atomistic level. Atoms, or even sets of them are taken as individual entities in molecular dynamics [All89, Fre01], for instance.

In the same way, since the nuclear movement is much slower than that of the electrons, the former is considered in a fixed (equilibrium) state to describe the electronic wave function which constitutes the so-called Born-Oppenheimer or adiabatic approximation [Bor27].

Another beautiful example of multiple scales comes from biology: the DNA [Bec07]. The chemical composition beyond the nucleotides is responsible for the ester bonds between the two antiparallel chains, the nucleotide as an entity suffices to codify the genetic sequence, and only groups of nucleotides (genes) are relevant when studying Mendelian genetics.

3.1.1.2 Tools and Techniques

Different tools are commonly used to model and solve multi-scale problems.

Spatial multiple scales

- Division of the system: there is no need to consider the whole system to understand the dynamics of those systems composed of repeated units. Often it suffices with studying a fraction of the system because increasing the size does not alter the dynamics. This is the case for instance in some problems of molecular dynamics, where the whole system is subdivided in grids or cells and the dynamics of some of them with the appropriate boundary conditions properly captures the dynamics of the whole system.
- Coarse-graining: the details of a system needed to solve a given problem depending on the nature of the latter. By coarse-graining one reduces the granularity and the degrees of freedom, making it easy to tackle the problem. The simplest unit is changed and the interactions between them must be modified accordingly. The number of interactions involved is largely reduced [Bec07].

Temporal multiple scales

When more temporal scales (say two) are involved in a problem, one can analyze it by *looking* at both scales separately, using the **singular perturbation method** [Kev96, Smi09]. In this method, first, the constant rates (parameters) associated to both scales must be identified and a small variable is defined as their ratio. The parameters of the problems are redefined in a dimensionless way. So it is the time variable, once for every time scale giving rise to two different sets of equations, one for the fast variable and the other for the slow variable. The slow variable is considered constant and the evolution of the fast variable is analyzed. Then, the slow variable is studied considering that the previously analyzed fast variable evolves instantaneously. Thus a typical behavior of such a system is composed of sudden jumps followed by slow changes.

A prototypical system analyzed using this technique is the Van der Pol oscillator. The method can also be used for studying spatial multiple scales, for instance when investigating the boundary layer in fluid mechanics. An application closer to ATM arises in the equations of flight mechanics, where the flight-path angle is usually considered a fast variable. The method is usually applied to two-scale problems, but it can be generalized to three or even more.

If instead of an analytical solution one is performing a simulation of the problem, it must be paid attention to assure that different phenomena take place at different rates. The equations describing this type of systems are usually stiff (meaning that most numerical methods would produce unstable solutions unless the step size is taken extremely small) [Mir01], thus specially adapted solvers are needed to produce accurate simulations.

For some systems the problem is far less complicated, because the temporal scales are very different and therefore one can consider some properties of the system to be fixed (long time scale, slow variables) to investigate the evolution of other (fast) variables operating in a faster scale. However, the interplay of fast and slow variables is also present in some chaotic systems. In those systems, the evolution of the slow variable moves the system between regions where the fast variables have very different behaviors, producing a non-trivial evolution of the global system.

Statistical modelling

In systems which show multiple scales, some of them are often neglected to address a particular problem. However, the questions pursued might demand information of the neglected spatial details or time variations. Statistical modelling allows capturing the behaviour or states of finer structures and temporal scales with a level of detail sufficient to the problem that is the object of research. A detailed evaluation at the microscopic level can be used to select the most appropriate model for a certain variable, which is then incorporated into the macroscopic model e.g. in the form of a probability distribution.

Therefore, it is important to find the proper statistical modelling which enables to identify the salient features of parts of the system relevant for the scales separation. The first effort to follow this scheme is to find out which are the salient features of system components to properly conduct further investigations within other scales.

3.1.1.3 Gaps, Challenges, Barriers

- Reducing the graining eliminates possible applications of models.
- Using parts of the systems and specially applying boundary conditions to reproduce the influence of the surroundings may introduce ad-hoc effects for very small samples.
- It is difficult to evaluate the loss when approximating parts or events in a system.

3.1.2 Research Threads

- Identify the relevant temporal scales associated to single phenomena within the ATM.
- Identify the spatial scope, if any, in which the dynamics of different ATM phenomena take place.
- Investigate how to apply the scale separation to interrelated phenomena in the ATM context.
- Design suitable coarse-graining of different elements of the ATM for single specific purposes and research topics.
- Estimate the loss of accuracy in the global performance of specific purposes due to coarse-graining processes of single ATM elements or time averages of slow processes within the ATM.

3.2 Non-Determinism and Uncertainty

3.2.1 State of the Art

3.2.1.1 Definition and Concepts

Disturbances and perturbations

Disturbance and perturbation are often used as synonyms. Both refer to activities or phenomena that represent a malfunction, intrusion or interruption in a system. They are also defined as a "secondary" influence on a system that causes it to deviate slightly from its nominal behaviour.

Mathematically speaking, when describing a system by a set of equations (usually nonlinear), perturbations or disturbances are usually regarded as extra terms (sometimes unknown, sometimes impossible to model, or just difficult to study analytically) that play a role in the equations modifying the solution. To be mathematically tractable (given the nonlinear behaviour of such systems), these terms are usually assumed "small" and perturbation theory can be used to analyse the behaviour of the perturbed system. Historically, perturbation theory was born in the field of celestial mechanics; for instance, when computing orbits of a planet around the Sun, the influence of other planets (or moons) can be thought of as a perturbation on the nominal orbit (which does not take into account the other planets or moons). This perturbation is perfectly known (and unavoidable), however it is difficult to describe (due to the complex movement of the planets and moons viewed from the point of view of another planet).

In systems theory, disturbances and perturbations are studied as extra inputs entering the system. When designing control mechanisms for a system, it is frequent to consider "disturbance attenuation" as an objective. That is, to minimize the impact that the disturbances entering the system have in the system output. The use of feedback is the main tool to diminish the sensitivity of the system to disturbances. Robust control theory is a subfield of control theory that concerns itself with the design of feedback laws that guarantee a desired performance of a system even for a wide set of disturbances.

In the context of ATM, we consider a disturbance or perturbation as any influence that causes the ATM system (as a whole, or any of its parts) to deviate from its nominal behaviour. For instance, considering an individual aircraft, we consider a disturbance any effect that makes the aircraft trajectory differ from its nominal (preferred) trajectory. Since the ATM system is subject to an enormous quantity of perturbations and disturbances, it never functions in nominal conditions; for instance, flights seldom depart and arrive at the exact scheduled times. However, the ATM system incorporates many robust control mechanisms (in the form of procedures, regulation and human intervention) that help minimize the impact of the disturbances and make the ATM system robust.

Uncertainty

Uncertainty is defined as the condition of being partially unknown or in doubt. The sources of uncertainty can be several. A distinction between objective uncertainty and subjective uncertainty should be done.

In the first case (objective uncertainty) the system is intrinsically non-deterministic. Even if the present and past states of the system are perfectly known, the mathematical laws of evolution are perfectly known, and one has an infinite computing capability, the future state of the system cannot be predicted. For instance, quantum systems are non-deterministic.

Subjective uncertainty can have different sources. The first case is when the system state is known, the mathematical laws of evolution are deterministic and known, but the system is chaotic. Chaotic systems are those where small variations in the initial conditions may lead to large variations in output. Even though these systems are deterministic, in practice they give rise to uncertainty since the initial conditions can never be perfectly known. Small discrepancies grow in unexpected ways, producing uncertainty in the output for the long term.

The second form of subjective uncertainty arises when the present state of the system is known (possibly with some uncertainty), but more important the mathematical laws of evolution, and the forces (inputs) that affect the dynamics of the system are known only probabilistically. This might be due to the fact that the inputs are themselves the result of the common action of a very large number of individual inputs. To quote an important example, consider the Brownian motion. A small particle (a grain of pollen, for example) fluctuates randomly when it is immersed in a fluid. The reason is that its motion is determined by the collision with a huge number of fluid molecules. Despite the fact that one could describe deterministically these collisions, the large number of molecules involved and the lack of knowledge of their initial state lead to a different type of description. To analyse an uncertain system of this type it is useful to consider it as if it were a non-deterministic system.

This leads to a mathematical approach based on stochastic processes, i.e. mathematical laws of evolution where the inputs are random variables, rather than deterministic functions. The use of stochastic equations to cope with systems characterized by subjective uncertainty is extremely successful in a huge variety of disciplines, including from physics, chemistry, biology, medicine, economics, social sciences and many other disciplines.

In physics the probabilistic approach has also proven extremely successful when a large collection of particles (as opposed to a single particle interacting with many others) needs to be described. The typical example is the description of a gas. Despite the fact that the deterministic mathematical laws of evolution for individual molecules are known, the large number of particles needed to be described makes impossible to use a deterministic approach. Therefore a probabilistic approach should be used, which is the core of statistical mechanics. Note that statistical mechanics has been applied in the recent years to a large number of "non-physical" systems. In fact, the characteristic of being composed by many interacting units is a common feature in society, ecological systems, or economy, among others. Finally, it is worth mentioning the Knightian uncertainty. While uncertainty defined above assumes that the inputs of the system are known in probabilistic terms, in the Knightian case this knowledge is absent or partial.

In the ATM system these definitions of uncertainty have an important role. Most likely objective uncertainty (or non-determinism) is not relevant for ATM. On the other hand subjective uncertainty is key to model and control properly the ATM system. The sources of uncertainty are disparate, ranging from the weather, to operational problems, logistic delays, etc... Each source of uncertainty introduces a disturbance in the planning and in the functionality of the system. A careful characterization of the different possible sources of uncertainty is therefore extremely important in ATM. This characterization has at least three components:

- First, it is important to characterize the statistical properties of these disturbances. In risk management, for example, it is of paramount importance to characterize carefully the probability of extreme disturbances, because they are likely to have a devastating effect on the system.
- Second, it is important to characterize the dependence structure between different sources of uncertainty. Very often in a large variety of systems (for example in economics or finance) this dependence structure is severely underestimated, especially because it is computed in "normal" times, while the dependence becomes significantly larger during extreme events.
- Finally it is important to characterize the effect of a disturbance (or a combination of disturbances) on the system or subsystem of interest. At the simplest level this entails to know the response of the system (or subsystem) to a disturbance. At a higher level the response of the system or subsystem (e.g. an aircraft that must change route because of adverse weather condition) can affect other elements (e.g. other aircraft or airports) and the way in which other elements respond to the disturbance (in the example, the weather). These two forms of propagation of disturbance, direct and indirect, are very important in any complex system and are likely to be very important in ATM.

Relationship between disturbance and uncertainty

Relating the concept of uncertainty with the concept of perturbation and disturbance, it can be said that disturbances and perturbations are sources of uncertainty for a system or subsystem. Disturbances are usually also uncertain, in the sense that they cannot be known a priori. For instance, wind is an uncertain disturbance since it cannot be perfectly described (but can be statistically modelled) which causes uncertainty in the aircraft position.

An open question is whether emergent behaviour is to be considered a disturbance or not. For instance, an emergent phenomenon at a certain scale might be thought of as a disturbance for larger scales.

Example of the evolution of uncertainty for a single flight

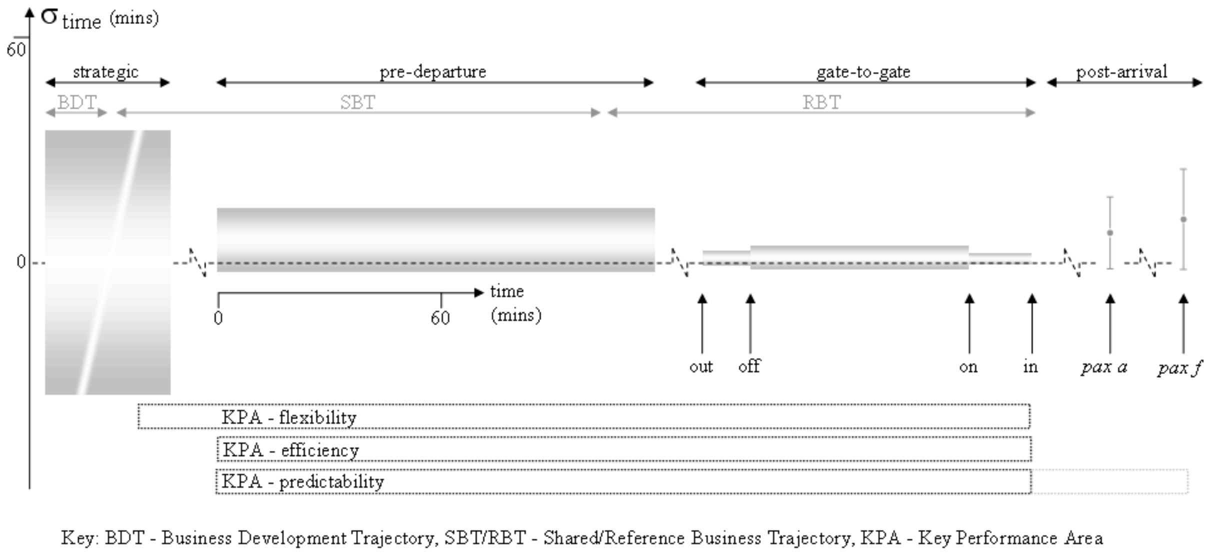

Figure 2. Evolution of uncertainty for a flight

The concept of uncertainty and its evolution is illustrated for a single flight. Figure 2 shows uncertainty evolution (measured as standard deviation of time) associated with a typical IFR flight, as a function of time. Each stage is discussed next.

