Resilience

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5.1. Introduction

Thanks to the influential work by Hollnagel and other researchers (2006), the value of resilience in air transportation has been well recognised in behaviour sciences. The objective of this chapter is to show that air transportation can benefit significantly by studying resilience from the complementary complexity science perspective. This allows to combine the knowledge from behavioural sciences with the systematic modelling and analysis approach of complexity science.

Civil air transportation is an example of a large complex socio-technical system. It comprises interactions between different types of entities, including technical systems, operational stakeholders, regulators, and consumers (DeLaurentis and Ayyalasomayajula, 2009). Technology plays a central role as does the social context within which the various parties operate. This complex socio-technical air transportation system copes with many internal and external disruptions of different nature that implicitly test its resilience on a regular basis. These events may interact with each other, potentially creating a cascade of other events that may span over different spatial as well as time scales, ranging from affecting only one aircraft or crew, up to a group of aircraft. In current air transportation, disruptions are managed by operators at airlines, airports, and ATC centres, and may impact the overall performance of the socio-technical system, e.g. some flights are rerouted, some aircraft or crew are exchanged, and some passengers are rebooked. Managing disruptions involves trade-offs which are created by the complexities inherent to the processes managed and the finite resources of operational systems (Hollnagel, 2009). For instance, in the case of congested airspace, air traffic controllers might ask airlines to reroute their flights. In such a situation, improving the key performance area (KPA) ‘safety’ comes at the cost of the KPA ‘economy’. Potentially, there are conflicting goals leading to dilemmas and bottlenecks that must be dealt with. Nevertheless most problems are adequately solved, and most of these events pass without substantial inconvenience for passengers.

In some cases, however, the resilience of the air transportation system falls short resulting in significant flight delays. A typical example is bad weather, which may jeopardise the normal operation of an airport or a sector and induces ‘ripple’ effects (propagation) throughout the air transportation network. Another example is that of a malfunctioning aircraft being stuck with its passengers at a distant airport, as a result of which all passengers are delayed many hours.

In addition to regular cases with limited consequences, also rare cases happen with very severe consequences. These severe consequences are of two categories: catastrophic accidents involving one or more aircraft; and network-wide consequences that may push the dynamics of the air transportation system far away from its point of operation, and therefore dramatically affect the performance of the system. The latter happens in case of external events for which the air transport network is vulnerable (see Section 3.6), such as outbreak of a viral disease causing passengers and airlines to change their travel behaviour (e.g. SARS in

2003 and Ebola in 2014) or volcanic ash impacting air travel in a large area (e.g. the Icelandic volcano in 2010). Cases of the former are fatal runway incursions (e.g. the Linate runway collision in 2001), fatal mid-air collisions (e.g. the Überlingen mid-air event in 2002), and loss of control of an aircraft flying through a hazardous weather system (e.g. the Air France crash in the Atlantic Ocean in 2009). Some external events belong to both categories, e.g. the 9/11 terrorist action in 2001 led to fatal accidents and caused closing down of air travel in a large area.

The examples above show a wide variety of significant events with major consequences. However, thanks to the resilience of the air transportation system, there also are many significant events having negligible consequences. In order to increase the resilience of the air transportation system, there is a need to identify, understand, and model system interdependencies of the complex socio-technical air transportation system and analyse its response to the large variety of possible disruptions. This chapter aims to show that a complexity science perspective can be a valuable asset in meeting this need. In particular, the chapter aims at answering the following questions: What is resilience and how is it measured? Why use complexity science to model and analyse resilience? Which complexity science approaches can be used? The chapter also demonstrates the benefits of applying complexity science and behavioural science to an airline problem. The specific application concerns airline operations control, which core functionality is one of providing resilience to a large variety of disruptions that happen on the day of operation.

This chapter is organized as follows. Section 5.2 addresses resilience capacities. Section 5.3 examines various resilience metrics from the literature. Section 5.4 introduces complexity science approaches for studying resilience. Section 5.5 provides a convincing resilience application of using complexity science in air transportation. Section 5.6 provides conclusions.

5.2. Resilience Capacities

Resilience comes from the Latin word resilio, meaning ‘to jump back’, and is increasingly used in various disciplines to denote the ability to absorb strain and bounce back from unfavorable events. The term 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 the 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 resilience have been introduced in other domains, such as economics, organisational science and safety science.

Recently, Francis and Bekera (2014) conducted a systematic review of the complementary resilience developments across multiple domains, and identified the following three resilience capacities: (i) absorptive capacity, (ii) adaptive capacity, and (iii) restorative capacity. Absorptive capacity is the degree to which a system can absorb the impacts of system disruptions and minimise consequences with little effort (Vugrin et al., 2010). The practice of incorporating adequate buffer capacity in anticipation of increased stress on the system is for example an absorptive endowment. It is considered to be a proactive measure to absorb potential shocks. Adaptive capacity is the ability of a system to adjust to undesirable situations by undergoing some internal changes. Adaptive capacity is distinguished from absorptive capacity in that an adaptive system can change its response. A system's adaptive capacity includes the ability to forecast adverse events, recognise threats, and reorganise after the occurrence of an adverse event. Finally, restorative capacity is the ability to recover or bounce back from disruptive events and return to normal or improved operations.

Table 5.1 shows what the three resilience capacities mean for resilience related concepts like robustness and dependability. Robustness is defined as the ability of elements, systems, and other units of analysis to withstand a given level of stress or demand without suffering degradation or loss of function (MCEER, 2006). This definition is consistent with the absorptive capacity described by Francis and Bekera (2014). Hence, a socio-technical system that has absorptive capacity only is robust. System dependability is the collective term used in system engineering to describe a system's availability performance and its influencing factors: reliability[1] performance, maintainability performance and maintenance support performance (IEC, 1990). Thus, a dependable system has both absorptive and restorative capacities. In comparison to dependability, resilience is an endowed or enriched property of a system that is capable of effectively combating (absorbing, adapting to, and rapidly recovering from) potentially disruptive events.

Table 5.1: Resilience capacities in relation to robustness and dependability

Related System properties	**Resilience Capacities**		
	Absorptive	**Restorative**	**Adaptive**
Robustness	+	-	-
Dependability	+	+	-
Resilience	+	+	+

Robustness and dependability are system properties that are well addressed through system engineering. For air transportation this means that the key resilience challenges are not only to address a complex socio-technical system rather than a complex technical system, though also to learn improving the adaptive capacities. These adaptive capacities of the socio-technical air transportation system concern both the phase of disruption absorption and the phase of recovering from a system performance degradation due to disruptions.

