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Applying complexity science to air traffic management

Andrew Cook [a,*], Henk A.P. Blom [b], Fabrizio Lillo [c,d], Rosario Nunzio Mantegna [d,e], Salvatore Miccichè [d], Damián Rivas [f], Rafael Vázquez [f], Massimiliano Zanin [g,h]

[a] Department of Planning and Transport, University of Westminster, 35 Marylebone Road, London NW1 5LS, UK
[b] Delft University of Technology, Section Control and Operations, Kluyverweg 1, 2629 HS Delft, The Netherlands
[c] Scuola Normale Superiore, Piazza dei Cavalieri 7, Pisa 56126, Italy
[d] Dipartimento di Fisica e Chimica, Università degli Studi di Palermo, Viale delle Science Ed. 18, Palermo 90128, Italy
[e] Central European University, Center for Network Science and Department of Economics, Nador u. 9, 1051 Budapest, Hungary
[f] Department of Aerospace Engineering, Escuela Superior de Ingenieros, Camino de los Descubrimientos, Universidad de Sevilla, 41092 Sevilla, Spain
[g] The Innaxis Foundation & Research Institute, José Ortega y Gasset 20, 28006 Madrid, Spain
[h] Faculdade de Ciências e Tecnologia, Universidade Nova de Lisboa, 2829-516 Caparica, Portugal

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ABSTRACT

Complexity science is the multidisciplinary study of complex systems. Its marked network orientation lends itself well to transport contexts. Key features of complexity science are introduced and defined, with a specific focus on the application to air traffic management. An overview of complex network theory is presented, with examples of its corresponding metrics and multiple scales. Complexity science is starting to make important contributions to performance assessment and system design: selected, applied air traffic management case studies are explored. The important contexts of uncertainty, resilience and emergent behaviour are discussed, with future research priorities summarised.

1. Introduction

This paper introduces key features of complexity science with a focus on its application to air transportation in general, and air traffic management (ATM) in particular. These applications relate to many aspects of performance assessment and system design, not least, ultimately, through effective service delivery to the passenger. As we will explore, complexity science is the multidisciplinary study of complex systems, of which air transport networks and integrated airspace blocks are prime examples. We illustrate the current and future capacity of complexity science techniques to make valuable contributions to the management of air transport.

The foundations of complexity science can be traced back to statistical physics, non-linear dynamics and information theory (Anderson, 1972). Its focus is on the importance of the heterogeneity of system components and on the structure of their interaction. Complex network theory plays a central role in complexity science (Newman, 2003; Boccaletti et al., 2006), since all complex systems have many interconnected components. Such components interact with and adapt to each other, such that the system exhibits emergent behaviour – the hallmark of complex systems. These features cannot be understood from information at the individual agent level alone. Complex network theory and its associated metrics and tools presents an apposite approach to developing the study of air transport networks beyond what classical techniques have to offer. Indeed, the marked network orientation of complexity science lends itself well not only to ATM but also to other transport contexts (Angeloudis and Fisk, 2006; Kaluza et al., 2010; Sen et al., 2003).

Our objectives in this paper are firstly to introduce the reader to complexity science and its main facets, before illustrating example applications in the air traffic management context. Section 2 introduces these concepts, focussing on complex network theory and the metrics it employs. We then discuss the important topic of uncertainty in the context of network scales, before developing various ideas related to (network) resilience. The more theoretical part of our paper concludes with classifications of emergent behaviour, with supporting air transport examples.

* Corresponding author.
E-mail address: cookaj@westminster.ac.uk (A. Cook).

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Although applied examples of complexity science in air transport modelling are very limited, two such air traffic management case studies are summarised in Section 3. Both draw on the analysis of communities in complex networks. Our conclusions and an outlook are presented in Section 4.

2. Complexity science

2.1. Complex networks in ATM

Since the origins of the theory and application of complex networks (Albert and Barabasi, 2002), this field has experienced tremendous growth. Complex network theory (CNT) has been successfully applied to different transportation contexts, including road and (underground) rail. In recent years, there has been a growing interest in the use of CNT in air traffic management: for a recent review see Zanin and Lillo (2013).

A network is composed of a set of nodes (vertices) connected pairwise by a set of links (edges). These can be directed and/or weighted, i.e. associated with real or integer values. For example, in an airport network, each node is an airport and a link directed from a node to another can be weighted by the number of flights or passengers in a given time window. By considering sectors or navigation points as nodes, one can build other network representations of the airspace with different spatial resolution. Indeed, such is the power of CNT that one can assign almost any kind of nodal representation, including those related to delays and the associated infrastructural and passenger costs.

The interest in the study of networks stems from the observation that some generic topological properties are present in different complex systems, suggesting that some general principles govern the creation, growth, and evolution of such networks. Moreover, CNT has introduced a large set of metrics that are able to characterise the network and its organisation, thus identifying the critical nodes. Let us examine three examples:

- **Degree**. The degree of a node is the number of edges connected to it, while its strength is the sum of the weights of these edges. The degree (or strength) distribution gives important information about the heterogeneity of the nodes. Several empirical analyses of airport networks (Barrat et al., 2004; Guimerà et al., 2005) have found that the probability that the degree k (or the strength) is greater than x is described by an exponentially truncated power law: $P(k > x) = N\,x^{-g}\,e^{-ax}$, where g is the tail exponent, typically between 1 and 2, a is a parameter controlling the rapidity of the exponential decay, and N is a normalisation constant. Networks with power-law distributed degrees are termed 'scale-free' networks (Barabasi, 2009) and have attracted considerable attention in recent years. As a randomly distributed network increases in size, the ratio of high-degree nodes to other nodes decreases, whereas in a scale-free network this ratio remains constant as a function of network size. (We comment on the importance in a transport management context below.)
- **Betweenness**. The betweenness of a node is a centrality measure quantifying how important a node is regarding paths inside the network. Node betweenness is defined as the proportion of shortest paths, among all possible origins and destinations, that pass through a node.
- **Clustering coefficient**. The clustering coefficient of a node is the fraction of pairs of its neighbours that are directly connected (i.e. the number of triangles in the network). Empirical studies (Guimerà et al., 2005; Bagler, 2008) show that airport networks have relatively high average clustering coefficients across nodes. This, together with small average shortest path lengths, indicates that airport networks have the 'small-world' property (Watts and Strogatz, 1998). Indeed, many real world networks demonstrate this property: that is, they exhibit a low average shortest path, characteristic of random networks, while maintaining the high clustering coefficient found in regular networks.

There exists a strong correlation between the degree of a node, and the quantity of flights and passengers managed through it (Barrat et al., 2004; Guimerà et al., 2005; Wu et al., 2006). The more connections a node has, the more passengers are likely to use that node to reach their destination, and thus the frequencies of such connections strongly increase.

The analysis of the structure of flight networks in air transport, especially when focused on individual airlines, is motivated by the aim of defining the most efficient structures for flights for a given airline – both in terms of yields (and thus profit) and of passengers' mobility. For this reason, a large number of studies have focused on the long-term dynamics of airport networks, with the aim of investigating the transition from point-to-point to hub-and-spoke structures observed first in Europe and the US, and more recently in emerging economies. For example, in the European air network between 1990 and 1998, it has been observed (Burghouwt and Hakfoort, 2001) that medium-sized airports have attracted most of the intra-European traffic, creating specialised internal hubs, while intercontinental traffic has also been concentrated, but on different hubs, usually large airports.

The structure of the air transport network strongly affects the capability of a passenger to reach their destination from a given origin in the shortest possible time and with fewest changes. However, purely topological metrics can be poor indicators for assessing passengers' needs. In fact, a short path (in terms of number of flights) can be (relatively) useless for a passenger if the constituent flights are very infrequent or if their scheduling renders the connections unworkable. One can therefore adapt many complex network metrics to describe both direct and indirect connectivities for passengers (Cook et al., 2013a; Malighetti et al., 2008; Zanin et al., 2009). We pursue this theme in Section 3.2.

CNT is also important in assessing the resilience of the air transport network, i.e. its ability to adjust its functioning prior to, during, and following internal and external disturbance. It has been shown that the network topology is critical to model failure cascades. Scale-free networks are extremely resilient to random failures. However, this comes at a high price, because they are also extremely vulnerable to targeted attacks (Albert et al., 2000) and other forms of localised failure. This suggests that a suitable characterisation of air traffic topologies and the identification of the most central nodes, according to CNT, can give valuable insights into modelling the resilience of the network and identifying critical elements of the system.

Finally, the topologies of air transport networks play an important role, not only for the mobility of people, but also for the dynamics of entities that depend on human mobility. An important example is the spread of an epidemic, for which air passenger transport constitutes one of the most important vectors for long-range spreading. For example, Colizza et al. (2006) used real data on passenger mobility to build a large-scale agent-based model to predict epidemic spreading worldwide.

We have focused here mainly on the airport network. However, navigation-point networks and sector networks are receiving increasing research interest because of their importance in modelling air traffic control (Cai et al., 2012; Gurtner et al., 2014). In contrast with airport networks, these are geographically constrained and therefore (almost) planar. Centrality analyses, for example, can be used to identify potential bottlenecks of the air traffic. Moreover, as we will show in Section 3.1, the use of community detection in navigation-point and sector networks has been recently suggested (Gurtner et al., 2014) as a means to improve the design of airspaces by using a bottom-up, traffic-driven approach.

2.2. The context of uncertainty

The application of complex network theory in air transport must also take account of a fundamental property of such operations: uncertainty. Understanding how uncertainty affects the ATM system is key to properly modelling and controlling it, and ultimately improving its performance. There are different sources of uncertainty that affect ATM, which can be classified into the types shown below (see also Heidt and Gluchshenko, 2012).

- **Data uncertainty**. This type of uncertainty exists when there are known data but with some level of uncertainty, and/or when there are imperfect models.
- **Data unavailability**. In contrast to the previous source of uncertainty, this affects predictions made without precise knowledge of the system: knowledge which could be obtained by sharing the necessary information, but whereby this is prevented by managerial and/or technological barriers.
- **Operational uncertainty**. Decisions taken by humans (e.g. managers, pilots and air traffic controllers) have a significant influence on operations but are difficult to predict.
- **Equipment uncertainty**. This type of uncertainty refers to problems with equipment, such as aircraft or vehicle breakdown, or other system failure modes.
- **Weather uncertainty**. Meteorological conditions comprise a wide group of sources of uncertainty (Matthews et al., 2009). In particular, adverse weather can introduce high levels of localised or widespread uncertainty and poses problems with clear links to resilience (which we discuss in Section 2.3).