- Strategic planning stage. Temporal variability is at its greatest during this stage, covering from months before the flight up to two hours before the off-block time. This includes the filing of flight plans but not the ATFM slot allocation process.
- Pre-departure stage. This stage begins with slot allocation (commencing two hours beforehand) and continues up to the aircraft off-block time. Based on intra-European flights in 2008, the standard deviation of delay during this two hour timeframe is 17 minutes [EUR10].
- Gate-to-gate stage: This stage covers the flight. Figure 1 illustrates temporal uncertainty associated with taxi-in and -out phases and how it is slighter greater during the airborne phase (with a standard deviation of around 5 minutes for intra-European flights [EUR10]). A 15 minute take-off slot tolerance is available (-5 minutes to +10 minutes in relation to CTOT) for ATC departure sequencing purposes [EUR10c], however 18.5% of regulated flights in 2008 took-off outside this tolerance [EUR09]. In Europe, delays tend not to be exacerbated during the gate-to-gate stage. The main driver of arrival delay is departure delay.
- Post-arrival stage. This stage commences once the aircraft is on-block. The point estimates *'pax a' and 'pax f'* in Figure 2 represent uncertainty relating to the arrival time of passengers without and with connecting flights, respectively. Temporal uncertainty for *'pax a'* has a standard deviation of around 19 minutes for intra-European flights [EUR10]. The corresponding temporal uncertainty for *'pax f'* is more difficult to estimate.

Propagation and network effects

Delay propagation and its effect on the network follows on from the post-arrival stage. The late arrival of an aircraft (causing 'primary' delays) can trigger 'knock-on' effects in the rest of the network (known as 'secondary' or 'reactionary' delays). Longer primary delays generally lead to worse reactionary delays, as do primary delays that occur earlier in the day. How the delay is propagated through the network can depend on internal factors such as the airline's ability to recover from the delay and external factors such as bad weather [Coo10b].

3.2.1.2 Tools and Techniques

The basic methods to describe and quantify non-deterministic systems are those coming from probability and statistics, in particular from the theory of stochastic process (Markov chains, stochastic differential equations). Some classical methods are the following:

- Monte Carlo methods [Has70]
- Sequential Monte Carlo methods [Liu98]
- Polynomial chaos expansions [Pra10]
- Queing analysis [Kim09]

3.2.1.3 Gaps, Challenges, Barriers

Gaps:

- Uncertainty and its propagation have not been widely studied in ATM.
- Different parts of the ATM system modelled in very different ways; no unified model

Challenges:

- Finding a set of performance metrics that incorporate uncertainty in its definition.
- Measuring the robustness of the ATM system.
- Identifying and quantifying all the sources of uncertainty in the ATM system.
- Finding the right stochastic models that allow describing the ATM system with sufficient accuracy while being tractable enough.
- Describing human performance in the ATM system as a non-deterministic model.
- Studying the cost of delay, using passenger-centered metrics.
- Developing new tools and techniques beyond classical methods.

Barriers:

- Not enough data from the ATM system.
- Lack of computational power for some of the proposed techniques (e.g. Monte Carlo).

3.2.2 Research Threads

(a) Impact of Uncertainty and Accuracy on the System's Behaviour

The goal of this research thread is to investigate and understand how sensitive the system is to measurement errors, lack of precise data, and the uncertainties introduced by intrinsically unpredictable phenomena present in ATM. This research will help build a true performance-driven ATM system, by allowing the development of a set of performance metrics that incorporate uncertainty and accuracy as part of their definition. It will also address how robust the ATM system is and how to built a robust ATM system in relation to the propagation of uncertainty.

(b) Trajectory Uncertainty

This thread includes analysis of trajectory uncertainties and how they propagate upstream through the larger scales of the ATM system. Uncertainty also propagates along the different phases of the flight; thus, climb trajectory uncertainty impacts the descent phase operations and descent trajectory uncertainty further impacts the terminal area operations. Any uncertainty that would cause an aircraft to deviate from its nominal (preferred) trajectory should be considered:

- Uncertainties in the departure airport: ATFM slot delays, uncertainty in taxy times. See for instance [Kwa07].
- Uncertainties in the arrival airport: delays due to sequencing and traffic. See for instance [Kim09].
- Wind. See for instance [Mat09], [Yen03], or [Nil01].
- Uncertainty in the initial conditions. See for instance [Pra10].
- Uncertainty in the aircraft performance. See for instance [Pra10].
- Navigational errors. See for instance [Gre00].
- FMS errors. See for instance [Kim09].
- Changes in aircraft intent. See for instance [Pep03].

(c) Propagation of Disturbances

This thread includes analysis of system dynamics, analysis of ATM system in terms of integration versus segregation, identification of core links and connections, etc. Techniques developed in the Complex Networks domain can be adapted and applied effectively. The understanding of how the effects of a disturbance propagates after the disturbance is "resolved" by the system will shed light on the robustness of the system and on the scale of the optimization method used to resolve the disturbance. Thus understanding disturbance propagation could help to improve disturbance resolution methods.

(d) KPAs

An often-used, useful and intuitive performance metric for ATM is average flight delay. However, the **cost** of delay is not a linear function of the length of delay, so the cost of delay may often be a better metric than average delay (reducing the total system delay does not necessarily reduce the associated total cost - it depends on the **distribution** of the delays). Also, passengers with connecting flights may be subject to (further) delay, or experience delay recovery, during onward flights. A better metric for these passengers is their time of arrival at their final airport (or, ideally, at their final destination). The objective of this research thread is to develop KPAs that include the **cost** of delay and that extend the scope to **passenger-based** metrics.

(e) New Tools and Techniques to study uncertainty in ATM

The tools and techniques described above are of great utility if one wishes to analyze a simple, isolated system. However, new specific methods have to be developed if non-determinism and uncertainty is to be analyzed taking into account all aspects of ATM. These new techniques might be based on classical approaches but need to capture complex, non-classical phenomena such as the emergent behaviour of the ATM system.

3.3 Emergent Behaviour

3.3.1 State of the Art

3.3.1.1 Definition and Concepts

The concept of emergence is a key concept in complexity theory. Emergence occurs when several interacting parts self-organize in structures or interrelations presenting a collective state, some patterns and/or performing coherent actions. The pattern, the collective state and/or the coherent action cannot be explained in terms of the properties of the constituent parts of the system.

The concept of emergence has a long history. The first use of the term emergence with the above meaning occurred in philosophy. The term was used by G.H. Lewes **[Lew74]** to synthesize the philosophical concept introduced by J.S. Mill and illustrated with an example about water. Mill **[Mil72]** stated that "The chemical combination of two substances produces, as it is well known, a third substance with properties different from those of either of the two substances separately, or for both of them taken together".

The overall system arising from the interaction of the different parts is therefore essentially different from just the collection of the parts. New properties, patterns and processes emerge from a set of interacting elements. When emergence is possible, a basic question concerns the way an observer is able to recognize the existence of patterns, phases, coherent structures, processes and properties of the considered system, especially under the unavoidable presence of exogenous or endogenous sources of randomness. The detection of emergence requires an observer. Different observers can conclude differently and therefore emergence detection is relative to specific observers and might present a subjective nature **[Cru94]**.

3.3.1.2 Tools and Techniques

The modelling of emergent behaviour in complex systems requires a multi-disciplinary approach. Tools and techniques are borrowed and adapted from disciplines such as computer science, mathematics and physics. Other disciplines like biology, economic and social sciences, engineering sciences, medical sciences, etc, provide the framework to better focus on the constituent aspects of the investigated systems. In the case of recent new research areas the multidisciplinary approach is observed in the process of the setting and development of the research community and in the selection of the research topics. Examples are the development of network theory **[Alb02,New03]** and system biology **[Bor05]**.

Main classic conceptual tools used to describe and model emergent behaviour in complex systems are: 1) phase transitions and critical phenomena **[Sta71,Bin92]**; 2) hierarchical organization **[Sim62]**; 3) self-similar structures, scaling **[Kad90, Sta99]** and fractals **[Man77]**.

The concept of phase transition and criticality is probably the most important one when a physically oriented modelling of emergent behaviour is accomplished. In the simplest setting, a model (often a highly stylized toy model such as the Ising model **[Hua87]**) of many elementary elements interacting locally, presents a collective state (called phase of the system), whose properties are controlled by the temperature of the system and are characterized by a variable named order parameter. By changing the temperature of the system (or any variable that can play its role in complex systems) the system presents an abrupt transition between different phases of the system (e.g. a transition from a paramagnetic to a ferromagnetic phase). The nature of the phase of the system cannot be related to the microscopic nature of the basic element composing the system (a two state up or down variable in the Ising model). Different phases are separated by a critical state. The physical properties of the system near the critical state can belong to universality classes characterized by the nature of the order parameter of the system **[Bin92]**.

Statistical physics has also developed the concept of self-organized criticality **[Bak87]**. This is a concept showing that a critical state is not only encountered when a system switches between two distinct macroscopic phases but that criticality can also be observed for complex systems that naturally converge to a critical state without an external tuning.

The modelling of emergent behaviour in biological and social sciences has pointed out the importance of the hierarchical structure of complex systems. In the classic setting of this concept H.A. Simon stated that a hierarchic system is "a system that is composed of interrelated subsystems, each of the latter being, in turn, hierarchic in structure until we reach some lowest level of elementary subsystem" **[Sim62]**. The presence of a hierarchical organization with different levels makes natural to observe that intrinsically different scientific descriptions are needed in the modelling of different levels of the system. Anderson pointed out this concept by stating "the behaviour of large and complex aggregates of elementary particles, it turns out, is not to be understood in terms of a simple extrapolation of the properties of a few particles. Instead, at each level of complexity entirely new properties appear, and the understanding of the new behaviors requires research which I think is as fundamental in its nature as any other" **[And72]**. In other words, at different hierarchical levels, emergent properties set up and they might need a scientific explanation, which cannot be given in terms of the scientific laws describing the constituent parts of the lower hierarchical level.

When the hierarchy of the system is of self-similar nature the concepts of scaling and fractal geometry naturally apply. Scaling **[Kad90, Sta99]** is a concept that has originated in different areas of mathematics and physical sciences. It is observed in: (i) the absence of a specific scale for some variables of a system, which is at a critical state; (ii) the allometric laws **[Wes97]** observed between variables characterizing a system. Deviation from isometric scaling is often due to dimensional constraint as it is observed, for example, in turbulence; (iii) the relationships among observables which are functions of random variables (for example linear sum, maximum or minimum value, etc.) and their number. In all the cases the presence of a scaling relation implies a power-law relation or a power-law distribution of some of the investigated variables.

Some techniques used to characterize and model complex systems are briefly summarized hereafter.

Real or model complex systems are usually empirically or numerically characterized in terms of statistical regularities of some macroscopic indicators of the system. For example in a financial market basic indicators are asset return and its volatility, which is the standard deviation of asset return. The statistical regularities of these indicators observed in empirical systems are then compared with the statistical regularities predicted or simulated by agent based models describing the system of interest. Agent based model **[Tes01, Hea09]** is a broad term addressing both simplified "toy" analytical models and numerical models where each single agent has a defined set of rules controlling agent's action as a function of the state of the system and agent rule.

Analytical (when feasible) and numerical investigations of an agent-based model can highlight the presence of an order parameter describing different phases of the system. A paradigmatic example of an agent based model describing agents' decisions in a framework of inductive reasoning of economic agents extensively investigated both analytically and numerically is the so-called El Farol bar problem **[Art94]** and the corresponding formalized version of the minority game **[Cha97]**.