Placing emphasis on improving the adaptive capacity in absorbing disruptions concurs with the **resilience engineering** definition of Hollnagel et al. (2009) for use in air traffic management research: "a system is called to be resilient if it has the intrinsic ability to adjust its functioning prior to, during, or following changes and disturbances, and thereby sustain required operations under both expected and unexpected conditions". In the safety domain, Hollnagel (2014) explains that this resilience engineering view reveals a need to study "what may go right", rather than the traditional approach of studying "what may go wrong" only. The traditional and novel approaches are referred to as Safety-I and Safety-II respectively.

5.3. Resilience Metrics

[1] In system engineering, reliability is the ability of a system or component to perform its required functions under stated conditions for a specified period of time. One should note that this system engineering definition of reliability is more restricted than what is meant when we refer to a 'reliable' airline. Such an airline is indeed reliable in the sense of the system engineering definition. However, an airline also needs to be adaptive in response to unexpected adverse conditions, in order to perform in a competitive market. This entails getting passengers (and their bags) to their destinations (reasonably on time) and, indeed, having a reputation for doing so. Successful airlines thus have an adaptive capacity, rendering them resilient.

This section examines resilience metrics from the literature, covering different domains including ecosystems, critical infrastructure systems, networks, organizations, information systems, psychology, and transportation systems.

5.3.1. Ecosystems

For ecosystems, Gunderson et al. (2002) distinguished between two resilience measures: **ecological resilience** and **engineering resilience**. The latter considers resilience as the ability to return to the steady state following a perturbation (Pimm, 1984; Varian, 1992; Tilman, 1996; Scheffer, 2009), i.e. it implies only one stable state and global equilibrium. The former concept, considers resilience as the amount of disturbance that a system can absorb before it changes state (Holling, 1996; Gunderson et al., 2002; Scheffer, 2009), i.e. it emphasises conditions far from any stable steady-state, where instabilities can 'flip' a system into another regime of behaviour (Gunderson et al., 2002). So, ecological resilience is measured by the magnitude of disturbance that can be absorbed before the system redefines its structure by changing the variables and processes that control behaviour (Gunderson et al., 2002). For engineering resilience, the only possible measures for resilience are near-equilibrium ones, such as a characteristic return time to a global equilibrium following a disruptions, or the time difference between the moments of disruption and of full recovery.

5.3.2. Critical Infrastructure Systems

The earthquake engineering community (Tierney and Bruneau, 2007) suggested measuring resilience by the functionality of an infrastructure system after a disaster has occurred, and also by the time it takes for a system to return to pre-disaster level. Their suggestion was based on the observation that resilient systems reduce the probabilities of failure, the consequences of failure, and the time for recovery. This concept is illustrated by the 'resilience triangle' in Figure 5.1, which represents the performance degradation due to damage caused by earthquake disruption(s), as well as the pattern of restoration and recovery over time.

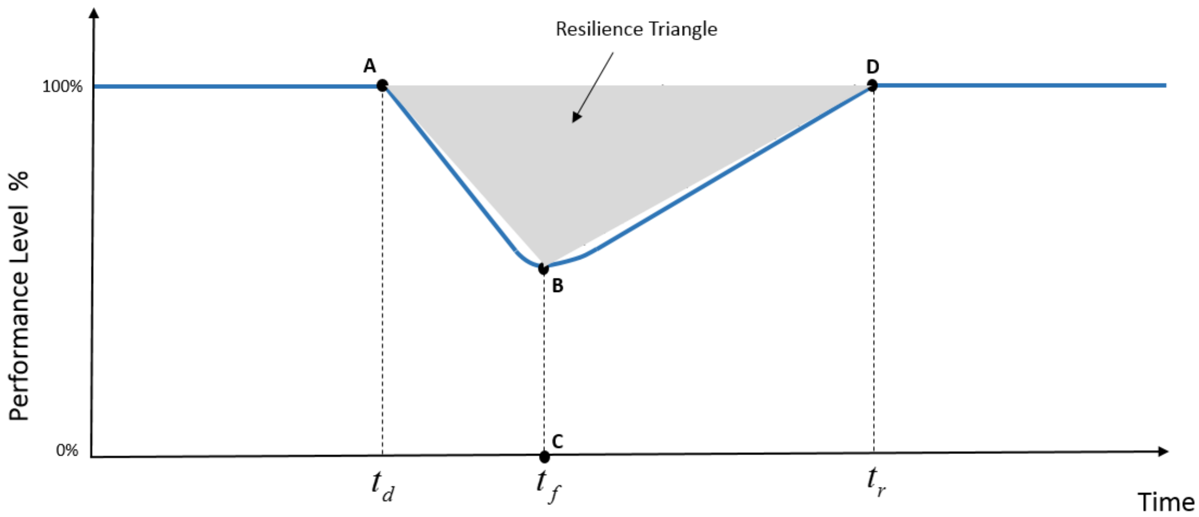

Figure 5.1: Resilience Triangle adapted from Tierney and Bruneau (2007), with disruption moment t_d, moment of full performance impact t_f and moment of full recovery t_r.

The higher the resilience of a system, the smaller the size (depth and duration) of the triangle. Bruneau et al. (2003) expressed resilience as follows: $R_e = \int_{t_d}^{t_r} [100 - Q(t)] dt$, where $Q(t)$ is the performance level percentage at moment t, t_d is the moment of disruption, and t_r is the moment of recovery.

In a later earthquake engineering community work (Renschler et al. 2010), a framework was proposed to measure resilience at the community scale, integrating several dimensions such as population, environment, physical infrastructure, and economic development into one resilience index.

Li and Lence (2007) defined resilience $R_e(t_f, t_r)$ as the conditional probability that given full performance impact at time t_f, the system is fully recovered at time t_r, i.e.

$$R_e(t_f, t_r) = P\left[(F(t_r) \geq F_0) \middle| (F(t_f) < F_0) \right]$$

where $F(t_f)$ and $F(t_r)$ are the performance levels at t_f and t_r respectively, and F_0 is the original stable system performance level (100% level in Figure 5.1). Attoh-Okine et al. (2009) extended the conditional probability approach of Li & Lence (2007) with a 'belief' function to capture incomplete data in urban infrastructure systems.