The analysis of uncertainty in ATM must take into account the time horizon under consideration and the different scales of the system, because, depending on these, the various uncertainty sources affect the system in different ways. According to the time horizon, one can find two types of problem: (1) estimation of the present state, e.g. over a short-term time horizon, identifying primary actions for maintaining safety; and, (2) prediction of the future state, i.e. with regard to actions over medium- and long-term time horizons, identifying efficient planning for flights in the context of weather forecasts and predicted traffic, etc. Three scales of the system can also be clearly differentiated:

- **Microscale** – a single flight. At this smallest scale one must analyse all the uncertainty sources that affect the flight, at its different stages. These stages are: (a) strategic, covering the timeframe from months before the flight up to two hours before the off-block time, including the filing of flight plans but not the flow-management slot allocation process; (b) pre-departure, which includes flow-management slot allocation (commencing two hours before the flight and continuing up to the off-block time); (c) gate-to-gate, including the ground phases (such as taxi-in and taxi-out) and the airborne phase (where one must consider the dynamics of the aircraft and the changing environment through which it moves: see for instance Vazquez and Rivas, 2013); and, (d) post-arrival, which commences once the aircraft is on-blocks. Uncertainty affects both the spatial and temporal dimensions; while the spatial uncertainty affects mainly safety issues (ranging from potential loss of separation to collision risk) and efficiency, the temporal uncertainty manifests itself primarily as delay (flight delay being an important phenomenon that affects all scales, see Cook et al. (2013b) and Section 3.2).
- **Mesoscale** – air traffic. This is an intermediate scale that allows one to focus on a given area that contains many individual aircraft that interact following a given set of rules. Examples include terminal manoeuvring areas or sectors. The analysis of flow management problems can be also framed within this scale (Clarke et al., 2009). Mesoscopic models exploit probabilistic methods to account for details of the microscopic scale without completely losing the macroscopic and strategic view of the system. This scale still considers individual aircraft, but describes their activities and interactions based on aggregate relationships. At this scale, safety has to be enforced whilst, at the same time, capacity needs to be maximised and deviations from user-preferred trajectories minimised. To accomplish this effectively, it is necessary to develop algorithms that include uncertainty models in their formulation (Tomlin et al., 1998).
- **Macroscale** – the air transport network. Air transport can be considered at the level of regional, national, or supra-national networks, or even at the level of the global ATM system. This scale integrates the state of multiple ATM elements and allows one to focus on the network properties, giving a high-level view of the system. It is important to study how uncertainty in flights and air traffic (the microscopic and mesoscopic scales) propagates to affect the macroscale. At this scale, it is best to abstract and integrate the various complex and heterogeneous ATM elements in a way that allows one to assess uncertainty and other properties of interest without needing to include fine detail. Among other methods, CNT is a particularly useful framework for analysing the macroscale (Boccaletti et al., 2006), although it may also be used on mesoscale applications.

We discuss these scales in the context of emergent behaviour in Section 2.4. According to the scales of the system, the time horizon under analysis, and the types of uncertainty, different research challenges can be identified in terms of using CNT to offer insights into progressing performance assessment and management.

2.3. Defining and modelling resilience

Air transportation constitutes a complex socio-technical system that is constantly influenced by internal and external disturbances of various forms. These disturbances may interact with each other, potentially creating a cascade of adverse events that may span over the different scales outlined in the previous section. Such disturbances could affect a single aircraft or crew, or impact a whole network.

Thanks to decades of evolutionary development of the air transportation system, many disturbances may not cause significant disruptions for passengers. However, in some cases the disruption is significant (e.g. due to convective weather), and in some exceptional events the disruption is of great impact. There are two categories of rare exceptional events: (i) (catastrophic) accidents involving one or two aircraft; and, (ii) events that push the dynamics of the air transportation system far away from its point of operation and therefore dramatically affect the performance of the system. Examples of the former category are: fatal runway incursions (e.g. Linate, 2001); fatal mid-air collisions (e.g. Überlingen, 2002); loss of control of an aircraft flying through a hazardous weather system (e.g. Air France crash in Atlantic Ocean, 2009). The latter category poses particular challenges for tactical management, examples including: terrorist actions causing the closing down of air travel in large areas (e.g. the events of '9/11' in New York, in 2001); a disease causing passengers to change their travel behaviour (e.g. the SARS outbreak in Asia, in 2003); or, volcanic plumes impacting air travel over much of northern Europe (Eyjafjallajökull ash cloud, April–May 2010).

The term 'resilience' was initially used in the field of mechanics as the "ability of a metal to absorb energy when elastically deformed and then to release it upon unloading", e.g. Hoffman (1948). Holling (1973) extended this resilience concept to ecological systems as the "persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables". Since then, various other extensions of the resilience concept have been introduced in other domains, such as social science, economic science, organisation science and safety science.

Based on a review of the complementary resilience developments in the various domains, Francis and Bekera (2014) identified the following three key capacities of resilience: (i) absorptive capacity, (ii) recoverability, and (iii) adaptive capacity. These key capacities have been integrated into a unifying resilience framework for complex socio-technical systems (Francis and Bekera, 2014). Since the air transportation domain covers so many resilience sub-domains, this integrated resilience framework is expected to be of great value for air transportation and the management of its performance from both a strategic and tactical perspective.

In the literature, corresponding metrics have also been proposed to quantify resilience. Gunderson et al. (2002) introduced two such key metrics: (1) *ecological* resilience is the "amount of disturbance that a system can absorb before it changes"; (2) *engineering* resilience is the "time of return to a global equilibrium following a disturbance". In the study by Francis and Bekera (2014), the quantitative metric (3) 'resilience factor' has been proposed in order to take account of all three key resilience capacities.