Statistical regularities observed in complex systems are often described in terms of non Gaussian processes obeying to a generalized central limit theorem **[Lev37, Gne54]**. Power-law distributions are therefore quite ubiquitous in complex systems and their presence can originate from several different reasons ranging from aggregation of independent random variables, to the presence of specific heterogeneities, to random multiplicative processes with specific constraints **[Mit04, New05, Gab09]**.

Another quite ubiquitous characteristic of complex systems is the presence of a multiplicity of scales. In the presence of multiplicity of scales some properties of the complex system can become long-range correlated **[Ber94]** and therefore their evolutions cannot be described in terms of Markovian processes.

3.3.1.3 Gaps, Challenges, Barriers

- Need for tools which are effective in the analysis and modeling of heterogeneous complex systems.
- Modelling of out of equilibrium, self-organized, self-assembling systems.
- Development of effective and flexible complexity quantitative indicators.

3.3.2 Research Threads

- Characterization and estimation of the field and limit of application of different classes of Agent based models to the ATM, suitable for the specific issue of investigation addressed.
- Adaptation and development of theoretical and data mining tools effective in the empirical analysis and modeling of the ATM system understood as a heterogeneous complex system.
- Development of statistical mechanics models which are stylized versions of agent based models and can be treated with analytical and/or simulation approaches.

4 CARRYING THEORY INTO ACTION: MODELLING AND MANAGING ATM COMPLEX, SYSTEMIC BEHAVIOUR.

The purpose of this section is to show how the tools/techniques/methodologies/etc. described in section 3 can be combined and customise to (first) model and (second) manage the ATM system. The following issues are addressed: intelligent modelling; calibration and validation of complex systems models; design, control and optimization; and information management and decision-making mechanisms.

4.1 Intelligent Modelling

4.1.1 State of the Art

4.1.1.1 Definition and Concepts

Intelligent modelling is a term which has been coined in many different contexts and refers, thus, to an ample variety of techniques.

- Bio-inspired models and techniques. Nature is probably the most perfect system. Mimicking it turns out often to be the best way to address several problems. Both, robotics and the development of (mostly computational) algorithms find in nature inspiration to achieve their goals.
- Auto-regulated processes as those of control theory are said to be intelligent. The outputs of the system feedback the algorithm and inputs are modified until the desired outputs are met.
- Decision-making algorithms based on logic bifurcations as decision trees or neural networks, are considered as intelligent algorithms.
- Simulation methods and techniques in which some components have the ability to learn, as machine learning or agent-based models are also often referred to as intelligent.

4.1.1.2 Tools and Techniques

To intelligently model a new approach of the ATM, accounting for operational and technological improvements, a great many of the methods which have been used to adequately describe complex systems and (some) described in Section 3 should be properly combined. In addition, other tools coming from close disciplines may be very helpful.

- Adaptive and complex networks
- Genetic algorithms and artificial immune systems
- Control theory
- Pattern recognition
- Cause-effect identification
- Decision theory
- Agent-based models together with game theory
- Influence analysis: Bayesian networks

- Multi-scaling: identifying the right scale to investigate specific problems, accounting for those which are neglected by averaging their essential features

4.1.1.3 Gaps, Challenges, Barriers

Gaps

- To apply the methods and tools of Complex Systems and Data Mining in a context that has not been dealt as a quantifiable system in this sense.

Challenges

- To investigate a very complex system within the novel approach of Complexity Science by integrating elements of different disciplines at different levels of the modelling and research process.

Barriers

- The interdisciplinary character of the approach makes it difficult to coordinate members and integrate techniques of different research communities.

4.1.2 Research Threads

Intelligent modelling lately aims to improve the current models of ATM to improve the understanding and prediction power. A thorough research on this direction making use of the techniques and tools discussed above should work out some or (preferably) all of the following points:

- Analysis of the behaviour of the actual system: patterns, relations between elements, multi-scales.
- Modelling of the ATM system or parts of it within the framework of agent-based models on a network structure. One must take into account the right scale for the issue of investigation. Several questions may be addressed (they may require different models): assessment of the SESAR-defined KPIs, evaluation and propagation of delays, passenger-oriented metrics, etc.
- Evaluation of different scenarios issued within the context of the model.
- Use of Data Mining techniques as neural or Bayesian networks to assess the existence of behavioral patterns as well as cause-effect relations under different problems and scenarios investigated.

4.2 Calibration and Validation of Complex System Models

The problem of validating and calibrating a complex system model is still an open issue and a variety of approaches have been proposed **[Tes07]**. As detailed below there are many reasons for this. A foundational reason is the fact that the concept of "complex system models" is vague and includes a large heterogeneity of model types. Despite the fact that generally complex system models are constructed with a bottom-up approach, i.e. starting by modeling the microscopic elements of the system, the main source of heterogeneity is the level of detail of the model. On one side of the spectrum statistical physicists (but sometimes also prominent economists like Thomas Schelling or mathematicians like John von Neumann) tend to build minimal models that are able to reproduce a given set of empirical facts. These models are sometimes called "toy models". On the other side other scholars, such as economists, believe that a model that does not take into account some important characteristics of the agents is not well posed and probably useless. This is in part a response to the Lucas critique that economic models should be carefully micro-founded. Given this wide spectrum it is difficult to find universal standards for the validation and calibration of models. The other reasons why the problem of validation/calibration is still an open issue do not pertain to the nature of the models and will be detailed in the following.

It is however important to stress that the problem of calibration and validation of complex system models is of timely interest due to the recent availability of detailed datasets of many complex systems. As a consequence of the digital revolution between the 80s and the 90s, more and more data have become available for investigating new empirical facts and for finding stronger support to models. Therefore the recent availability of large data sets on the behavior of agents in different complex systems is opening up the development of modeling which is more empirically grounded and therefore a greater need for techniques of calibration and validation is expected.

4.2.1 State of the Art

There is a significant and rapidly growing literature on calibration and validation of complex system models. Axtell et al. **[Axt96]** develop the basic concepts and methods of an alignment process for agent-based models to test whether two different computational models can be considered similar. In Carley **[Car96]**, there is a first stress on model validation with a focus on computational modeling in general. Gilli and Winker **[Gil03]** present an agent-based exchange market model and introduce a global optimization algorithm for calibrating the model's parameters via simulation. Troitzsch **[Tro04]** enumerate many issues concerning the validation of simulation models to describe and predict real world phenomena. Fagiolo et al. **[Fag07a, Fag07b, Win07]** present a review of the ways agent-based modelers have tried to face the empirical validation of their models. Finally, without any presumption of being complete and exhaustive, we cannot forget the mainly theoretical and methodological contributions by Kleijnen **[Kle95]**, Sargent **[Sar98]**, Kleijnen **[Kle98]**, Klevmarken **[Kle98b]**, Epstein **[Eps99]**, Barreteau et al **[Bar03]**, Judd **[Jud06]**, and Marks **[Mar07]**.

4.2.1.1 Definition and Concepts

When one builds a model, there is the underlying assumption that the real world can be considered a causal data generating process. The modeling effort is aimed to find a parsimonious description of this causal process. An important assumption is that the model must be simpler than the reality under investigation. It is therefore clear that there is always a tradeoff between accuracy and parsimony of the model. A more complicated model will often be able to model better the reality simply because of the increased number of degrees of freedom. However this statistical effect can misguide the modeler in the direction to follow.

An important dichotomy on the role of the model is the one between instrumentalism and realism. Some scholars believe that the final aim of any model (and in particular complex system models, such as, for example, agent based models) is the ability to forecast the behavior of the system even if the causal process of the model might be very different from the real causal process. The other point of view posits that forecasting is not the main purpose of complex system model. On the contrary, these models serve to understand causal relations between micro and macro phenomena or the origin of relations between macro variables. Models are useful to test counterfactual proposition and to answer "what if" type questions. The validation and calibration of these models is done primarily in the setting of the model rather than by comparing the output with the reality.

4.2.1.2 Tools and Techniques

According to Fagiolo et al. **[Fag07a]** the validation/calibration approaches to complex adaptive system models can be divided in three categories.

- **Indirect calibration approach**. The main steps are: i) identification of the (macro level) stylized facts or statistical regularities that one is interested in reproducing with the model, ii) model building taking the microscopic description as close as possible to the empirical evidence, iii) restriction of the parameter space (and the initial conditions) by using the comparison of stylized facts in reality and in the model as a guide.
- **Werker-Brenner approach** to calibration **[Wer04,Wer07]**. The main steps are: i) use of empirical knowledge to calibrate the parameters and the initial conditions of the model; if no data are present on an aspect, leave the model as general as possible, ii) use Bayesian inference procedure to validate the model reducing the space of possible parameters; this is done by retaining only model specifications associated to the highest likelihood, iii) recalibrate the model on the surviving set of parameters.
- **History friendly approach [Mal99]**. This modeling approach seeks to bring modeling in line with empirical evidence by using specific historical case studies to model parameters, interactions, and rules.

A different classification of validation schemes of complex system models is the following **[Bia08]**:

- **Descriptive output validation**. This is an ex-post comparison between the output of the model and the real data (similar to 1 above) .
- **Predictive output validation**. In this case the main objective of the validation/calibration scheme is to forecast out of sample the behavior of the real system modeled. This out of sample forecasting can be done on yet-to-be generated data or by using hind casting. This amounts to pretending to be at a given reference point in time and forecasting known "future" values. (Forecasts are made for points that are in the future relative to the reference point, but in the past relative to the present, and therefore known). This is a specific instance of the statistical technique known as cross-validation. It is a much more reliable measure of the forecasting ability of a model than goodness of fit, even with parsimony measures such as Akaike Information Criterion.
- **Input validation**. This can also be called ex-ante validation and it focuses on the calibration of the input parameters rather than on the final output of the model.

4.2.1.3 Gaps, Challenges, Barriers

There are many problems in the properties of complex system models that makes difficult their validation and calibration compared to other types of models **[Fag07a]**.

First of all, as mentioned in the introduction, complex system models are very heterogeneous in their properties, level of sophistication, number of parameters, etc. The spectrum ranges from toy models often inspired by Statistical Mechanics and that aim to capture the essence of the phenomena with the smallest number of parameters, to carefully micro-founded models where most of the effort is placed in the proper characterization of the behavior of the simplest entities (agents) of the model. Given this large heterogeneity of complexity it is very difficult to ascertain the connection between different models. This difficulty is often present also when models of similar complexity are compared.

The second problem is related to the calibration/validation process itself. As we (will) see, very often the calibration/validation process is done by comparing the output of the model with some statistical properties observed in the real system under investigation. These statistical properties, sometimes termed "stylized facts" (especially in economics) are regularities (e.g. distributional and correlation properties) observed in different realizations of the complex system. Now while the stylized facts can be often parameterized with few parameters (or qualitative behaviors), complex system models depend on many more parameters and therefore there is typically a strong degeneracy in the number of model parameter sets that are able to reproduce the empirical facts (overfitting).

A third issue concerns the lack of standard techniques for analyzing complex system models. **[Leo06]** Different modelers have different standards of what they consider a proper calibration/validation of a complex system model and how to perform a sensitivity analysis of the model.

A fourth point concerns the ergodicity of the model and the role of initial conditions. If the model is not ergodic the output of the model is strongly dependent on the initial conditions also after a long simulation time. In this case the calibration/validation process must be performed also on the initial conditions and not only on the parameters of the model.

As we have seen above an important role is played by the process of model calibration. Calibration is important but presents several critical issues **[Fag07a]**. First, calibration is not helpful in establishing if the model is correct. In other words, a calibration always gives optimal values of the parameters, even if the model is profoundly wrong. Second, calibration affects the type of models that we are able to build. If some variable is impossible to calibrate for lack of data, there might be a tendency to develop models in which this variable is excluded. Related to this point there is the problem of biases and censorship in the calibration process due to the available data. Third initial conditions, time dependent parameters, and the possible existence of multiple regimes in the calibration window can affect severely the quality of the calibration.

4.2.2 Research Threads

- Development of techniques for validating and calibrating complex system models of ATM through:

  (i) descriptive output validation, i.e. validation/calibration obtained by matching the model output with the aggregate empirical statistical regularities,

  (ii) input validation, i.e. calibration of the model parameters from survey data and interviews of ATM stakeholders,

  (iii) predictive output validation, i.e. validation obtained by considering the predictive power of the model.
- Construction of empirically based agent based models [Jan06], i.e. agent based models constructed starting from the statistical regularities of individual agents observed in ATM data.
- Development of statistical mechanics models of the ATM and their validation/calibration with analytical and/or simulation approaches.