Francis and Bekera (2014) have proposed quantifying resilience R_e as follows:

$$R_e = S_P \frac{F(t_r)}{F_0} \frac{F(t_f)}{F_0}$$

where F_0 is the original stable system performance level (100% level in Figure 5.1); $F(t_f)$ is the post-disruption performance level (at point B in Figure 5.1); $F(t_r)$ is the performance at a new stable level after recovery efforts have been exhausted (at point D in Figure 5.1); and S_P is the speed recovery factor (slope of BD).

Ayyub (2014) proposed to express the resilience R_e metric as follows:

$$R_e = \frac{t_d + \alpha(t_f - t_d) + \beta(t_r - t_f)}{t_r}$$

where α and β are the ratios of mean performance levels during periods (t_d, t_f) and (t_f, t_r) respectively versus the pre-disruption performance level.

Musman and Agbolosu-Amison (2014) proposed to capture resilience in terms of mission risk. According to their definition, resilience can be computed as being either: (1) a utility-based performance metric that indicates how well the system responds in the face of one or more incidents (where incidents are assumed to have occurred); (2) a probability that some events might occur to bring the system to some specified unacceptable level of performance; or (3) a risk estimate that combines the probability of incidents with the system utility-based measure of performance changes that result when the incidents occur.

5.3.3. Networks

In the area of networks, Najjar and Gaudiot (1990) proposed network resilience $R_N(p)$ and relative network resilience $R_{NR}(p)$, where $R_N(p)$ is defined as the number of node failures a network can sustain while remaining connected with a probability $(1-p)$, and $R_{NR}(p)$ is defined as the ratio of network resilience $R_N(p)$ to the number N of nodes in the network.

Garbin and Shortle (2007) generalised this to a network resilience metric in the form of actual network performance (or percentage of the normal network performance) as a function of the network damage (see Figure 5.2). Examples of parameters that characterise networks are demand, topology, capacity, and routing. Garbin and Shortle (2007) also proposed to use the area under the curve in Figure 5.2 as a resilience index metric for a network.

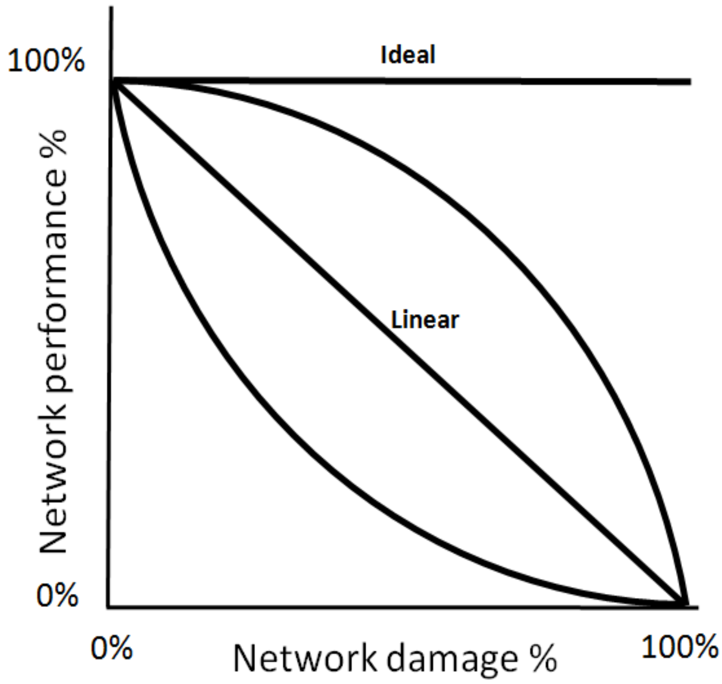

Figure 5.2: Examples of network resilience curves, showing network performance percentage as a function of network damage percentage; adapted from Garbin and Shortle (2007).

Rosenkrantz et al. (2009) proposed metrics to quantify the resilience of service-oriented networks under node and edge failures. The metrics are based on the topological structure of the network and the manner in which services are distributed over the network. They made a distinction between network edge resilience and network node resilience. A network is said to be *k*-edge failure resilient if no matter which subset of *k* or fewer edges fails, each resulting sub-network is self-sufficient. A network is said to be *k*-node failure resilient if no matter which subset of *k* or fewer nodes fails, each resulting sub-network is self-sufficient. In the same work, Rosenkrantz et al. (2009) presented algorithms to determine the maximum number of node and edge failures that can be tolerated by a given service-oriented network, and to optimally allocate services over a given network so that the resulting service-oriented network can tolerate single node or edge failures.

Henry and Ramirez-Marquez (2012) expressed resilience as the ratio of recovery to loss suffered by the system. This means that if the recovery is equal to the loss, then the system is fully resilient, and if there is no recovery, then no resilience is exhibited. They acknowledged that quantifying resilience requires identification of a quantifiable and time-dependent system-level delivery function, also called a 'figure-of-merit' (such as delay, connectivity, flow, etc.). In systems where multiple figures-of-merit are considered, an event could be disruptive with respect to one figure-of-merit but not disruptive with respect to another figure-of-merit. Therefore for a holistic analysis of system resilience, the system must be analysed with respect to all figures-of-merit that are relevant and important (Henry and Ramirez-Marquez, 2012).

5.3.4. Organisations and Information systems

Dalziell and McManus (2004) suggested measuring resilience through assessing the total impact on Key Performance Indicators (KPIs) between the time of disruption and the recovery time, where the KPIs are real-valued measures at a certain moment in time for the corresponding KPAs. The variation of a specific KPI is measured and plotted against time from the start of the disruption t_d until full recovery t_r. The resilience then represents a weighted sum of the areas under the KPI curves.

Zobel and Khansa (2012) introduced a general approach for characterizing cyber infrastructure resilience in the face of multiple malicious cyber-attacks. Their proposed technique accounts for the amount of loss incurred by an information system in the face of multiple cyber-attacks, and it captures the strength and timing of these attacks.

5.3.5. Psychology

In psychology, various psychometric scales have been developed to assess the resilience of individuals, i.e. Likert scales. For instance, Wagnild and Young (1993) developed a resilience scale, the purpose of which was to identify the degree of individual resilience, considering a positive personality characteristic that enhances individual adaptation. The scale consists of 25 items each rated with a 7-point agreement scale. Smith et al. (2008) proposed a 'brief resilience scale' to assess the ability to bounce back or recover from stress.

Other Likert scales include the Baruth protective factors inventory, the Connor-Davidson scale, and the resilience scale for adults (see Ahern et al. (2006) for a detailed review).