A common view in the literature is that for the analysis of resilience of complex critical infrastructures, there is a need for systematic modelling approaches. Recently, Ouyang (2014) has provided a rather complete overview of the various modelling approaches available, such as those comprised of, or based, on: empirical modelling; agent-based modelling; system dynamics; economic theory; network topology; network flow; Petri nets; control system theory; hierarchical holographic modelling; high level architecture; and, Bayesian networks. These modelling approaches have been systematically assessed against various resilience improvement objectives for critical infrastructure systems (Ouyang, 2014). In addition, ComplexWorld (2012) has identified some complementary stochastic modelling and analysis techniques that are able to capture the various forms of uncertainty in ATM, i.e.: stochastic hybrid systems (Blom and Lygeros, 2006; Cassandras and Lygeros, 2007); viability analysis (Martin et al., 2011); and, reachability analysis (Bujorianu, 2012).

Triggered by the resilience engineering paradigm of Hollnagel et al. (2006), qualitative modelling of resilience in ATM started some five years ago (Eurocontrol, 2009). A good illustration of the associated qualitative results obtainable for ATM is provided by Woltjer et al. (2013). In view of the complexity of the air transportation system, there is also a need for the systematic application, validation and integration of complementary modelling approaches. Although high-level architecture modelling is the most generic approach, it faces many challenges in realising a mature application in a complex safety-critical infrastructure (Ouyang, 2014). Overall, agent-based and network-flow based approaches have the widest and proven applicability. With regard to uncertainty, as discussed in the previous section, viability and reachability analysis of stochastic hybrid systems are particularly adept at allowing researchers to model and analyse the various forms of uncertainty in air transportation – hence, this should be combined with agent-based and network flow approaches. In addition, there is the need to assure data access (European legislative change is currently helping Europe to catch up with the more open culture in the US) and the systematic collection and empirical modelling of these data.

2.4. Emergent behaviour

Another key feature of complex systems is emergent behaviour (Anderson, 1972). This cannot be fully determined by knowledge of a system's components when considered as isolated elements, i.e. without taking into account their interactions. A physical analogue is the highly complex structures of water, not predictable a priori from knowledge of the properties of hydrogen and oxygen atoms. Emergent behaviour that is not well understood often leads to poor performance. Only after such emergent behaviour is better understood, may it be exploited by researchers and managers to deliver better performance.

Air transportation is indeed challenged to accommodate much higher future traffic demand, whilst maintaining performance across a number of key performance areas (KPAs), including safety and delay metrics. Awareness is growing (e.g. Holmes, 2004) that this cannot be accomplished by focussing on the individual elements of the socio-technical air transportation system. Instead, it is essential to study and understand the interaction between the many individual elements, i.e. their joint emergent behaviours (ComplexWorld, 2012; Eurocontrol, 2010; Shah et al., 2005). Furthermore, with the introduction of advanced ATM concepts, as yet unknown emergent risk may appear (Eurocontrol, 2010). Whilst new paradigms (such as self-separation) could give rise to new vulnerabilities, they could also remove existing ones (Woods et al., 2010). In the literature, a number of types of emergent behaviours are discussed. In order to bring some order to these emergent behaviour types, Bouarfa et al. (2013) identified that the classification proposed by Fromm (2005) is useful for ATM:

- **Type I emergence** is totally predictable due to the controlled and planned interaction of the individual components. In air transportation this applies, for example, to the multitude of technical systems either on-board an aircraft or on the ground, including their reliability.
- **Type II emergence** is characterised by top-down feedback from the components (agents) imposing constraints on the local interactions. Without conducting simulations, it is not predictable (Bedau, 1997). Type II behaviour is observed, for example, when cognitive processes of pilots and controllers are involved. For example, in a sequence of airborne aircraft with limitations on their possible speed adjustments, each flight crew adjusts its behaviour and role in the group according to the context, e.g. following an ATC instruction or a traffic collision avoidance system warning.
- **Type III emergence** is characterised by multiple positive and negative feedback loops appearing in complex systems with many agents. Completely new roles can appear while old ones disappear. The behaviour is not deterministic and can be chaotic – hence it poses significantly more challenges for simulation.
- **Type IV emergence** is not predictable, even in principle, because it describes the appearance of a completely new system in a multi-level or multi-scale system. This is often referred to as 'strong' emergence, although there is no universally agreed definition. Combinatorial factors render futile any attempt at explaining emergent macroscopic phenomena in terms of microscopic phenomena. A mesoscopic level often protects the macroscopic level from the microscopic one (i.e. the microscopic layer is irrelevant to behaviour at the macroscopic level). Life is a strongly emergent property of genes, the genetic code and

nucleic/amino acids; culture is a strongly emergent property of language and writing systems. In the air transportation domain, one can think of the safety culture, inter alia, as the product of routine aspects of everyday practice and rules, and of management and organisational structures (Ek et al., 2007; Gordon et al., 2007). However, even agent-based modelling and simulation do not reveal an understanding of the causal relationships (Sharpanskykh and Stroeve, 2011).

Type III exceptional, safety-critical behaviour may be observed where the propagation of hazards through the socio-technical air transportation system creates a condition under which the application of established procedures by crew or ATC unintentionally causes the situation to deteriorate. This may, for example, occur when situation awareness differences arise amongst different agents in the system, and these differences cannot be recognised by any of the agents (De Santis et al., 2013).