4.3 Design, Control and Optimisation

4.3.1 State of the Art

4.3.1.1 Definition and Concepts

It has been shown in previous sections that the ATM system requires unconventional modelling techniques to be able to capture its full behavior as a complex system. This also implies that classical methods of design, control and optimisation are not well suited to be directly applied to the ATM system. This section presents some ideas of how the previously derived (and verified) complex models can be managed to improve the performance of the ATM system.

In the context of complex ATM, the concepts of design, control and optimisation are defined as follows:

- **Design** refers to the use of the complexity tools and complex models when planning changes or new additions to the ATM system. For instance, tasks such as the design of new procedures, the planning of routes or the assignment of resources can benefit from the application of techniques and models that capture the complex behavior of the ATM system and include aspects such as emergent phenomena or uncertainty.
- **Control** refers to the management of the ATM system. This management might be automatic or human-based, but in any case involves the use of procedures or mechanisms that modify some of the available inputs of the system, based on measurements or estimations of its states, to get the system to behave in a desirable fashion (with features such as robustness, safety, stability, and good performance). These procedures or mechanisms are usually known as control laws. The complexity of the ATM system requires the use of advanced techniques of control that will be described next.
- **Optimisation** refers to the adjustment of some of the tunable parameters of the system, in a way that the behavior of the system is the best possible (or at least, close to the best possible) with respect to some measurable cost index. Optimisation and control can be blended together in what is known as optimal control, where the inputs of the system are used not only to get a well-behaved system but also an optimally-behaved system (with respect to some cost index). Regular optimisation techniques are not able to deal with complex aspects of the ATM system such as uncertainty, therefore special methods have to be used.

4.3.1.2 Tools and Techniques

There are several advanced methods from the field of control and optimisation that are able to cope with some of the complex aspects of the ATM system. For instance:

- **Stochastic optimisation**: this includes optimisation methods that incorporate probabilistic elements, either in the optimisation algorithm (e.g. random optimisation techniques), in the problem data (e.g. the cost index to minimize or maximize is the expected value of some random variables) or both [Spa03].
- **Stochastic control**: this is a subfield of control theory than considers uncertainty in the system to be controlled, which can be in the form of parameter uncertainty, random noise entering the system, or unmodelled dynamics. Techniques of stochastic control include robust control (dealing with bounded modelling errors and noise), non-linear stochastic control (dealing with non-linear systems with uncertainties), Kalman filtering (to estimate the states of uncertain systems), etc [Ast06].
- **Hybrid control**: this area of control theory deals with hybrid systems, which are systems described by both continuous and discrete states [Cas06].
- **Distributed (decentralized) control**: for systems (such as ATM) which are composed of many parts, it is not possible to design a unique, centralized controller that manages the whole system. Instead, it is more desirable to design a network of distributed controllers that locally manage parts of the system and coordinate through a communication network. Distributed control deals with all the issues raised by the design of these types of control laws [Lav08].
- **Multi-agent planning and optimisation**: this involves coordinating the resources and activities of multiple objects that interact among themselves and with the environment, so that some common objective is fulfilled [Ned10].
- **Stochastic optimal control**: a blend of stochastic optimisation and stochastic control, this area encompasses a set of techniques (such as dynamic programming, stochastic programming, particle methods, differential games) that design optimal control laws for uncertain or non-deterministic systems with deterministic or probabilistic constraints [Ste86].

- **Singular perturbation control methods**: this involves the use of singular perturbation theory for multiple-scale systems, which allows order reduction and the separate design of control laws for the different scales of the system [Kok87].

4.3.1.3 Gaps, Challenges, Barriers

Gaps:

- Most applications of the previously described techniques to the ATM system have been very limited (with very simplified models).

Challenges:

- Develop method that are implementable in the ATM system, i.e., technologically feasible and that can be accepted by all the agents present (ATCs, users, etc.).
- Develop real-time algorithms for tactical planning.
- Modelling and taking into account users' preferences.
- Guaranteeing safety.

Barriers:

- Lack of knowledge of all parameters involved.
- Many algorithms too slow to be used even for strategical planning.
- Distrust of the ATM community (based on safety-related concerns).

4.3.2 Research Threads

- **Reduction of the impact of uncertainty in the ATM system:** Including re-design parts of the ATM system and/or use control methods in its management in order to reduce the impact of uncertainty in the system, making the ATM system more robust and predictable.
- **ATM process optimisation**: For instance, analysis and design of algorithms for ATM processes such as pre-departure flight planning, (tactical) algorithms for trajectory re-planning during flight, tactical or strategical conflict resolution, etc. Such algorithms should take into account all known information and uncertainty models.

4.4 Information Management and Decision-making Mechanisms

4.4.1 State of the Art

4.4.1.1 Definition and Concepts

Although the current ATM system is highly mechanized and automated, the role of humans in the design and management of the system, and in particular the role of humans as sender, receiver and handlers of information, is not to be disregarded. Flights, airlines, air traffic control, or airports are all ruled by persons who interact with each other to ensure a smooth running of the ATM as a whole. Many daily operations, unexpected events, or changes are the result of human failures and decisions. Accounting for the human factor, first in the system design, through predictive models, and lately in the daily activity of ATM, is a promising path to improve the performance of the system.

Characterization of actors

The dynamics of the ATM is shaped, among other factors, by the actions and interactions of a heterogeneous set of actors standing for different key groups. Their decisions play an important role in several and different temporal scales; from the reaction of a pilot to an unexpected and hazardous event in tens of seconds, the substitution of a crew in a period of hours, up to the assignation of a slot in a scale of months, to name a few.

A suitable characterization of the actors taking part in the dynamics is the first requisite to develop a reliable model based on the simulation of agents' interactions.

Some open, exciting questions to be investigated, related with the characterization of agents are listed below:

- Is it possible to classify the behaviour of the agents involved in ATM processes along the following three abstraction dimensions:
    - temporal dimension (i.e., transitions between subsequent time points vs. emerging patterns over longer time periods),
    - process abstraction dimension (i.e., from physiological functioning of agents via cognitive and affective processes to behaviours), and
    - clustering dimension (i.e., from individuals to subgroups to teams as a whole)?
- How do behavioural or cultural constraints condition expectations and commitment in different cultures? For instance, are there any differences between North and South Europe? What are the foundations to achieve cooperation?
- How do persons, passengers or service providers, react in case of risk, threat, or crisis?
- To what extent is the cost of image important and how does it depend on the origin of the receiver? This is related with what has been referred to as reputation in game theory, a mechanism that enhances cooperation.
- Let's assume that individual behaviour depends on the reward and that interactions could be modelled by game theoretical algorithms. Within this context, how does the strategies space vary, depending on the number of players, their nature, and the information available? What is the role of noise in single actions, does it change potential choices? We refer to noise as the lack of information about others' reactions to own actions.
- How are 'norms' established in many persons games and how do the mechanisms differ from each other for an increasing number of players? What is the role of punishment, policing, and self-policing in changing the agents' behaviour if they interact more than once?
- What is the impact of agents' emotions on the dynamics of the ATM process? This may include both intra-agent aspects (e.g., interaction between affective and cognitive aspects) and inter-agent aspects (e.g., contagion of emotional states between individuals in a team).

The role of information

The last years have provided us with many examples in which unexpected events have stricken the ATM system, such as the Eyjafjallajokull eruption, the unusual strong snowfalls in central Europe in the last winters, or the controllers strike in Spain in December 2010. All these examples may be classified as black swan, irregular or unexampled events, which probed the resilience of the system. Furthermore, in all of these cases the time the system has needed to recover and go back to normal conditions of operation has been very long, sometimes longer than the crisis period itself. When facing such threats, it is of utmost importance for responsible stakeholders to count on efficient and available flows of information, in order to make timely decisions. Moreover, a proper information system may reduce the problems for passengers, as unnecessary waits at the airport terminals.

Improving this shortage is finely related with the access and flow of information, and particularly how this conditions the decision making process. Some questions of research regarding this issue have been identified and are listed below:

- Application of advanced modelling for processing and managing stochastic information (e.g., trajectory prediction and performance management). Agent based modelling and game theory principles may be used to model and analyse interactions among different stakeholders and to design robust CDM protocols.
- How to estimate and represent the uncertainty related to the information exchanged by stakeholders? How confidence intervals can be narrowed down? How uncertain information affects decision making and performances at the different phases?
- How does the available information modify the strategies of the stakeholders? In particular, what are the differences between the information to which stakeholders are aware they don't have access (inherent restrictions), and the information which may or may not arrive depending on the efficiency of propagation and the uncertainty related to it (circumstantial restrictions)?

The dynamics of the decision making process

Once agents and information flows are modelled, they must be brought together to understand their impact on the system dynamics as a whole. Some interesting related questions and research threads regarding this point are:

- Multi-agent situation awareness [Str03]. Due to measurement imperfection, or processing and communication delays, different aircraft can see the same situation differently. These differences can be related to aircraft states and intents and can result in different situation awareness, in particular conflict detection.
- Appealing questions related to this problem are: how can a consensus (i.e. an agreement on what all the involved aircraft perceive) be achieved with minimum additional information exchange? How stable is this consensus in time? How does the lack of information condition the nature of this consensus?
- How to implement collaborative decision making with several stakeholders having asymmetric access to information? To what extent is an agent-based modelling able to capture and reproduce this dynamics?
- Modelling collaborative decision making, for scheduling, ATFM, optimization, resource allocation.

5 OPEN RESEARCH QUESTIONS

No order of prioritisation is implied.

Question 1

SESAR's performance-based approach measures outcomes through KPIs. Inherent contradictions exist between these KPIs, however, in that it is not possible to optimise all of them simultaneously. For example, over multiple scales, fundamental conflicts may arise between efficiency (minimising the cost function) and equity (the absence of systematic bias against certain flights, airlines or origin-destination pairs). How can complexity science help to optimise these scales on a metric-by-metric basis, and deliver needed insights into the complex interactions between them? Is it possible to derive better KPI classifications (through data reduction, for example) to reduce such conflicts?

(See also Annexes: 3.3, 3.5, 3.6, 3.8 and 3.9)

Question 2

Thousands of elements have to be considered at an airport, e.g. aircraft, fuelling vehicles, push back cars, passenger buses, and gates. Depending on the task and desired resolution not all of them are always relevant. Different views and levels of abstraction exist. Small perturbations in on view, however, may affect another view and may have consequences on the whole system.

How can complexity science help to model the system in the right way? How can we predict the future behaviour of the system and last but not least how can be influence its behaviour although disturbances are present and we have only incomplete knowledge of the system?

(See also Annexes: 3.3)

Question 3

Adverse weather represents a challenging limiting factor of the capacity of the ATM system. In practice, it requires traffic managers to reroute all flights affected. Today's methods for rerouting traffic are such that the reroute alternatives provided are limited, leading to high air traffic congestion. An open research question is how and which complexity science tools can be used to widen the set of operationally acceptable reroutes (selected according to a set of metrics that must be defined), so that the available airspace capacity is maximized, while maintaining a safe airspace throughput, taking into account the inherent uncertainty that characterizes adverse weather.

(See also Annexes: 3.4, 3.7 and 3.9)

Question 4

Which complexity techniques seem best suited to differentiate 'resolvable' uncertainty (which arises due to lack of appropriate data and enabling technologies) from 'irresolvable' (or 'residual') uncertainty (which arises through factors such as weather) and estimate their corresponding contributions to KPA outcomes (an example discussed is airport emissions)? Such research needs to embrace the multiple scales involved (e.g. remote actions impacting ground movements at the airport) and the multiple stakeholder objectives (e.g. airline cost minimisation c.f. ANSP capacity utilisation c.f. airport LAQ targets).

(See also Annexes: 3.4 and 3.6)

Question 5

The ATM systems will face a massive increase of the air transport in the next years. The quantitative characterization of the way disturbances and delays propagates across the airspace sectors will be more and more relevant. Related to this point are the questions: is it possible to identify early warning signals of critical events in air traffic? How does the propagation depend on the ATM (for example actual vs SESAR scenario)? Is it possible to design ATM schemes, which are robust and resilient to disturbances?

(See also Annexes: 3.2, 3.3, 3.4 and 3.7)

Question 6

Safety events are typically considered and studied in isolation. However in an heavily congested traffic situation, single safety events (and their resolution by the ATM system) might trigger other safety events in a cascade fashion, eventually leading to catastrophic events. This is the result of a local optimization and a lack of sharing of information among stakeholders. Is it possible to quantify and characterize the propagation of safety events? Is it possible to design a robust safety control system?