5.3.6. Transportation Systems

Chen and Miller-Hooks (2012) defined a resilience indicator that considers the ability of the freight transportation network to cope with the negative consequences of disruptions. The indicator explicitly accounts for the network topology, operational attributes, and the impact of potential recovery activities. Such activities might be taken in the immediate aftermath of the disruption to meet target operational service levels while adhering to a fixed budget.

Omer et al. (2013) identified three resilience metrics to measure the impact of disruptions on the performance of a road-based transportation system. The three identified metrics were the travel time resilience, environmental resilience, and cost resilience. The resilience values were measured by introducing hypothetical disruptions to a network model of a regional transportation network.

Gluchshenko and Foerster (2013) proposed a qualitative measure for resilience in air transportation based on recovery time. They introduced three degrees of resilience, namely:

(i) high resilience, when the time of deviation is considerably longer than recovery time; (ii) medium resilience, when the time of deviation and recovery time are approximately equal; and (iii) low resilience, when the time of deviation is considerably shorter than the recovery time.

Hughes and Healy (2014) proposed a qualitative framework to measure the resilience of road and rail transport system, through dedicated measurement categories for technical and organisational dimensions. The framework involves an initial determination of the context of the resilience assessment, followed by a detailed assessment of resilience measures, which combine to generate a resilience score ranging from 4 (very high resilience) to 1 (low resilience).

Janic (2015) provides an alternative resilience indicator for air transport network analogous to the indicator proposed by Chen and Miller-Hooks (2012) for intermodal freight transport. Such indicator considers the network's inherent properties and the set of actions for mitigating costs and maintaining the required safety level. Because mitigating actions include delaying, rerouting and/or cancelling flights, Janic (2015) defines this indicator as the ratio of the actually realized on-time and delayed flights to the total number of scheduled flights during specific time period. Janic (2015) also proposed to measure the resilience of an air transport network consisting of N airports by estimating the sum of the weighted resilience of each individual airport.

Following the proposal of Musman and Agbolosu-Amison (2014) resilience can be expressed in terms of mission risk. In air transportation, a well-studied mission risk metric is the reach probability for an aircraft trajectory (Prandini and Hu, 2006, 2008; Blom et al., 2007b, 2009). Let $P^{i,j}_{\mathrm{Reach}}(h,d)$ be the probability that the difference in 3-dimensional position $(s^i_t - s^j_t)$ of aircraft pair *(i,j)* hits or enters a disk $D(h,d)$ of height *h* and diameter *d*, on a finite time interval $[0,T]$, i.e.

$$P^{i,j}_{\mathrm{Reach}}(h,d) = \mathrm{Prob}\{\exists t \in [0,T] \text{ such that } (s^i_t - s^j_t) \in D(h,d)\}$$

Then the reach probability $P^{i}_{\mathrm{Reach}}(h,d)$ for aircraft *i* is obtained by a summation over these $P^{i,j}_{\mathrm{Reach}}(h,d)$'s for all $j \neq i$, i.e.

$$P^{i}_{\mathrm{Reach}}(h,d) = \sum_{j \neq i} P^{i,j}_{\mathrm{Reach}}(h,d)$$

In Section 6.4 this reach probability is evaluated for an air traffic application with $h = 0$ and *d* ranging from 0.1 NM till 6 Nm. Hence $P^{i}_{\mathrm{Reach}}(h,d)$ is here a metric for the probability that the mission fails in realizing a horizontal miss distance of *d* or higher between aircraft *i* and all other aircraft. Similarly, the complement $1 - P^{i}_{\mathrm{Reach}}(h,d)$ is the probability that the mission succeeds in realizing a horizontal miss distance of *d* or higher between aircraft *i* and all other aircraft.

5.3.7. Usability in air transportation

From the literature review of resilience metrics one may conclude that there are multiple approaches to measuring resilience. Hence, the key question is which of these resilience metrics from various domains are most appropriate for air transportation? In order to make some progress we address this for the possible types of consequences identified in the introduction:

i) Negligible consequences.
ii) Catastrophic accidents involving one or more aircraft;
iii) Significant local performance consequences
iv) Network wide performance consequences.

For the latter types (iii) and (iv) consequences, it is tempting to use the triangle in Figure 5.1 as a measure of the lack of resilience of the system considered in response to the disruption(s). Then **engineering resilience** is very effective in measuring the duration (A-D) of the resilience triangle in Figure 5.1. Typically, this duration is a measure for the extra time needed to implement and realise a (safe) recovery from the disturbance. However, the real difficulty is how to measure the depth (A-B) of the immediate post-disruption performance degradation in the resilience triangle. The resilience metrics developed in various domains form an illustration of the difficulty in measuring this depth. As suggested by Dalziell and McManus (2004), a possible approach would be to measure this depth in terms of a weighted sum of multi-dimensional KPIs that are commonly in use by the air transportation community.

Types (i) and (ii) consequences are not well captured by the resilience triangle interpretation. Consequence (i) means that there is no triangle at all. Consequence (ii) simply implies that there may be loss of aircraft hull(s) and passenger lives, rather than recovery. The measure needed for type (i) consequences is of **ecological resilience** type, i.e. which characterises the (amount of) disruptions that can be handled in such a way that the consequences are negligible. This leads to a shortlist of two remaining metrics: the psychological metrics (e.g. Likert scales) and the mission risk metric (e.g. reach probability). Because resilience metrics for individual humans only are insufficient for the complex socio-technical air transportation system, the mission risk metric seems to be the best candidate. A complementary advantage of the mission risk metric is that its complement forms a metric for mission success.

It should be noted that none of the metrics measures the individual contribution of the adaptive capacity separately from measuring the contributions of the absorptive and restorative capacities. This means that in order to capture the effect of adaptive capacities, one has to conduct two measurements: one for the full complex system, and another one for the complex system in which the adaptive capacities have been nullified.

A complementary problem is the challenge of collecting real resilience data from the complex socio-technical air transportation system. To do so, one has to await particular disruptions to happen in reality. Even for the existing air transportation system this is a challenge, let alone for the design of a novel operational concept. This asks for the use of appropriate complexity science modelling and analysis approaches.