Type III emergent behaviour is also associated with other particularly interesting properties with regard to the management of air traffic: phase transitions and percolation. A phase transition refers to many locally interacting elements causing a collective phase change (returning to the example of water, a physical analogue is the melting of ice, i.e. a transition from the solid to liquid phase). Typically, there exists a critical point that marks the passage from one phase to another (e.g. Helbing, 2001). Particularly remarkable is that the well-known phase transition behaviour of road traffic on a highway seems to be absent in air traffic.

Percolation refers to probabilistic, network-wide emergent behaviour, between sites or sub-systems, across links in the network. In air transportation, there are several networks where percolation may happen. For example, the spatio-temporal propagation of congestion over airspace sectors (Ben Amor and Bui, 2012; Conway, 2005) or how passenger disruption propagates through the entire air transportation system (Cook et al., 2013a). We take up the conclusions to be drawn for air traffic management with regard to emergent behaviour in Section 4.

3. ATM case studies

The two case studies summarised in this section are both examples of SESAR Exploratory Research program projects. The aim of this section is to illustrate the practical use of complexity science in the context of ATM. Both of the case studies draw on community analyses. An important characteristic of a complex network is its organisation into communities (Fortunato, 2010). Communities are generically defined as sets of nodes that are more connected among themselves than with the rest of the network. Communities are, therefore, important to the understanding of airspace structure and operation.

In the first case study, we present the results of a recent investigation performed within the ELSA project (Gurtner et al., 2014), whereby network community detection algorithms were used to monitor current use of the airspace and to improve it by informing the design thereof. In the second case study, we show how the POEM project (Cook et al., 2013a) has demonstrated the need for dedicated passenger metrics in performance assessment and how community functionality and vulnerability may be radically changed under flight prioritisation rules.

3.1. From network behaviour to better airspace design

The application of complex network theory to air traffic is not new (Zanin and Lillo, 2013), although such studies have mainly focused on the topological characterisation of the airport network (Bagler, 2008; Colizza et al., 2006; Guida and Funaro, 2007; Guimerà et al., 2005; Li and Cai, 2004; Lillo et al., 2011; Popovic et al., 2012; Quartieri et al., 2008; Wang et al., 2011; Xu and Harriss, 2008). In Gurtner et al. (2014), community detection algorithms were applied to different types of air traffic network. We will illustrate this case study by considering a network of airports, which is probably the most studied type of air traffic network. This network was constructed using the DDR (Demand Data Repository) dataset maintained by EUROCONTROL.

Airspaces are complex systems already partitioned, mainly for reasons related to air traffic control. In fact, at the lowest level, airspaces are partitioned into several sectors. In European airspace, each National Airspace (NA) comprises between one and five area control centres (ACCs). The two-dimensional boundaries of an NA are often very close to the country's national borders. At a more aggregate level still, we have functional airspace blocks (FABs), comprising several NAs. Reorganising NA blocks into FABs is one of the cornerstones of the Single European Sky first legislative package, and was further enhanced in the SES second package. Nevertheless, only a few of the planned nine FABs are currently operational.

We suggest that community detection in air traffic networks is important for two reasons. Firstly, it improves the characterisation of networks, powerfully complementing other complexity metrics (such as degree distribution, betweenness centrality, small world effects, etc.). Secondly, we believe that community detection could be helpful to guide, in an unsupervised way, the design of new airspaces in order to achieve better management of the air traffic based on actual conditions. In fact, network community detection may provide information on the appropriateness of the airspace design, based on the sole knowledge of the actual air traffic data. Therefore, methods devised for identifying communities in networks could be used to help design the structure of airspace, starting from the observed behaviour of the system.

An example of a partition is presented in Fig. 1, where we show the different communities of the European airport network for 06 May 2010. Each circle is an airport, its radius proportional to its strength. Each community is represented by a different colour. The links between nodes have been omitted for legibility. This partition is obtained by using an algorithm (Blondel et al., 2008) that maximises the modularity. Modularity is a network metric that measures the excess of the number of links within a community with respect to a null hypothesis of the random presence of links.

As illustrated, the typical size of a community is supra-national, roughly the same as an FAB. The communities are mainly geographical with the majority of nodes close to each other in a single community. Moreover, the borders of the communities seem to be more or less consistent with national borders. Nevertheless, some nodes are geographically far away from the majority of the nodes in their communities. As mentioned above, this might be due to the fact that such nodes are gathered together in the same community on the basis of their common air traffic profile, rather than their geographical proximity. A detailed comparison between existing and unsupervised partition is beyond the scope of this paper; interested readers should refer to Gurtner et al. (2014).

When considering the whole AIRAC (Aeronautical Information Regulation and Control) period from 06 May to 02 June, 2010, the average number of communities is 9.4 ± 1.2. The average value of the minimum number of communities which include 90% of the nodes in the network is 7.2 ± 0.4. The number of FABs and NAs considered is 12 and 42, respectively.[1] The average number of FABs

[1] Since we are considering the whole ECAC airspace (which is only partly covered by FABs), we included in our partition the nine FABs planned by EUROCONTROL plus three pseudo-FABs defined by the authors and based on geographic proximity.