(See also Annexes 3.7, 3.8 and 3.10)

Question 7

In ATM decision-making, how do we evaluate the worth of obtaining further information and of evaluating the cost of providing such information (e.g. through SWIM) as the multiple scales evolve (with increasing uncertainty over greater scales)? Classical statistical decision theory informs rational choices when information is incomplete and uncertain. Bayesian decision theory allows us to evaluate the expected value of 'best' information. How can we develop Bayesian network models (apply Bayesian statistics in the context of graph theory) to identify new ATM optima, using revised probabilities, as additional, empirical information becomes available?

(See also Annexes: 3.3, 3.5 and 3.7)

Question 8

Resilience is widely recognized as one of the tenets of the future ATM system, and is defined by its capacity of tolerate disturbances without dramatically reducing its performance. Within this wide field of research, the first problem to be solved is the assessment of the resilience of the actual ATM system, i.e., the estimation of the sensitivity of the system to some standard perturbations, in terms of reduced capacity, predictability, or safety, by using historical data.

(See also Annexes: 2 and 3.2)

Question 9

Although the main objective of air transportation systems is to cover people's needs, which usually measure large distances in time and money, rather than kilometers, this aspect is not always taken into account when the problem of routes and scheduling optimization is tackled. In this context, deeper studies are needed to focus this problem from a citizens' mobility perspective, using Complex Systems' tools as random, time-dependent graphs, as well as Stochastic Optimization and Stochastic Optimal Control.

(See also Annexes: 3.1, 3.4, 3.7 and 3.9)

Question 10

Another proposed research question is how to use the complexity science techniques for the provision of safety analysis feedback to advanced Air Traffic Management (ATM) designs. Advanced ATM design involves much more demanding changes than those commonly addressed by established safety case practices: because of the many interactions, such safety analysis is expected to greatly benefit from using complexity science techniques.

(See also Annexes: 3.8 and 3.10)

ANNEX I. GLOSSARY

ABM	Agent-Based Models
ACC	Area Control Centre
AMAN	Arrival Manager
ANSP	Air Navigation Service Provider
ATC	Air Traffic Control
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
BDT	Business Development Trajectory
CDA	Continuous Descent Approach
CDM	Collaborative Decision Making
CTOT	Calculated Take-Off Time
DLR	German Aerospace Centre
DMAN	Departure Manager
DNA	Deoxyribonucleic Acid
FAA	Federal Aviation Administration
FAB	Functional Airspace Block
IATA	International Air Transport Association
ICAO	International Civil Aviation Organisation
KPA	Key Performance Area
KPI	Key Performance Indicator
RBT	Reference Business Trajectory
SAM	Safety Assessment Methodology
SBT	Shared Business Trajectory
SES	Single European Sky
SESAR	Single European Sky ATM Research
SJU	SESAR Joint Undertaking
SWIM	System Wide Information Management
TBO	Trajectory-Based Operations
TMA	Terminal Manoeuvring Area

ANNEX II. RESILIENCE AND SYSTEM STABILITY

The concept of resilience in the literature

In literature, resilience is well studied in the following four fields:

- Ecology
- Sociology
- Organization Science
- Safety Science

In each of these fields the topic of resilience has been (and is still being) the focus of a high number of research activities. In order for ATM to take maximal advantage of earlier resilience developments, this section provides a short overview of these four fields.

Ecology has been one of the first fields of research where the concept of resilience has been successfully developed: see, for instance, the first works of [Bed76] and [Pim84], up to more recent reviews of [Gun02], or [Ber03]. In this context, resilience is defined as the capacity of an ecosystem to tolerate disturbance without collapsing into a qualitatively different state, which is controlled by a different set of processes. For instance, an ecosystem may be shocked by the entrance of a new animal, which may interact with the original species and change the availability of foods and of other resources inside the region; if the original species are able to react and survive the change, the ecosystem is defined as resilient. Therefore, a resilient ecosystem is characterized by its ability to withstand shocks and rebuild itself when necessary. When these shocks are unexpected, they are usually called black swans [Tal07]. Regarding ecosystems, black swans have three interesting characteristics: they are treated as outliers (that is, extremely rare events), they have a high impact in the way the system is functioning, and finally they are usually retrospectively viewed as predictable [Mur09]. It is also interesting to note the positive effect of these events: they do not only modify the way the system works, but also the way we understand the system; in other words, they usually trigger a learning process.

A complementary approach toward resilience has been developed in social sciences, and specifically by sociology [Ber03] and human development [Lut00]. Resilience was defined here as the dynamic process encompassing positive adaptation, i.e., leading to an improvement of the social and personal conditions of the individual, within the context of significant adversity. Implicit within this notion are two critical conditions: (1) exposure to significant threat or severe adversity; and (2) the achievement of positive adaptation despite major assaults on the developmental process. Although this definition may seem equivalent to the one presented above, social systems have an added capacity with respect to ecological ones: the humans' ability to anticipate and plan for the future. This ability allows the human being to act proactively, and improve resilience before the adverse events impact the system.

The third development of resilience concerns organizations. The building of resilient organizations has been proposed by [Rob00b], integrating ideas on the structure and dynamics of organizations that successfully survive and develop in complex and turbulent environments ([Arg96], [Sta96]). In order to construct a Resilient organization, the numerous parts or units composing its complex structure should be organized in two intermingled and integrated streams. The first one, called Performance System, is in charge of pursuing excellent performances in the short term, which are of course essential for the organization to survive in the market. While in classical organizations this Performance System is static, within this new view to resilient organizations it is dynamically created and dissolved to respond to the continuous changes in the environment: the management and coordination of this creation / dissolution process is performed by the Adaptation System. Although both systems must work together and be integrated in the whole organization, each one of them should be characterized by a different set of

Architectures, Skills and Culture. Performance systems are oriented toward production and tasks, with clear procedures and analytical and rational thinking, in order to obtain a competitive advantage in the market in the short term. On the other hand, adaptation systems prime innovation, experimentation and learning for the long term, focusing on the outside of the organization to detect uncertainties and changes in the environment.

In safety sciences, [Hol06] introduced the concept of resilience engineering with the aim to address the human and organizational aspects well in the design of safety critical socio-technical systems. In a Socio-technical system, introduced in [Eme60], there are complex interactions between humans, machines and environmental aspects. More recently, interaction of a socio-technical system with its environment has been identified as an essential ingredient (e.g. [Bad00]) of an open socio-technical system. Typically, these interactions are bidirectional: an open socio-technical system adapts to the environment, in order to be able to fulfill its objective in an ever-changing context, but at the same time it influences that environment with its actions. In safety science it is commonly recognized that established safety engineering approach falls short in adequately handling the challenges posed by the design of safety critical socio-technical systems, especially if open.

In order to fill this gap, resilience engineering is aiming at the human ability to manage performance variability to positively afford disturbance, or, in other words, on the active capacity of a socio-technical system to tolerate perturbations that are originating either internally, or from the environment. [Hol06] propose a categorisation of three types of these disturbances:

- Regular threats;
- Irregular threats; and
- Unexampled events.

[Hol06] also propose guidelines for improving resilience in (open) socio-technical systems, such as:

- Managing for sustainability: that is, not pushing the system to its limits, but maintaining diversity and variability; this implies that one should not optimize some parts of the system in an isolated fashion: instead of that, the whole system should be taken into account, thus maintaining redundancy, even if this may result in a higher cost.
- Assess types and sources of uncertainties, and also identify sources of flexibility.
- Importance of learning: resilience is built out of a broad repertoire of action and experience, the ability to recombine fragments of past experience into novel responses, and knowledge of how the system functions.

[Hol11] presented an integrated view of resilience, where it is understood as the intrinsic ability of a system to adjust its functioning prior to, during, or following changes and disturbances, so that it can sustain required operations under both expected and unexpected conditions. According to the authors of that paper, resilience is provided by four abilities:

- Responding: this ability includes the knowledge of what to do, that is, how to adjust the normal functioning of the system to minimize disruptions. This includes two main complementary abilities: first, the system should be able to decide whether it is necessary to react to a given situation, because it is a threat, or on the contrary if it does not require any special action; second, the system should be able to allocate enough resources, that is, a buffer of extra resources should be available when needed.
- Monitoring: monitoring the performance of the system, and even monitoring the external environment, is essential to detect incoming threats. Two kinds of mechanisms may be implemented: lagging indicators (that is, indicators that represent the past) and leading indicators (anticipating what may happen, before it will happen). Leading indicators also use

information of the past, but the difference is that lagging indicators determine e.g. an existing big delay or an unbalanced capacity-demand-ratio whereas leading indicators predict e.g. a future unbalanced capacity-demand-ratio As resilience also includes an adjustment prior to the disturbance, it is proposed that the main monitoring activity of the resilient system should be performed via leading indicators.

- Learning: although this ability seems straightforward, learning toward resilience should take into account several specific aspects. First of all, the learning process should be focussed on understanding how the system works, and not just why it has failed. Second, and as a consequence of the previous point, it should be a continuous process, not triggered just by adverse events. Finally, it is not enough to link causes with effects; instead of that, dependencies among different functions of the system should be unveiled.
- Anticipating: as monitoring refers to the analysis of the system and its environment in the near future, anticipating refers to the same activity, but focusing on a longer time horizon.

Resilience in ATM

As already introduced, the Air Transport System is constantly influenced by internal and external events. Every day, several times each day, and in different locations at the same time, the operation of the system is perturbed by the small disturbances that have been described in Section 3.2. Even worse, these disturbances may interact with each other, creating a cascade of adverse events that may span over different spatial and time scales, from affecting only one aircraft or a crew, up to a group of airways crossed by a thunderstorm; but, at the same time, they usually have small impact in the overall performance of the system, thanks to its own resilience – aircraft and crews may be rescheduled, flights may be rerouted, and so forth.

A complementary problem is represented by those events that push the dynamics of the Air Transport System far away from its normal point of operation. For instance, a large strike, the eruption of a volcano, or the closure of an airport dramatically affect the performance of the system. Note that these events are not small disturbances, affecting a single or a limited number of aircraft: they have system-wide consequences; moreover, these events were not predicted nor expected, and the process to go back to a normal operation is not trivial. Luckily, these black swan events are quite rare: but this low probability of occurrence also makes any analysis more difficult.

Air Transportation and ATM have experienced an important and fast evolution in the last decades, with a constant growth in the number of flights, aircraft and airports. Also, the market itself has changed significantly: from being composed by a small number of national airlines, up to the recent appearance of many companies with new business models.

In this context, the optimization of common airspace resources, along with more strict safety regulations, has reduced the flexibility of some actors, as well as their capacity to react to a changing environment, in turn, reducing the resilience of the system. Even the definition of which events are "normal", that is, taken into account in the design of the system, is not a trivial problem: and this is worsened by the ever changing nature of the ATM – an event may be extremely rare today, but not so rare tomorrow.

In order to continue having Air Transport one of the pillars of our society, allowing the connectivity and mobility of European citizens, and to be both competitive and complementary to other alternative transportation modes, resilience should be clearly included in future ATM research and engineering. Network-based operational techniques to absorb extraordinary and "black swan" events should be developed, trying to retain acceptable performance metrics in any condition.

Resilience as a strategic policy priority

The importance for the future Air Transport system of sustainability in general, and of resilience in particular, has been recently recognized in policy-making context. The Commission's new roadmap (White Paper) to a Single European Transport Area for 2050 [Eur11], opens with the following text:

> *Transport is fundamental to our economy and society. Mobility is vital for the internal market and for the quality of life of citizens as they enjoy their freedom to travel. Transport enables economic growth and job creation: it must be sustainable in the light of the new challenges we face.*

Once the Air Transport is recognized as one of the tenet of our society, it is necessary to identify which elements are central for its development; the same document goes on to stress the important role of airports:

> *A Single European Transport Area should ease the movements of citizens and freight, reduce costs and enhance the sustainability of European transport. The Single European Sky needs to be implemented as foreseen, and already in 2011 the Commission will address the capacity and quality of airports.*

Recent events have also stressed the importance of combining the growth of the Air Transport with strategies focused in improving its long-term resilience. Of particular interest, this White Paper specifically cites the issue of resilience:

> *The EU has already established a comprehensive set of passengers' rights which will be further consolidated. Following the ash cloud crisis and the experience of extreme weather events in 2010, it has become evident that Mobility Continuity Plans may be required to preserve the mobility of passengers and goods in a crisis situation. These events also demonstrated the need for the increased resilience of the transport system through scenario development and disaster planning.*

Another recently issued, high-level document from the European Commission addressing European transportation, specifically aviation, Flightpath 2050 - Europe's Vision for Aviation [Eur11b], cites resilience both in its foreword and many times in the main document:

> *The strategy addresses customer orientation and market needs as well as industrial competitiveness and the need to maintain an adequate skills and research infrastructure base in Europe. By 2050, passengers and freight should enjoy efficient and seamless travel services, based on a resilient air transport system thoroughly integrated with other transport modes and well connected to the rest of the world. This will be necessary in order to meet the growing demand for travel and to cope more easily with unforeseeable events.*

It is apparent that the concept of resilience is receiving more attention in policy planning than was previously the case.