5.4. Complexity science perspective

5.4.1. Complex system interdependencies

In order to improve the resilience of the complex socio-technical air transportation system, it is critical to identify, understand, and model system interdependencies (Ouyang, 2014). Today, the performance of air transport operations, particularly under disruptive events, is dependent upon a set of highly interdependent subsystems including airlines, airports, and ATC centres. These subsystems are often connected at multiple levels through a wide variety of mechanisms, such that an interdependency exists between the states of any given pair of subsystems or components. Rinaldi et al. (2001) defined an interdependency as a bidirectional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other. As a simple example, airlines and airports are interdependent. An airport closure (e.g. due to weather, limited capacity, or ATC strike) might cause airlines to cancel or divert their flights. At the same time, decisions made at an airline operations control centre influence and depend on airport processes (e.g. gate change, passenger luggage). In normal air transport operations, some interdependencies are invisible, but under disruptive scenarios they emerge and become obvious. An illustration of this is the 2010 Eyjafjallajökull volcano eruption in Iceland which caused the closure of airspace of many European countries, and millions of passengers to be stranded at airports around the world.

Rinaldi (2004) identified four primary classes of interdependencies in critical infrastructure systems; these are presented in Table 5.2. An infrastructure system is defined by the US President's commission on critical infrastructure protection (1997) as a network of independent, mostly privately-owned, man-made systems and processes that function collaboratively and synergistically to produce and distribute a continuous flow of essential goods and services. Such a system is considered to be critical when its incapacity or destruction would have a debilitating impact on defence and economic security.

Table 5.2: Interdependency types in critical infrastructure systems

Interdependency type	Definition
Physical interdependence	When the state of two systems are each dependent on the material output(s) of the other.
Cyber interdependency	When the state of a system depends on information transmitted through the information infrastructure.
Geographic interdependency	When the state of a system can change due to a local environmental event.
Logical interdependency	When the state of two systems are each dependent on the state of the other *via* another mechanism than one of the three above.

Modelling interdependencies in air transportation is a complex, multidimensional, multidisciplinary problem. Table 5.3 lists some of the dimensions associated with system interdependencies that complicate resilience analysis. To model such interdependencies, there is a need for the systematic application, validation, and integration of modelling approaches. This view aligns with a common view in the literature that for the analysis of the resilience of complex critical infrastructure systems, various modelling and simulation approaches need to be integrated into a unifying framework that accounts for various dimensions (Ouyang, 2014). Each approach is appropriate for a certain number of resilience applications, depending on the components being modelled. Overall, the unifying framework can be used to assess the effectiveness of various resilience improvement strategies, and therefore supporting both strategic and tactical decision-making.

Table 5.3: Dimensions and their implications for resilience analysis of the air transportation system.

Dimension	Implications for Resilience Analysis
Multiple stakeholders	Stakeholders have different motivations and problems that drive the modelling requirements.
Multiple	Scopes of scenarios range from airports to the whole European airspace or to the

spatial scales	global scale. Scale affects the resolution and quantity of interdependency data required for models.
Multiple time scales	Different events have varying time scales of relevance. The dynamics of the impacts vary from minutes (e.g. normal activities by the operators), to days (e.g. bad weather), up to years or even decades (e.g. catastrophic accidents).
Multiple KPAs	Multiple competing KPAs exist in air transportation; e.g. safety, capacity, economy, environment. Resilience analysis should be performed with respect to the full spectrum of these KPAs.
Cascading and higher order effects	Disruptions at one airport can propagate to other airports, creating second and higher order disruptions.
Socio-technical perspective	The air transportation system is a socio-technical system. Behavioural responses can influence the efficiency and safety of operations (e.g. situation awareness of operators, or passenger response to an infectious disease).
Disruption management plans	Recovery procedures influence the state of a system during a disruption and may affect coordination among various stakeholders; e.g., disruption management by airline operations control (AOC).
Regulations	Regulations influence operational behaviours as well as the response to and recovery from disruptions (e.g. cancelling a flight due to curfew at a destination airport).
Growing demand	Constant growth in the number of flights, aircraft and airports. Rapid change of the market (from a small number of national airlines to the recent appearance of many companies with new business models).

5.4.2. Complexity science approaches for studying resilience

Ouyang (2014) provided a comprehensive review of various complexity science modelling approaches and grouped them into several broad types: agent-based approaches, network-based approaches, empirical approaches, systems dynamics-based approaches, economic theory based approaches, and other approaches such as hierarchical holographic modelling, the high level architecture based method, Petri-nets, dynamic control system theory, and Bayesian networks. These approaches have subsequently been systematically assessed against several resilience improvement strategies for critical infrastructure systems, and the types of interdependencies they cover (Ouyang, 2014). Overall, agent-based methods and network flow-based methods appear to have the widest and proven applicability, since they cover most of resilience improvement strategies corresponding to the three resilience capacities when compared to other approaches. Complementary to this, viability theory and stochastic reachability analysis (Bujorianu, 2012; Martin et al., 2011) are particularly adept at allowing researchers to model and analyse the various forms of uncertainty (see Chapter 4) in air transportation, and can be applied in both agent-based and network-based models. These four complementary modelling and analysis approaches are discussed in subsequent sections.

5.4.3. Agent-Based Modelling and Simulation

Agent-based modelling and simulation (ABMS) is increasingly recognised as a powerful approach to model complex socio-technical systems and to capture their emergent behaviour (Chan et al., 2010; Holland, 1998). This is because it can represent important phenomena resulting from the characteristics and behaviours of individual agents and their interactions (Railsback and Grimm, 2011). Burmeister et al. (1997) discuss the benefits of using an ABMS approach in domains that are functionally or geographically composed of autonomous subsystems, where the subsystems exist in a dynamic environment, and the subsystems have to interact flexibly. According to (Burmeister et al. 1997), ABMS can be used to structure and appropriately combine the information into a comprehensible form. For a complex socio-technical system, ABMS provides the tools for analysing, modelling, and designing the whole system in terms of agents, each with its own set of local tasks, capability and interactions with the other agents. Agents can be described at a high level of abstraction, yet the resulting composition is very efficient. Burmeister et al. (1997) conclude that ABMS reduces the complexity in systems design by making available abstraction levels that lend themselves to a more natural way of modelling in the problem domain. In the same vein, Jennings (2000) outlines that ABMS and complex system development requirements are highly compatible. He shows that ABMS techniques are particularly well suited to complex systems because: (a) they provide an effective way of partitioning the problem space of a complex system; (b) they provide a natural means to modelling complex systems through abstraction; and (c) they capture the interactions and dependencies. In Chapter 6, ABMS is further explained regarding its capabilities in identifying emergent behaviour in complex socio-technical designs.