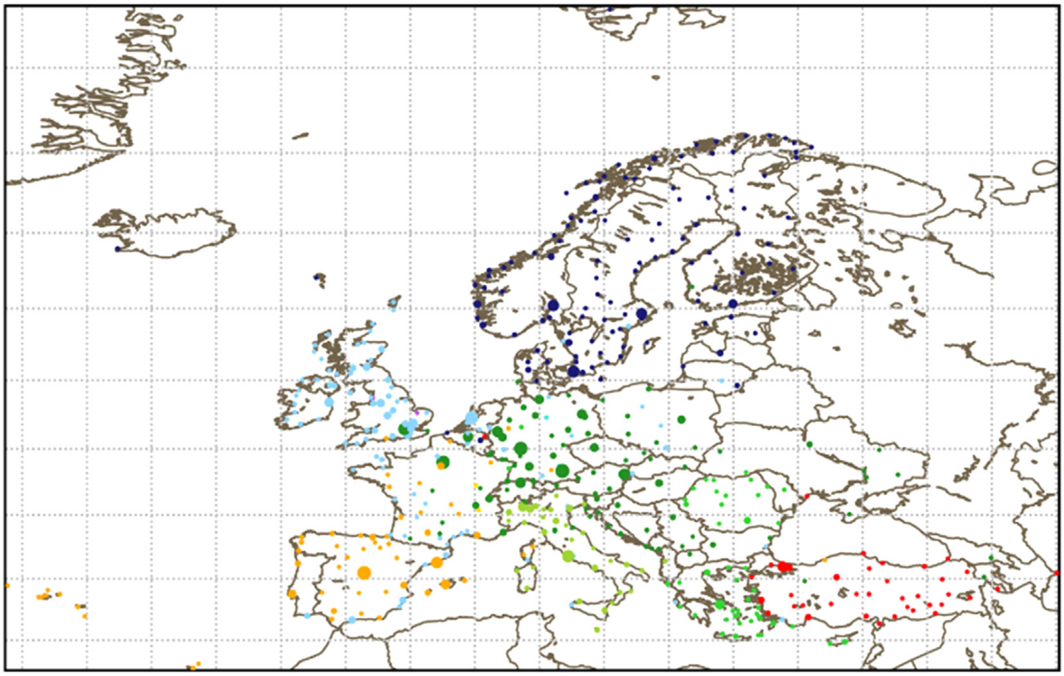

Fig. 1. European network of airports on 06 May 2010.

and NAs that include 90% of the nodes in the network is 9.1 and 21, respectively. Clearly, the number of detected communities is closer to the number of FABs.

A further quantitative comparison between unsupervised and existing partitions of the airspace can be obtained by computing the mutual information (Danon et al., 2005). The mutual information is a measure of the mutual dependence of two variables, based on the computation of their commonalities. The results are summarised in Table 1 (values of unity from modularity versus modularity, etc., and the duplicating value of 0.42 ± 0.02 (top-right cell) are not shown).

According to mutual information, the existing partition given by FABs seems well represented by a partition of the airport network obtained by using the modularity method. However, the match is not perfect. There could be two reasons for this. Firstly, geographical borders of communities are different from the FABs' tiling. Secondly, communities are actually non-geographical and some nodes of a given community are in the middle of another one, as shown in Fig. 1. Nevertheless, overall, these results support the introduction of FABs. Their actual boundaries could sometimes be different from those obtained by applying an unsupervised modularity-based community detection algorithm to the airport network, however, as detailed in Gurtner et al. (2014). Again, an obvious explanation might be that the communities detected by such algorithms are formed solely on the basis of their air traffic profiles. FABs, as well as other existing airspace structures, have been created on the basis of geographical or political constraints. These two types of criteria might indeed generate very different outcomes because, for instance, it is not unlikely to have airports in different nations more connected than airports in the same nation. Looking further ahead to concepts such as free routes and dynamic airspace structures, these types of community detection methods may make particularly valuable contributions to both strategic and tactical design, as they might provide design criteria informed by empirically observed air traffic flows.

Table 1
Comparisons of the partitions using the mutual information.

Mutual information	Modularity	National airspace
Modularity	–	–
National Airspace	0.42 ± 0.02	–
FABs	0.53 ± 0.02	0.70 ± 0.01

3.2. Evaluating new flight prioritisation strategies

The average delays of flights and passengers are not the same and they are even observed to move in opposite directions under certain types of flight prioritisation (Bratu and Barnhart, 2004; Calderón-Meza et al., 2008; Cook et al., 2013a; Manley and Sherry, 2008; Sherry et al., 2008; Wang, 2007). The air transport industry is lacking passenger-centric metrics; its reporting is flight-centric.

There is growing political emphasis in Europe on service delivery to the passenger, and passenger mobility (European Commission, 2011a, 2011b, 2013). However, how are we to measure the effectiveness of passenger-driven performance initiatives in air transport if we do not have the corresponding set of passenger-oriented metrics and understand the associated trade-offs in the context of delay propagation? How can we better characterise and differentiate the performance of the network from a flight and passenger perspective, under new types of flight and passenger prioritisation scenarios?

We set out to answer these questions by building the first explicit passenger connectivity simulation of the European air transport network, with full airline delay cost estimations. The two principal datasets used to prepare the input data for the model were IATA's PaxIS passenger itineraries and EUROCONTROL's PRISME traffic data. A baseline traffic day in September 2010 was selected as a busy day in a busy month – without evidence of exceptional delays, strikes or adverse weather. The busiest 199 European Civil Aviation Conference (ECAC) airports in 2010 were modelled, having identified that these airports accounted for 97% of passengers and 93% of movements in that year. Routes between the main airports of the (2010) EU 27 states and airports outside the EU 27 were used as a proxy for determining the major flows between the ECAC area and the rest of the world. This process led to the selection of 50 non-ECAC airports for inclusion of their passenger data.