ANNEX III. POTENTIAL APPLICATIONS FOR COMPLEXITY SCIENCE IN ATM

1. Airline routing and European Mobility

Nowadays most of the European citizens measure large distances in time and money, rather than kilometers. Airline routes are more than a business; they are covering people's needs. We should think out about European citizens mobility needs as a huge time-dependent random graph. This is a potential application for the techniques covered by the White Paper section XX. In particular Stochastic Optimization and Stochastic Optimal Control would help to build a decision making tool showing which paths are particular interesting in terms of European passenger mobility.

There are two remarkable keystones in this approach. On one hand one should be able to produce a time-dependent random graph catching the true demand (including non-accommodated demand). It is obvious that this is a highly valuable information, which is currently not available. Even it is not clear how to build up the true demand from the partial information given by the accommodated demand, a further step combining Complexity Science and Stochastic Approximation will be needed to do so. This breakthrough has been carried out in other fields. For instance, recently the application of Complex Sciences to the social networks have lead to well-known Complex Networks models, like the p*-models [1]. Population of these models has been largely studied [2] and in some cases with a considerable success. At this moment it is not clear whenever an existing model will fit in, or a completely new model will need to be developed.

Once the random graph -or a sufficiently rough approximation- is built, the Complex Systems Science will play again a fundamental role. This time Stochastic Optimization and Optimal Control might be used to evaluate the benefits of each path. The basics for Stochastic Control and Optimization are already wide known. There exist some accessible texts on the topic, like [3] and [4]. The challenge will be to conform those tools and use them to produce a single decision tool to detect key paths.

A successful implementation of this potential application would lead to a powerful tool, which will be able to identify promising new paths, in terms of EU citizens' connectivity and mobility. For instance this criteria may be used in any further regulation of the airline business.

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2. Assessment of European Air Transport Resilience

As developed in the ComplexWorld Network's White Paper, the Air Traffic System is a highly complex and complicated socio-technical system, composed by (and interacting with) a plethora of different heterogeneous elements, both technical, human and environmental. A high number of small perturbations are generated by these elements: coming both from the external environment, both from internal dynamics, these shocks push the system away from its normal point of operation. Along with this small-scale noise, some black-swan events may appear (like, for instance, a large strike or the eruption of a volcano), creating important disruptions and drastically reducing the utility perceived by customers.

Following this idea, one of the most promising research topics identified by the Participants of the Network through the Working Groups has been the assessment and improvement of the resilience of the system (see D3.4). Policy makers are also aligned with this view, and define resilience of the Air Transport System, that is, its capacity to tolerate disturbance without collapsing into a qualitatively different state, as one of the most important research lines in the next years (European Commission, 2011).

As a first step toward a more comprehensive management of resilience, the ATM community should develop a scientific and sounded methodology for the quantification of the resilience of the present system, that is, the quantification of the historical reactions of the system when faced to perturbations. In other words, it is recommended to estimate the sensitivity of the system to some standard perturbations, in terms of reduced capacity, predictability, or safety, by using only historical data. This estimation will be then used as a ground situation, against which new operational concepts should be compared.

An assessment of the sensitivity of the Air Transport system to perturbations should take into account the two main characteristics of its dynamics. First of all, the dynamics is embedded in different spatial and temporal scales: small perturbations, acting only in a small scale, may affect the behavior of a different scale, and may have consequences on the whole system. Also, there are uncountable sources of uncertainty: any analysis should exclude this background noise when estimating the system's reaction. Both characteristics should be tackled within a Complex Systems perspective, and with the tools and techniques described in the Section 3 of the Network's White Paper.

Furthermore, it is expected that the analysis of the relation between the magnitude of perturbations, and of the response of the system, will also shed new light on the importance of emergent behaviors in ATM.

References

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3. Complexity Science Techniques Applied to Total Airport Management

In this section we describe no Complex Science techniques and search for suitable ATM application of them. We try the opposite approach.

We describe a concrete ATM problem instance, scheduling of the limited resource at an airport. We search for the best Complex Science techniques to model the airport resources in order to predict future behavior and to enable what-if prediction to influence the future in the desired way.

Planning, particularly scheduling of limited resources is one of the main tasks of ATM. Previous approaches concentrate on the tactical layer, i.e. ad hoc scheduling of the next 30 minutes. This approach is more a reactive than an active approach. Applications are e.g. the xMAN systems (AMAN, DMAN, SMAN etc.).

Performance based ATM, however, requires a more holistic approach. TAM, Total Airport Management, is a first answer to this ATM challenge airports by collaborative airport planning, resulting in the Airport Operations Plan (AOP), which has to fulfill a defined service level agreement. For using collaborative airport planning, information has to be shared, which is supported by SWIM (System Wide Information Management).

Thousands of resources have to be considered at an airport:

- Aircraft: Acft1, Acft2, …
- Fuelling vehicles: FV1, FV2, …
- Fuel companies: FC1, FC2, ..
- Cleaning staff members: CleanS1, CleanS2,
- Push back cars, PBC1, PBC2, …
- Passengers buses: Bus1, Bus2, …
- Gates: G1, G2, …
- Pilots: P1, P2
- Etc.

A single flight, e.g. IBE453, consists of the clean staff (CleanS3), fuelling vehicle (FV1), aircraft (Acft2) and so on. The dispatcher of the passenger buses only considers the buses, and gates and the aircraft. The dispatcher of the first fuel company considers the aircraft his company his responsible for and the company's fuelling vehicles with the drivers. Using different views and levels of abstraction is one way to master complexity. Small perturbations in on view, however, may affect another view and may have consequences on the whole system.

Different temporal scales exist: Considering assignment of a specific runway we need an accuracy of seconds. If we however consider the runway usage strategy (runway only for departures or arrivals or used in mixed mode, close a runway, use direction 34 instead of 16) the planning accuracy is much broader, i.e. minutes and hours.

An assessment of the sensitivity of the Air Transport system to perturbations should take into account the two main characteristics of its dynamics. First of all, the dynamics is embedded in different spatial and temporal scales: small perturbations, acting only in a small scale, may affect the behavior of a different scale, and may have consequences on the whole system.

Many of the challenges that TAM is facing today have their origin in the large number of interactions between the different elements in the airport system. We have to consider

inbound and outbound flights with the runways and taxiways they use

the turnaround as linkage between arrivals and departures, containing of sub-processes like

  - cleaning
  - fuelling
  - deboarding/boarding, needing resources like
- check-in counters
- security
- baggage belts
- stands and gates
- de-icing,
- passengers

Scheduling and managing thousands of flight operations per day in a safe, punctual, fair, reliable and efficient manner has proved very challenging. When disturbances to the day-planned schedule occur, the involved people have already to do a very challenging job to keep things going. With TAM they get the knowledge about deviations earlier and a re-optimisation of the remaining day-plan can take place, based on the new constraints. This is the point where complex science comes into the game to investigate the question, how can we model this complex system and how can we predict the future behaviour of the system and last but not least how can be influence its behaviour.

Traditional simulation approaches already used for years in ATM have reached its limits. Are results from queuing theory a suitable tool to model the arrival rate to a resource and the service rate of the resource?

Agent-based modelling or gaming theory may help to capture the behaviour of the different involved decision makers (stakeholders), e.g. airlines, airport, turnaround dispatchers etc.

Semantic nets or dynamic network theory can help to model the relations between all the involved elements and the different views and to predict the future behaviour.

Even if the interactions between stakeholders and processes will be optimized with TAM, the airport system will keep complex with all its interdependencies between processes and lots of influencing variables. The airport with its TAM-advanced processes could be modeled, taking into account the interdependencies and the constraints (e.g. amount of resources). The next step could be an optimization of the AOP to fulfill the defined service level. The results could be compared to the results got by collaborative airport planning, which involves human experts, who negotiate and decide.

Modelling techniques already successfully used in other applications of Complex Systems Science should be applied to TAM, e.g. agent modelling, application of control theory. These results have to be compared with present TAM results obtained from traditional ATM approaches.

4. Impact of Unpredictable Adverse Weather on ATM Performance

Adverse weather represents one of the major challenges for future aviation, being a challenging limiting factor of the capacity of the ATM system, especially at the airport scale. Currently, it is responsible for more than 50% of all delays, no matter how, where and when that is accounted for, and it is a contributing factor to all accidents and incidents in more than 10% of all cases.

Weather is characterized by uncertainty. This is due to insufficient resolution of observational tools or measurement errors when e.g. retrieving satellite information. Furthermore, weather, beyond a forecast range of approximately seven days, becomes chaotic. Thunderstorm development still appears as a non-deterministic problem, at least partially.

Thus, there is a need for modelling the impact of weather on ATM taking into account all those uncertain factors and their interaction with all relevant actors.

Hazardous weather requires traffic managers to reroute flights that plan to pass through the area affected by the adverse weather, while balancing demand through sectors with reduced capacity or increased traffic volumes (resulting from other flights deviated from their original routes).

Today's methods for rerouting traffic are mostly manual, and have been historically employed due to the complexity of defining an operationally acceptable route in real time; thus, the reroute alternatives provided are limited. As the need to maximize all available airspace capacity is imperative, it is necessary to widen the set of operationally acceptable reroutes provided so that the impact of adverse weather on air traffic congestion is decreased.

The management of congestion due to severe weather events, while maintaining a safe airspace throughput, can benefit from the use of complexity science tools and techniques, providing improved methods for assisting decision makers and increasing operational efficiency.

The approach to be developed must be capable of providing a larger solution space of operationally acceptable reroutes, and of modeling the impact on congestion due to weather taking into account the uncertainties and the effects of the different interactions. Operational acceptability must be defined in terms of a given set of metrics; these metrics can then be used to select alternatives and to assess the improvement over traditional reroute options.

Classical approaches can be found in the literature. For example, an approach based on network optimization for dynamically generating operationally acceptable reroutes is presented in Ref. 1, where individualized reroutes for multiple flights under the same weather constraint are developed; the problem of solving multiple flights simultaneously is not addressed. In Ref. 2 the problem of synthesizing weather avoidance routes in the transition airspace is investigated, for a given deterministic weather forecast; however, the robustness of the routing algorithms to weather uncertainties is not analyzed.

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5. The expected value of information over multiple scales

ATM operates over multiple scales, although many decisions are often highly localised (even based on a single flight) and/or made in the absence of complete information. This application investigates decision-making in the context of the scale at which the decision is based. Uses of a Bayesian approach are discussed in the wider context of complexity science. Specific applications might be the scale over which KPIs are measured (where scales may be too wide) or delay propagation (where scales may be too local). The optimal course of action under a posterior analysis may well be different from that indicated by a prior analysis. In the former, enhanced by quantifying the value of additional information, insight may be gained through the calculation of the posterior expected value of 'best' information (taking into account irreducible uncertainty due to factors such as weather). Key challenges here in the ATM context are the difficulty of attempting to evaluate the worth of obtaining such further information to inform decision-making in a given instance and of evaluating the cost of providing such information, e.g. through new infrastructure and/or technologies. In the developing context of SWIM, it is important to consider the impact of improved information in terms of:

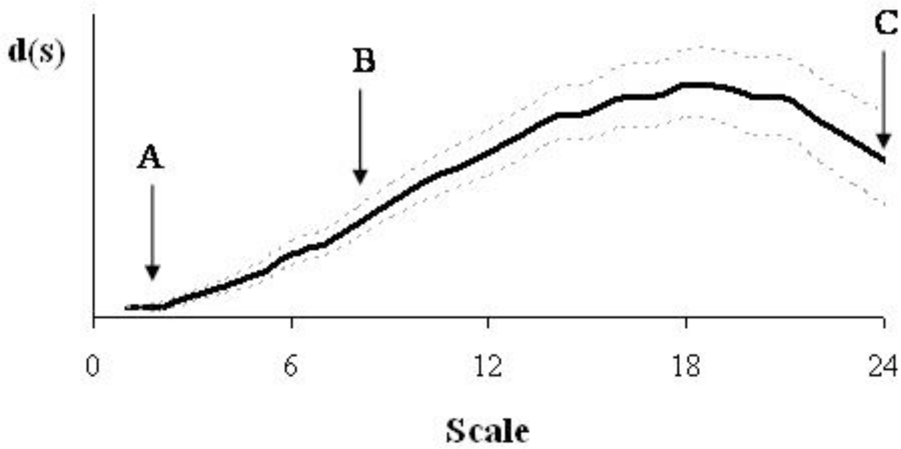
(1) the way information changes as a function of the scale at which it applies

(2) residual uncertainty (the extent to which the information can be reliable)

(3) its effects on stakeholder (especially airline) behaviour

(4) the extent to which stakeholders can actually respond to the information

(5) the cost of providing the information



The example in the figure above outlines the concept in the generalised terms of 'disutility' and 'scale'. 'Disutility' refers to a negative consequence, either specific, or generalised. A good example is cost; other examples are emissions or safety incidents. 'Scale' refers to the boundary applied when measuring the disutility. A good example is time (which is invariably associated with spatial extent, too, and vice versa, as the ATM system evolves); other examples are the number of stakeholders, or of KPIs, included in the scope of the assessment.