5.4.4. Network-based Methods

As we saw in Chapter 2, network theory is used to investigate the structure and topology of networks, and it has applications in many disciplines including computer science, economics, sociology and operations research. Network-based methods are particularly useful for analysing the complex structure of large-scale systems. For instance, centrality measures can quantify the relative importance of network nodes and links (Newman, 2004). Dependency analysis between the nodes can calculate higher-order and cascading effects. Ouyang (2014) has classified network-based methods into two main categories namely topology-based methods, and flow-based methods. The former category models a network based on its topology, and the latter takes into account the service or flow made and delivered by the system. According to Ouyang (2014), network flow-based methods cover all three resilience capacities, in contrast to topology-based methods which cover the absorptive capacity only. As explained in Sections 3.5-3.6, in air transportation, both types of methods are of relevance. Complementary examples of topology-based methods are presented by the work of Guimerà et al. (2005) who analysed the worldwide air transportation network topology, Chi and Cai (2004) who analysed how topological properties of the US airport network are affected when few airports are no longer operational (e.g. due to failures or attacks), and Li and Cai (2004) who studied the airport network of China. A complementary example of results obtainable by network-flow based approaches is the analysis of delay in the US airspace system (Meyn et al., 2004) using the airspace concept evaluation system (ACES) simulator.

5.4.5. Stochastic Reachability Analysis

The primary aim of stochastic reachability analysis is to evaluate the probability that a system can reach a target set starting from a given initial state. This is especially of interest in air transportation where the system should be kept outside an unsafe region of the state space, and the control input can be chosen so as to avoid this unsafe region. Modern applications of stochastic reachability analysis have become increasingly complex. This complexity is due to the rich interactions, complicated dynamics, randomness of environment, uncertainty of measurements and tolerance to faults (Bujorianu, 2012). Examples of illustrative applications in air transportation include the work of Prandini and Hu (2006, 2008), who use stochastic reachability analysis to study aircraft conflict detection, and of Blom et al. (2007b, 2009), who use stochastic reachability analysis to study collision risk in air traffic management (see Sections 6.3-6.4).

5.4.6. Viability Theory

Viability theory (Aubin, 1991) was originally developed to study dynamical systems which collapse or badly deteriorate if they leave a given subset of the state space. Therefore the objective is to keep the system in the part of the state space where it can survive, i.e. where it is viable. In follow-up research by Aubin et al. (2002), viability theory has been extended to hybrid dynamical systems. Recently, Martin et al. (2011) have explained that viability theory provides a natural mathematical framework for the modelling and analysis of resilience in complex systems. In general, viability theory can be applied to a wide range of applications ranging from cognitive sciences and finance, to economics and the sociological sciences. An example application in air transportation is obstacle avoidance, which also appears in numerous application fields. Other examples include using viability algorithms to compute wind optimal routes to reach an airport in minimal time, or computing safety envelopes of an aircraft in different phases of flight (Aubin et al., 2011).

5.4.7. Use in air transportation

The use of these methods in resilience modelling and analysis in air transportation may depend on the specific kind of application in mind. Below and in Table 5.4 we make this more precise for the four types of consequences addressed earlier, i.e. (i) Negligible consequences; (ii) Catastrophic accidents involving one or more aircraft; (iii) Significant local performance consequences; and (iv) Network wide performance consequences.

Table 5.4: Ability in modelling and analysis of types of consequences due to disruptions.

Modelling and analysis approach	Types of consequences due to disruptions			
	(i)	(ii)	(iii)	(iv)
Agent-based modelling and simulation	+	+	+	-
Network flow-based methods	+	-	+	+
Stochastic reachability analysis	+	+	+	-
Viability theory	+	-	+	-

For types (i), (ii) and (iii) consequences, pilots and controllers may play a key role in reacting in a proper way to various events. In such cases agent-based modelling and simulation seems the most appropriate approach. For type (ii) consequences, it is explained in Section 6.3 that agent-based modelling and analysis has to be combined with mathematical methods from the stochastic reachability domain; without these mathematical methods the MC simulation of an agent-based model might take too long. In contrast with traditional safety risk analysis, an ABMS approach can cover both Hollnagel's (2014) Safety-I (i.e. "what can go wrong") and Safety-II (i.e. "what can go right"). This dual capability of ABMS is clearly illustrated in Section 6.5 for an advanced airborne self separation concept of operations.

For types (i), (iii) and (iv) consequences, the network-flow-based methods seem to be the most logical fit as long as human involvement does not play a key role. Otherwise here also agent-based modelling and simulation might be the better choice. In this respect, it is of help to note that the earlier mentioned airspace concept evaluation system, used by Meyn et al. (2004), is a network flow-based method that uses an agent-based architecture, which reflects that, in practice, the network and agent-based methods tend to be integrated. If an agent-based or a network flow-based model has been developed in a proper mathematical setting, then this model can also be used to mobilise viability and reachability analyses for the specific application considered.

5.5. Airline disruption case

The aim of this section is to illustrate the use of agent-based modelling and simulation for measuring the effect of four coordination strategies on the response of an airline to a disruptions that influences many human and technical agents. In order to illustrate that resilience metrics from other domains may be of use in air transportation, the specific resilience metric used is engineering resilience from the ecosystem domain (Section 5.3.1).

5.5.1. Airline disruption management

Each day of operation, an airline's flight schedule is subject to a multitude of disruptions ranging from deteriorating weather, through passenger delays, up to aircraft or crew related problems. Each such disruption may be detrimental to the realisation of the daily fleet schedule of an airline and to the smooth and timely transportation of passengers from their origins to their destinations. Operators at the Airline Operations Control (AOC) centre take corrective actions in real-time in order to recover from disruptions. Obviously this can only be done through interaction with non-AOC teams, e.g. at Air Traffic Control (ATC) centres and airports. Within AOC centres, many operators with different roles interact and coordinate towards achieving a common goal, namely disruption management such that their airline operations adhere to the strategic plan (schedule) as closely as possible.

Bruce (2011a, 2011b) has systematically studied decision-making processes in six AOC centres. In these works (*ibid.*) the author has sought advice from an expert panel of AOC management staff in order to ensure broader views on airline AOC centres and AOC operators (e.g. in terms of gender, age, years of experience in the airline industry, years of experience in the AOC domain, and previous occupation). Figure 5.3 gives a high-level overview of a typical AOC organisation, showing the human agents, the technical systems, and the interactions between the agents involved.