The key results observed through (new and established) classical metrics were as follows. Firstly, both types of flight prioritisation rule operating during arrival management (i.e. (a) minimising the number of inbound delayed passengers; (b) minimising the number of onward delayed flights) were ineffective in improving overall performance. Secondly, a policy-driven scenario was considered, representing a special case not driven by current airline rules or ATM objectives but designed to benefit the passenger. This scenario, with rules rebooking disrupted passengers at airports based on minimising their delay at their final destination, produced very weak effects when current airline interlining hierarchies were preserved. When these restrictions were relaxed, marked improvements in passenger arrival delay were observed, although at the expense of an increase in total delay costs per flight (due to passenger rebooking costs). Thirdly, a prioritisation process assigning departure times based on cost minimisation markedly improved a number of passenger delay metrics and airline costs, the latter determined by reductions in passenger hard costs to the airline (falling on average by €40 per flight). The importance of using passenger-centric metrics in fully assessing system performance was repeatedly observed, since such changes were not expressed through any of the currently-used flight metrics at the common thresholds set (Cook et al., 2013a). This has important implications for SESAR's central concept of the User-Driven Prioritisation Process (SESAR, 2012).

In order to establish causal relationships within the data, it was necessary to turn to rather more powerful techniques than those simply describing associations. Granger causality (Granger, 1969) is held to be one of the only tests able to detect the presence of such causal relationships between time series. It is an extremely powerful tool for assessing information exchange between different elements of a system, and understanding whether the dynamics of one of them is led by the other(s). A network reconstruction was computed for the flight and passenger layers for the baseline (no prioritisation scenario) and cost-minimisation scenario simulations, i.e. four reconstructions in total. Granger causality was calculated over time series representing delays.

The two baseline networks are shown in Figs. 2 and 3 (with International Civil Aviation Organization airport codes). The colour of each node represents its eigenvector centrality, from green (in the web version) (low centrality) to red (in the web version) (most central nodes). The size represents the out-degree, i.e. the number of airports that a given airport Granger ‘forces’ in terms of delay. The eigenvector centrality is a metric defined such that this centrality of a node is proportional to the centralities of those to which it is connected (Boccaletti et al., 2006).

Comparing eigenvector centrality rankings through Spearman rank correlation coefficients showed that all four network layers were remarkably different from each other (r_s: 0.01–0.07). These rankings demonstrated that different airports have different roles with regard to the type of delay propagated (i.e. flight or passenger delay) and, furthermore, that these were further changed by the cost-minimisation prioritisation rules. Indeed, a trade-off was introduced under these rules: the propagation of delay was contained within smaller airport communities, but these communities were more susceptible to such propagation. The absence of major hubs in the top five ranking lists for in-degree, out-degree and eigenvector centralities was notable. Indeed, the largest airports present in these rankings were Athens, Barcelona and Istanbul Atatürk.

This modelling has also identified (Cook et al., 2013a) that smaller airports were significantly implicated in the propagation of delay through the network at a level that has hitherto not been commonly recognised. This is probably due to reduced delay recovery potential at such airports and whether a given airport has sufficient connectivity and capacity to reaccommodate disrupted passengers.

4. Conclusions and outlook

In this paper we sought to identify the key features of complex systems and to illustrate the current and future capacity of complexity science techniques to make valuable contributions to the management of air transport. Its applicability to performance assessment is readily apparent, not least due to the flexibility with

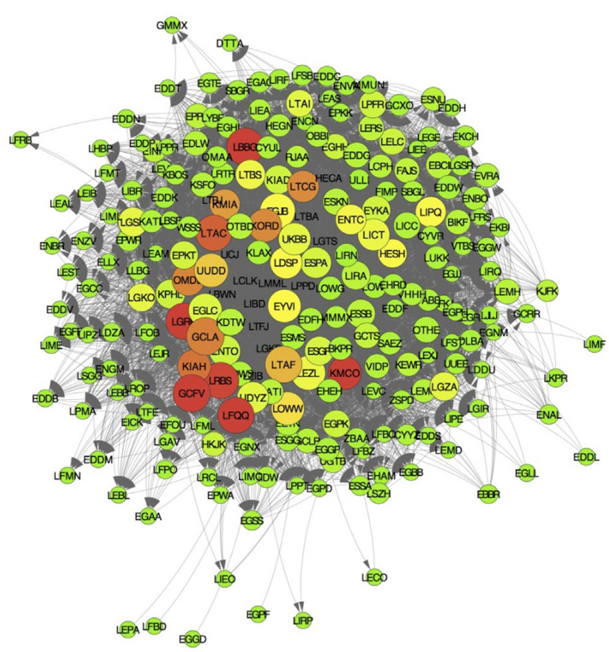

Fig. 2. Flight delay causality network for baseline simulation.

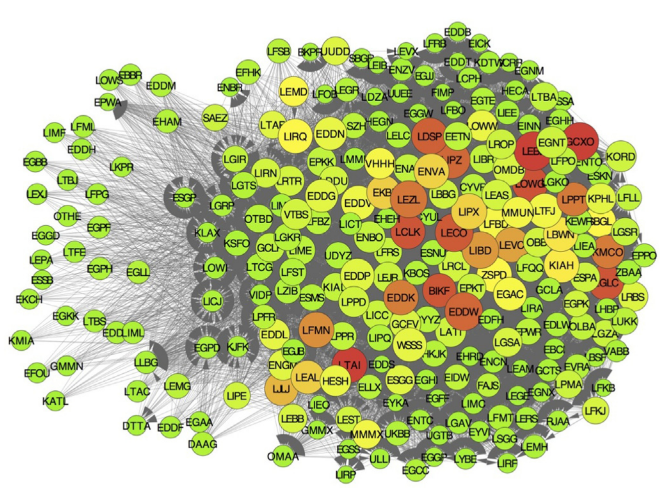

Fig. 3. Passenger delay causality network for baseline simulation.

which we may define the constituent nodes in a network representation.