If we take the example of disutility as cost, and let the scale represent hours, it may be considered that the cost implications of, say, a primary 20 minute delay for an aircraft may 'locally' be relatively low (region 'A', where it affects only one flight leg). As we look further out in time, the propagated effects in the network (other aircraft, passenger and crew delays) causes the estimated cost of the primary 20 minute delay to increase ('B'). These may reach a peak, and could then even fall after 20 hours, if certain mitigating tactics are successful (such as spare aircraft being repositioned, or a cooperative passenger reaccommodation protocol with an alliance partner). Cost recovery and flight prioritisation decision-making also depend on the type of metric used (e.g. flight-centric or passenger-centric). Over multiple scales, fundamental conflicts may arise between efficiency (minimising the cost function) and equity (the absence of systematic bias against certain flights, airlines or origin-destination pairs).

The dashed line either side of the estimated cost projection illustrates the increasing uncertainty of the estimate the further it is projected forward. This is both due to unknown information and unknowable information (the irreducible uncertainty mainly attributable to exogenous events, e.g. due to imperfect weather forecasting). In the language of Bayesian decision theory, if we calculate the expected gain (e.g. avoidance of disutility) with perfect information, then subtract the expected gain under uncertainty, we evaluate the expected value of 'perfect' information (EVPI). In a situation such as ATM, we may define the expected value of 'best' information, i.e. taking into account the irreducible uncertainty.

One opportunity here might be to apply Bayesian statistics in the context of graph theory, to produce a Bayesian network model. The Bayesian approach involves statements or formulations of conditional probabilities, known as 'posterior' or 'revised' probabilities, which should give superior insights than simple or 'prior' probabilities (prior to an empirical observation). This calculates the probabilities of causes based on observed effects, or, of revising the probabilities of events as additional, empirical information becomes available. The value of using Bayesian networks for analysing (and visualising) how system-level effects arise from subsystem-level causes in complex systems, in the context of delay propagation, has been demonstrated by researchers at George Mason University. These researchers used the Bayesian network development software 'Netica' (Norsys Software Corp., US).

Whereas (classical) statistical decision theory informs rational choices when information is incomplete and uncertain, Bayesian decision theory is designed to take account of shorter- or longer-term consequences. By considering the probabilistic costs of various outcomes, we can calculate the expected utility (benefit) of choosing the optimal act under uncertainty (as compared with its counterpart, the expected opportunity loss through failing to take the best possible action). The decision-maker's behaviour may be captured through agent-based modelling (indeed, Bayesian decision theory specifically allows for subjective probabilities, as well as empirical ones).

As the status of the system evolves as we move along the curve above, we could assess the reliability of each subsequent prediction on the basis of additional information. For example, each time a flight has suffered a primary delay of 20 minutes, the prediction that this will be recovered in the next two rotations could have been found empirically to be reliable only 80% of the time. Such additional evidence can be applied as weights to revise the prior probabilities, to give posterior probabilities associated with each possible outcome. We thus produce 'posterior' expected values, as analogues of what we can now refer to as the 'prior' expected values above.

The key here is that the optimal course of action under a posterior analysis may well be different from that indicated by a prior analysis. In the former, insight may be gained through the calculation of the *posterior expected value of 'best' information*, again taking into account the irreducible uncertainty, but now enhanced by *quantifying the value of additional information*: previously observed (or newly estimated) as the multiple scales evolve. This is, of course, the counterpart of quantifying the corresponding cost of uncertainty. If, say, the posterior expected value of 'best' information is less than the prior value, this indicates that the cost of uncertainty to the decision-maker has been reduced (the availability of the best information is not as valuable as it was prior to the additional information). Key challenges in the ATM context are the difficulty of attempting to evaluate the *worth of obtaining* further information to inform decision-making in a given instance (due both to the stakeholder's ability to act and due to the non-monotonic nature of d(s)) and of evaluating the *cost of providing* such information (e.g. through new infrastructure and/or technologies).

6. Impact of uncertainty on airport emissions

The impacts of aircraft ground movements are often overlooked in ATM studies, although they are important both in terms of being a critical link in the gate-to-gate management of aircraft and their contribution to local air quality, which may be a legally binding constraint (Directive 2008/50/EC) to airport expansion. This technical study would seek to assess how uncertainty, traffic scenarios, and control logic and procedures, variously contribute toward the creation of environmental inefficiencies. The key research question is whether complexity techniques can help to model and understand the contributions to such environmental inefficiencies, which are brought about by uncertainty across several scales. Can we separate 'resolvable' uncertainty, which arises due to lack of appropriate data and enabling technologies, from 'irresolvable' (residual) uncertainty (arising through factors such as weather) and estimate their corresponding contributions to emissions? The approach should attempt to address both the multiple stakeholder objectives and the multiple scales involved.

It is the convergence of the air traffic network at airports where some of the most intricate logic and trade-offs in ATM come into play. This applies both to how the traffic is managed within given constraints (shown schematically below) and what metrics are used to measure performance. The performance of the system is measured using metrics such as capacity, safety, delays, emissions, and noise (SESAR Target Concept, D3, 10.2.4 - Sustainability Assessment). Even within the noise and emissions metrics, non-trivial trade-offs exist, e.g. with regard to CO2, NOx (quantity and location), particulate matter and noise.

The key questions which may be addressed are, can complexity techniques help to model and understand the contributions to inefficiencies, which are brought about by uncertainty across several scales. In particular, can these techniques:

- allow us to functionally separate resolvable uncertainty which arises due to lack of timely and appropriate data (e.g. through CDM/SWIM and appropriate enabling technologies) from irresolvable uncertainty through factors such as weather, and estimate their corresponding contributions to emissions?
- bring an increased understanding of the interactions between these emissions metrics (and, indeed, other KPIs), in a way which also sufficiently embraces both the multiple stakeholder objectives (e.g. airline cost minimisation c.f. ANSP capacity utilisation c.f. airport LAQ targets) and the multiple scales (aircraft ground movements in a given time-window are, in turn, related to preceding and subsequent ATM decision-making)?

The environmental impact of the air traffic movements could be assessed using an aircraft performance model linked to an emission inventory. The performance model would be based on EUROCONTROL's BADA (Base of Aircraft Data) energy share model or, alternatively, the PIANO aircraft performance model (Lissys ltd, UK).

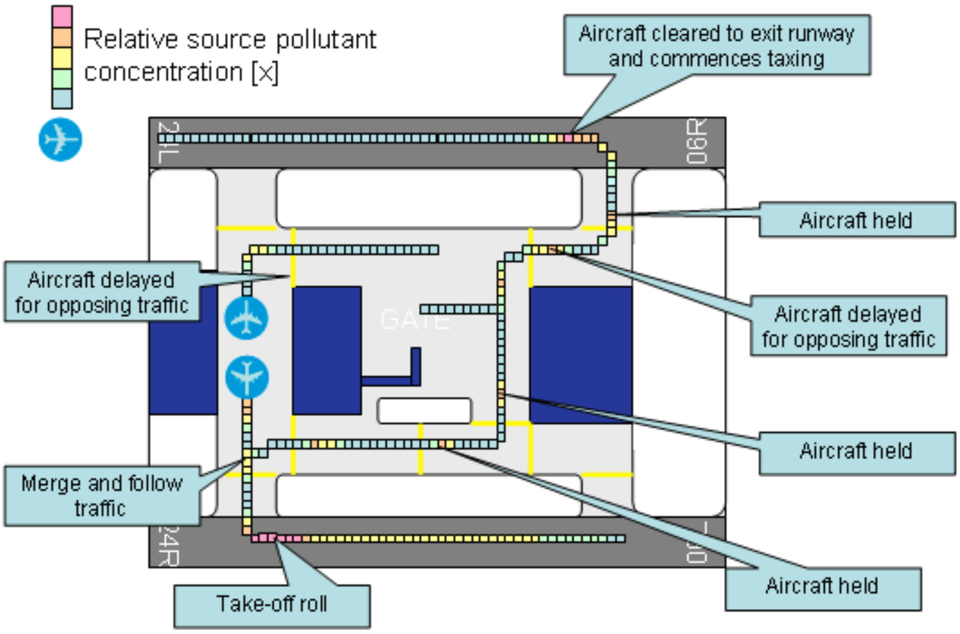


Figure courtesy Alex Goman

It is proposed that the results could be presented visually by overlaying concentrations of aircraft pollutants on a map of the airport surface (i.e. integrating them over time). This will indicate the 'hot spot' locations around the airport, i.e. where system inefficiencies (due to irresolvable uncertainty) are causing high levels of emissions to be produced and hence opportunities exist for future optimisation. (The overall magnitude of the potential emission savings could be assessed and compared with other on-airport emission control strategies, such as bus and service vehicle fleet management and pollutant reduction through adsorption of gases.)

The best data to use would be FDR data, which have the advantage of synchronous powerplant setting and positional information, although these are challenging to acquire due to commercial sensitivities. Model outputs could also be compared with fast-time simulation results. Ideally, airport case studies would be undertaken, which would include examples where advanced surface guidance and control systems, and where delegated procedures, are in place.

7. Spatio-temporal propagation of disturbances in ATM systems

In the next years, the ATM systems will face a massive increase of the air transport worldwide. This increase will be very significant in Europe. Moreover, there will be an even more pronounced need of integration amongst national air control agencies so that the spatio-temporal structure of the air transport system will be more and more critical. There will be a need for quantitative methods to monitor the airspace structure, in order to identify emerging properties, like the size and time duration of disturbances in the ATM system and the interrelation of this emergence with properties of the ATM system. Strongly related to the characterization and the development of models of propagation of disturbances is the problem of the identification of early warning signal of critical events. In an heavily loaded air traffic space, knowing the spatio-temporal configurations that are more likely to generate systemic events could help to forecast and control the traffic.

In this respect, tools and methodologies of complex systems theory can be useful to give insight about the way disturbances trigger deviation from the typical state and propagates across sectors, as well as to understand whether disturbances have a clustered structure in space and time. Finally complex system methods to identify early warning signals could be useful to improve the control of air traffic.

The first step is to select appropriate variables/proxies of disturbances in order to characterize specific aspects of the ATM system in certain space and time range (e.g. daily, weekly, monthly and yearly, intra-sector, sector and inter-sector interrelation, etc).

A first investigation could therefore be devoted to characterize which indicator has statistical properties, which are characterized by a leptokurtic profile of the probability density function and/or which indicator can be described in terms of a stochastic variable with long range memory (and therefore with the indication of a presence of a multiplicity of time scales). Leptokurtosis indicates deviations from Gaussian distribution and, broadly speaking, refer to the fact that extreme events are more likely than expected under the standard Gaussian hypothesis. Long range memory processes are characterized by the absence of a typical time scale, which can also be seen as the presence of multiple time scales. In a long range memory process the future is strongly determined by the whole past history of the process.

In order to study the spatial interrelations between sectors, one potential approach will be to build up a network. Networks might be physical communication networks and/or correlation based network where a similarity measure is used to characterize a certain variable describing a specific process of the ATM system. The analysis of such networks will provide insights about those sectors that have a similar profile in terms of the selected variable/proxy. These clusters of sectors are therefore the possible channels through which disturbances propagate. Networks can be constructed at different time ranges, thus allowing investigating how the spatial properties of the network change over time.