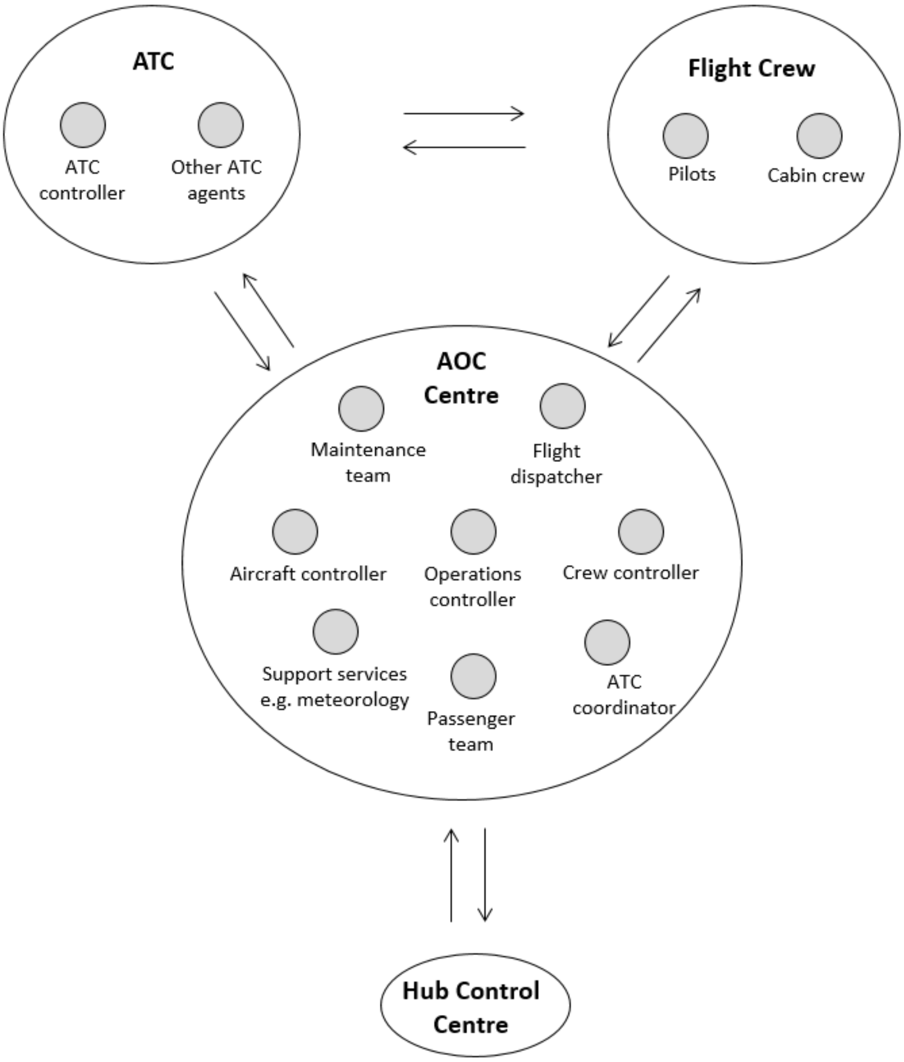

Figure 5.3: Overview of the organisation of Airline Operational Control (AOC) including the communication with Air Traffic Control (ATC); adapted from Bouarfa et al. (2014).

5.5.2. Four disruption management policies

In order to understand the impact of various policies on the performance of airline disruption management, four different policy types have been defined. Three of them (P1-P3) are based on established practices, the fourth one (P4) is based on recent coordination theory.

Policies P1-P3 are based on (Bruce, 2011a, 2011b). As shown in Table 5.5, these three policies capture three different decision-making styles and coordination strategies by airline controllers. Under P1, airline controllers identify straight forward considerations such as aircraft patterns and availability, crew commitments and maintenance limitations. Under P2, airline controllers have a greater comprehension of the problem. They take into account more complex consequences of the problem. Under P3, airline controllers demonstrate thinking beyond the immediacy of the problem. They examine creative ways to manage the disruption.

Table 5.5: Classification of Activities by Airline Controllers (Bruce, 2011b)

Aspect	Policy 1 Elementary	Policy 2 Core	Policy 3 Advanced
Maintenance Information	Accept information source and content and act on information given about a maintenance situation.	Challenge/ query information about a maintenance situation.	Seek alternative information and recheck source and reliability.
Crewing	Await crew from inbound aircraft.	Challenge crew limits/ Seek extensions to crew duty time.	Seek alternative crew (e.g. from nearby base or other aircraft).
Curfews	Curfews are not taken into account.	Identify curfews and work within them.	Seek curfew dispension.
Aircraft	Seek first available aircraft.	Request high speed cruise.	Combine flights to free up aircraft.

The fourth policy (P4) is based on the theory of Klein et al. (2005) regarding coordination of joint activity by multiple actors. This theory identifies three process types that are required for effective coordination, namely: (A) criteria for joint activity processes; (B) satisfying requirements for joint activity, and (C) choreography of joint activity. The criteria for joint activity (A) are that participants in the joint activity agree to support the coordination process and prevent its breakdown. If these criteria are satisfied, the parties have to fulfil certain requirements (B) such as making their actions predictable, sustaining common ground, and being directable. The choreography (C) for achieving these requirements is a series of phases that are guided by various signals and coordination devices, in support of an effective coordination. In order to apply this novel policy to AOC, Bouarfa et al. (2014, 2015) have studied and defined (informal) coordination rules that AOC agents should adhere to in order to follow this P4 policy.

Table 5.6 shows which of the three resilience capacities apply to each of the four AOC policies. Only policies P3 and P4 have adaptive capacities. Under P3, individual controllers examine creative ways in managing or avoiding disruptions thereby adjusting their strategies. Under P4, controllers develop adaptive capacity at the team level through coordinating with each other (Klein et al., 2005). Policy P1 is not only lacking adaptive capacity but also restorative capacity. The explanation is that under P1, controllers act on information given about a certain situation without challenging it. For instance, if information is coming about an instrument indication problem from the pilot, the controller would turn the aircraft back to the airport with its passengers. However, such decision is not always needed, as it could be a loose wire when the instrument was changed and could be fixed at the next airport. Therefore, the rapidity of return to normal operations and ability to adjust are lacking in P1. Finally, P2 is different from P1 in that it does have restorative capacity, as controllers take into account more complex consequences of the problem, challenge and request additional information, therefore expediting the recovery process.