Complex network theory has a range of metrics and methods well adapted to developing the study of air transport networks. Some results can be obtained only through complexity science methods, in particular, those that are related to emergent behaviours. Other results may be recovered through conventional analyses, but at a much greater cost. An example of the latter is airport vulnerability. Classically, estimation thereof would require either great simplification (based on counting flights, for example) or a simulation, whereas CNT offers several straightforward metrics that may be readily calculated without simulation, such as betweenness and eigenvector centrality. Indeed, within the POEM project (discussed in Section 3.2), it was also apparent (Cook et al., 2013a, 2013b) that applying CNT techniques and exploring community properties such as vulnerability, afforded performance insights rather more readily than using classical techniques alone. We believe that a complementary approach using both complexity and classical approaches offers managers and designers, both on the supply and demand side, the most powerful insights into performance.

The importance of CNT in assessing network resilience, e.g. through characterisation of air traffic topologies and the identification of vulnerabilities, will become even more useful as further performance demands (e.g. from high-level target-setting) and traffic demands are placed on the system. Based on the resilience developments for complex socio-technical systems in other domains, we may identify four key directions for addressing resilience in air transportation. The first is the elaboration of the unifying resilience framework of Francis and Bekera (2014) for the air transportation domain – one of the challenges here is to incorporate the various stakeholders into a unifying framework, with clear links to the SESAR objectives of collaborative decision making (CDM). The second is the further investigation and incorporation of dedicated resilience metrics in air transportation, as discussed in Gluschenko and Foerster (2013) and Francis and Bekera (2014). The third direction is the improvement of access to, inter alia, appropriate resilience data, coupled with the systematic collection and empirical modelling of these data. The fourth direction is the modelling and analysis of future air transportation design from a resilience perspective, using the most suitable approaches identified in Section 2.3 and illustrated in the case studies of Section 3. The practical alignments with ATM paradigms are apparent, from FAB implementation and high-level network design down to modelling the tactical practicalities of flight prioritisation rules, each of which are key issues in future ATM design.

Looking ahead, it seems that emergent behaviour research in ATM, and many other fields, would be most productively focused on Type III emergence. This implies the following main research lines. Firstly, increasing our understanding of phase transitions in air traffic management. Why do these not arise in conventional air traffic situations, and which types of change in air transportation in the future could lead to, or further avoid, phase transitions from impacting air traffic? (One possible explanation for the lack of some types of phase transition is that in the current air transportation system traffic demand within each sector is regulated through flow control such that certain critical points are often not reached, but there is still only a relatively poor understanding of how phase transitions from nominal behaviour to propagated network delays occur.) Secondly, a better understanding of various percolation phenomena in air transportation is required, again including the context of future operational paradigms, and of exceptional emergent behaviours and the corresponding implications for safety. Thirdly, we need to develop better macroscale models that capture the characteristics of emergent behaviours, e.g. in terms of the associated power laws. Such models would allow the communication of learning from Type III emergent behaviour with other experts in air transportation, not least (tactical) network managers and (strategic) system designers.

Considering future tools and methodologies, automatically detecting patterns that may compromise the safe operation of the ATM system has to overcome several challenges. One of these is the nature of ATM data, *i.e.* the fact that they emerge from the interaction of a plethora of elements. Due to this, once again, classical techniques like multiple linear regression are not suitable. The high number of elements composing the system also results in the generation of large datasets that cannot easily be aggregated and suitably codified. This process requires automated mechanisms that can filter and organise high volumes of heterogeneous, incomplete or unreliable information in an intelligent manner. Not all such challenges have yet been met, with many benefits to the air transport community yet to be realised, although early research has yielded highly promising results constructing predictive models able to successfully forecast unsafe events. Such tools may have a particular role to play in future, more automated environments.

Any attempt to build a truly holistic performance assessment framework must also take account of uncertainty, another inherent property of real-world complex systems. We are here obliged to consider the multiple temporal and spatial scales associated with such systems, in addition to the various types of uncertainty and the degree to which some of them may be mitigated. Much research has focused on the macroscale, thus rather following the level at which performance targets are set, but there remain particular opportunities to improve our understanding and modelling at the mesoscale. We have also demonstrated the need to differentiate between the passenger and flight layers of such analyses and to ensure that the metrics used are appropriately sensitive to the changes we are trying to measure. Whilst much of this work has focused on operational network models, with corresponding attention on airport functionality, these methods are equally adept at assessing the performance impacts of new policies and working at the airline (sub-)network level.

A key remaining challenge is the appropriate treatment of the multi-dimensional nature of performance in air transportation and the trade-offs between its KPAs. Such complex interdependencies and non-linearities are often overlooked. In on-going work, using CNT with interacting elements and feedback loops, we are investigating such trade-offs for various stakeholder investment mechanisms (such as new technologies to increase capacities) in the context of uncertainty. We foresee that complexity science is set to make significant contributions to the management challenges of improving our understanding and optimising the design of future ATM, from both the strategic and tactical perspectives.

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