More generally the concept of scaling, i.e. how the properties of the system are invariant when one changes the spatial or temporal scale of observation, and its breakdown can give relevant information on the system dynamics and can be used to extrapolate (or interpolate) the behavior of the system at other scales.

A complementary approach can be used to investigate the temporal propagation of disturbances. In fact, having selected the appropriate variables/proxies, standard time series analysis tools can be used in order to reveal whether or not disturbances have a clustered structure in time. It is worth mentioning that such approach can be applied both to the variables/proxies describing disturbances and for the time-series obtained by characterizing the networks constructed at different time ranges.

Finally, many complex systems have critical thresholds, sometimes called tipping points, at which the system shifts abruptly from one state to another. Systemic events are often characterized by the presence of these transitions. These are typically hard to forecast but a series of techniques have been developed in the context of dynamical models of complex systems and applied successfully in several contexts, such as ecology, climate change, physiology, etc. The application of such approaches to ATM is potentially fruitful and of significant practical value.

The statistical characterization of disturbances of the ATM system can be achieved with a large set of classic tools of complex systems including Hurst exponent estimator, probability density function comparative tests, etc. For example for the estimation of deviations from the Gaussian behavior and power law decay of the probability density function a quite efficient and unsupervised tool is the one discussed in Ref. (1). More generally, technique from extreme value theory (2) would be very useful to characterize the frequency of extreme events in the ATM. Techniques of spatio-temporal data mining (3) and modeling techniques inspired by spatio-temporal pattern formation (4) could be profitably be employed for the characterization and modeling of spatio-temporal disturbances.

Networks can be analyzed with standard tools of network theory (5,6) and clusters of related or similar elements can be detected by community detection algorithm recently developed by computer scientists and by physicists developing network theory (7,8). In the analysis of the spatial properties of the networks one can also identify the most informative links of the network by building up statistically validated networks, along the lines of Ref. (9). Given the network, communities will be identified by using standard communities search algorithms (7,8). Finally, such communities can be characterized by using an ontological analysis as shown in Ref. (10). These successive steps might allow to identify and characterize the sectors that have a similar profile in terms of the selected variable/proxy and that are therefore the possible channels through which disturbances propagate.

In the analysis of the way disturbances propagate over time, one can also use standard tools of time-series analysis. A typical analysis might be performed by investigating the autocorrelation properties of the relevant time-series in order to understand whether these are long-range or short-range correlated processes, i.e. whether or not disturbances are clustered in time.

Finally, statistical tools and concepts developed for the detection of early warning signals of critical transition could be useful for the short term forecast of disturbances (11). Examples in the temporal domain include the critical slowing down, bifurcation analysis, skewness and flickering, increasing autocorrelation and variance. In the spatial domain, scale invariant power law structures or the emergence of regular patterns sometimes are associated to early warning signals.

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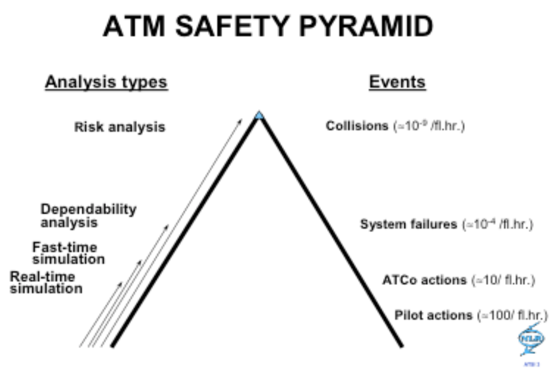
8. Safety Analysis Feedback to Advanced ATM Design

The design and validation of changes to an individual organization's local Air Traffic Management (ATM) system has become an acceptable practice in Europe. As part of this, Air Navigation Service Providers (ANSPs) are required, by applicable safety regulations, to hand over a positive safety case for regulatory approval prior to introducing a change. However SESAR is planning changes in air traffic operations in Europe that go much further than changes to a local ATM system. Because SESAR strives for ambitious objectives, addressing sometimes almost contradictory Key Performance Areas (KPAs), the changes to be made are fundamental. SESAR concepts of operation include changes for a multitude of stakeholders including many ANSPs, airlines and airports. The safety of such operations does not only depend on these stakeholders' individual performance, but also on their interactions. In the early design phase these interactions can relatively simple be designed as required. Hence safety analysis of advanced ATM ConOps should be done in the early phases of the development life cycle. As has been identified by the European Operational Concept Validation Methodology [E-OCVM, 2010], the early development phase is in need of safety analysis feedback to design, whereas the established safety case development process aims at safety assurance.

Safety Analysis feedback to design covers multiple time scales

As is depicted in the ATM Safety Pyramid figure below, the key challenge of safety analysis feedback to design is that the relevant events extend along multiple time scales, which varies from conflict resolution activities which may happen a few times per flight hour to Loss Of Separation events, which happen once per 10 thousand flight hours, to Mid Air Collisions which happen once in a billion flight hours. In order to identify and learn understanding emergent behaviour at various heights along the slope of the safety pyramid, there is an expected value in exploring complexity science techniques such as Agent Based Modeling and Gaming Theory. As remarked in the previous section, in applying these approaches effective use can be made of complementary techniques such as data mining, social models, sensitivity analysis, uncertainty analysis and optimization techniques.



9. ATM Performance Assessment

Performance assessment is crucial within the ATM context. It is essential in order to monitor the performance of the system in real time, thus enabling the application of specific policies if this performance deviates from its nominal value; furthermore, it is also essential to quantify the impact of new operational concepts, and reduce their adverse effects. Define a common performance framework is not straightforward, as different members of the ATM community may have very different requirements of performance: economic, efficiency, safety, predictability, etc. The former are integrated in the so-called key performance areas (KPAs), as defined by ICAO or SESAR.

Two complementary approaches have been developed within this field of research. The first one, focused on monitoring the past or present performance of the system, relies on the analysis of historical real data. Due to the complex nature of the ATM, those analyses cannot just be the result of some plain statistical result; instead, a step forward is needed, by introducing more complex statistical techniques, and other tools coming from the data-mining world. This would allow unveiling intriguing connections between different factors involved in the ATM and hidden in the actual data, as well as correlations, salient patterns, and cause-and-effect relationships.

The second approach deals with the estimation of improvements in the performance of the system when a new operational concept is introduced; thus, here the attention is centered on a hypothetical future. In the history of air traffic management, many models have been developed to address these questions. Nevertheless, they usually lack a holistic perspective to the problem, and only focused on specific aspects, as estimating aviation emissions (AEM, ALAQS), efficiency of self-separation tactics (TMX), or delays, resources, or capacity management (RAMS, SAAM, TAAM). Once again, and due to the complexity inherent the ATM system, there is a need for integrating different layers of operations (business, regulation, operations, etc.), accounting for the interactions at multiple spatio-temporal scales and the interconnections between each other. A solution depicted in the ComplexWorld Network's White Paper is the use of multi-agent based simulations, in which agents represent the relevant actors of the ATM system and are responsible of making decision. The interactions between agents, giving rise to emergent decision processes, are also a field of study within the context of game theory.

10. Safety from a Complex Systems perspective

The design and validation of changes within the ATM system, as well as within any of its sub-systems, is an essential tenet for safety. As part of this, Air Navigation Service Providers (ANSPs) are required, by applicable safety regulations, to hand over a positive safety case for regulatory approval prior to introducing a change; nevertheless, these cases usually suppose small and uncoupled changes, thus affecting just one element of the whole system.

In the near future, the new operational concepts that will be introduced with SESAR are expected to change this view to safety. Because SESAR strives for ambitious objectives, the changes to be made are fundamental; they will affect a multitude of stakeholders, including ANSPs, airlines and airports. The safety of such operations does not only depend on these stakeholders' individual performance, but also on their interactions. Thus, it is unrealistic to assume that old safety cases can be used to validate these new operational concepts.

In order to identify the novel safety needs that emerge for advanced ATM developments, during the SESAR definition phase, a series of in-depth studies have been conducted, each one of them addressing a specific aspect of importance for managing safe design and validation in SESAR. Together, these studies identified several novel safety needs, which include, between others: organizational safety, identification of unknown emergent risks, performance of human operators, the definition of a macro safety case, or the Concept life-cycle.

From the ComplexWorld network perspective, the first two threads deserve further research with highest priority. The first of them is related to the concept of resilience in open socio-technical systems. Those systems, the ATM being one of them, are characterized by a strong interaction between humans, machines, and their environment. Typically, these interactions are bidirectional: an open socio-technical system adapts to the environment, in order to be able to fulfill its objective in an ever-changing context, but at the same time it influences that environment with its actions. Resilience engineering aims at improving their active capacity to tolerate perturbations that are originating either internally, or from the environment, without collapsing into a qualitatively different state, thus maintaining the required level of safety.

The second thread is directly connected to the concept of emergent behavior. Due to the complex nature of ATM, i.e., to the high number of heterogeneous and interacting elements composing the system, unexpected behaviors may arise, which cannot be explained just by studying its individual parts. When we apply this concept to safety, we must take into account that some unsafe events may arise from the interactions between different parts of the systems, as for instance interactions between different stakeholders: therefore, validation cases cannot focus on stakeholders' individual performances, but should focus the ATM as a whole.

ANNEX IV. DATA REQUIREMENTS

Data Requirements

(a) Remit of this section of the White Paper

This section of the White Paper will coordinate barriers to further progress in the field of complexity science, applied to ATM, which relate specifically to shortcomings in the supply of data required to achieve a research goal. Potential data problems could include:

[A] non-existence
[B] inaccessibility (e.g. not in the public domain)
[C] unusable due to format (e.g. application-specific binary files; pooled identifiers)
[D] limited geographical scope (e.g. pertains to one EU state only)
[E] non-geographical limitation of scope (e.g. limited range of aircraft covered)
[F] too highly priced

(b) Protocol

If a Member or Participant of the Network requires particular data, it shall, in the first instance, contact the University of Westminster, which will respond to this request, identifying if the data are available from EUROCONTROL (PRISME, BADA; CODA, CFMU, etc), other international, public organisations (e.g. ACI, Eurostat, IATA, ICAO) or from commercial sources (such OAG, GDSs, IPS, national CAAs). If the University of Westminster is unable to verify the availability, or otherwise, of the data specified, it will circulate the request to other Members/Participants. The result of the request will be logged in a database of technical data requirements, see (c), below.

(c) Database of data requirements

Request (or query)	Raised by / [date]	Links with query	Summary	Objective	Response	Source (if any)	[Outstanding problem(s)] / status
1	UoW / [12SEP10]	N/A	Total data passenger flows between top European airports	To develop passenger-centric ATM metrics for new KPA	Available from ICAO, on subscription	ICAO	[C] / pending
2	UoW / [12SEP10]	[1]	Same as [1], but also with all transfer passengers	To develop passenger-centric ATM metrics for new KPA	Available as MIDT (Marketing Information Data Tapes) from GDSs	Sabre Amadeus	[F] / pending
3	INO participant / [08DEC10]	N/A	Sample traffic data for one (past) day in ECAC airspace	To help researchers who currently have no access to such traffic data	Would need permission from PRISME; data already exists	PRISME	[B] / pending
4	INO participant / [08DEC10]	[3]	Forecast traffic data for one future (2020?) day in ECAC	To help researchers who currently have no access to such	Needs to be organised through STATFOR?	STATFOR	[B] / pending

			airspace	traffic data			
5	INO participant / [08DEC10]	N/A	Currently no Europe-wide data available on cancellations	To supplement existing data on delays	May become available in 2011 through CODA?	CODA	[A] / pending
6	UoW / [28MAR11]	[1] [2] [3]	Fleet data (type, seats, MTOWs, etc)	To help researchers who currently have no access to such fleet data	Available from multiple sources (subscription required for some)	ICAO IATA PRIMSE	[C] / pending
7	UPC / [12APR11]	[8]	Aircraft performance data (fuel consumption, aerodynamic data)	To help researchers model aircraft performance outside "typical" cruise airspeeds and altitudes (i.e. beyond scope of BADA)	Highly sensitive data, some airlines may be willing to share if data are suitably anonymised	Airlines	[B] / pending
8	UoW / [13JUN11]	[7]	Aircraft FDR data	Potential case study / application in ComplexWorld White Paper	Highly sensitive data, some airlines may be willing to share if data are suitably anonymised	Airlines	[B] / pending

Table 1. Database of data requirements

ANNEX V. REFERENCES

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