Table 5.6: The four AOC policies and their relation to the resilience capacities

AOC policy	Resilience Capacities		
	Absorptive	Restorative	Adaptive
P1	+	-	-
P2	+	+	-
P3	+	+	+
P4	+	+	+

5.5.3. Airline disruption scenario

In order to assess the impact of the four policies (P1-P4) we consider a challenging AOC scenario that is well evaluated in the literature (Bruce, 2011a). The scenario concerns a mechanical problem with an aircraft on the ground Charles de Gaulle (CDG) airport, aiming for a long-haul flight to a fictitious airport in the Pacific, which is indicated by the fictitious code PC. The flight was progressively delayed at CDG for three hours due to mechanical unserviceability, to the extent that the operating crew were eventually unable to complete the flight within their legal duty time.

This scenario was also considered by a panel of AOC management experts. They developed several alternatives, and subsequently identified the best solution which was to re-route the flight from CDG to PC and to include a stop-over in Mumbai (BOM). In parallel a replacement flight crew was flown in as passengers of a scheduled flight from PC to BOM, in order to replace the delayed crew on the flight part from CDG to PC. The question thus, is how the outcomes of agent-based modelling and simulation of an AOC centre compares to this expert panel found best solution?

5.5.4. Agent-based simulation results

For each of the four disruption management policies P1-P4, an agent-based model has been developed (Bouarfa et al., 2015). The variations in these policies lead to differences in terms of the sequence of agent involvement, information being exchanged, and sequence of activities.

Table 5.7 presents some of the agent-based simulation results obtained for the four AOC policies. See Bouarfa et al. (2015) for more complete agent-based simulation results, such as various costs. P3 concurs with the best solution identified by the expert panel. However the outcomes of P1 and P2 are significantly worse, and the outcome of P4 even outperforms the expert panel result. In order to understand the background of these differences, the agent-based simulation results have carefully been analysed.

Table 5.7: Simulation results for policies P1-P4 in the agent-based AOC model. P3 outcome is equal to the expert panel outcome. P4 outcome is significantly better than P3, whereas P1 and P2 are less good.

AOC policy	Flight	Aircraft mechanical problem	Crew problem	Passengers problem (all at a cost to the airline)	Minimum disruption management time
P1	Cancelled	Fixed	Not resolved	Pax. accommodated in hotel	28 min
P2	Cancelled	Fixed	Not resolved	Pax. accommodated in hotel	28 min
P3	Delayed	Fixed	Resolved	Pax. delayed due to fixing aircraft and due to flying via BOM	28 min
P4	Delayed	Fixed	Resolved	Pax. delayed due to fixing aircraft	19 min

Under policies P1 and P2, AOC operators make decisions at the core or elementary level and with limited coordination, as a result of which the disruption considered is not efficiently managed. The aircraft mechanical problem was eventually fixed, however the flight was cancelled. As a result, the 420 passengers were accommodated in hotels (i.e. greatly inconvenienced). This unfavorable outcome can be explained by the possible actions at level 1 and 2 by the crew controller i.e. “await crew from inbound aircraft” and “see extensions to crew duty time.” Crew controllers at this level mainly consider crew sign-on time and duty time limitations and try to work within these constraints. In this scenario, none of the actions solves the crew problem.

Under policy P3, AOC controllers consider complex crewing alternatives such as deadheading crew from another airport. Therefore, under P3 the decision was made to divert the flight to BOM and position another crew from PC into BOM. Here, both delayed crew and replacement crew were able to operate in one tour of crew duty time. In comparison to policies P1 and P2, policy P3 has a much better outcome from both the airline and passenger perspective. Regarding the time required for managing the disruption, policy P3 is equal to P1 and P2.

Under policy P4, AOC agents make decisions at the elementary level, like P1-P2, though under a healthy coordination regime. Therefore the aircraft, crew, and passenger problems were resolved with minimum disruption. The main difference between P4 and the other policies P1-P3 is that AOC agents now act according to coordination rules (Bouarfa et al., 2015) that account for all joint activity phases (criteria, requirements, and choreography). Thus, for instance, when the crew controller can’t find a crew, he signals his understanding about the situation and the difficulties he is facing. Likewise, the airline operations supervisor signals his understanding back to the crew controller just to be sure of the crew situation or to give the crew controller a chance to challenge his assumptions. Such a process of communicating, testing, updating, tailoring, and repairing mutual understandings is aimed at building common ground prior to starting the choreography phase (Klein et al. 2005). By updating the crew controller on changes outside his view, and coordinating by agreement, precedent and salience, he managed together with the crew controller to solve the crew problem before moving to the next coordination phase. In the scenario considered, P4 was therefore able to identify a possibility that had not been identified by any of the other three policies, and neither by the expert panel: the flight crew that had landed the aircraft at CDG had received sufficient rest to fly the delayed aircraft directly to PC instead of enjoying their scheduled day-off in Paris. Passengers had a minimum delay compared to the previous policies (P1-P3), as they only had to wait for the aircraft to be fixed. Another relevant difference between P4 and the other policies P1-P3 is the shorter time needed to manage the disruption.

5.6. Conclusions

Thanks to scholars from behavioural sciences, it has become clear that for the future development of air transportation, resilience regarding various types of possible disruptions should be studied. The possible consequences of such disruptions may range from (i) negligible consequences, to significant consequences such as (ii) catastrophic accidents, (iii) significant local consequences, and (iv) very severe network-wide consequences. This chapter has conducted a systematic study of what complexity science has to offer to resilience in future air transportation for the various types of consequences.

A socio-technical system is said to be resilient when it has adaptive capacities in addition to absorptive and restorative capacities. A socio-technical system that has absorptive capacity only is called robust. A socio-technical system that has absorptive and restorative capacities is called dependable. Because system engineering is well developed regarding robustness and dependability, the main resilience research challenge is to significantly improve the adaptive capacities of the complex socio-technical air transportation system.

Robustness and dependability are system properties that are well addressed through system engineering. For air transportation this means that the key resilience challenges are not only to address a complex socio-technical system rather than a complex technical system, though also to learn improving the adaptive capacities. These adaptive capacities of the socio-technical air transportation system concern both the phase of disruption absorption and the phase of recovering from a system performance degradation due to disruptions.

Placing emphasis on improving the adaptive capacity in absorbing disruptions concurs with the **resilience engineering** definition of Hollnagel et al. (2009) for use in air traffic management research: “a system is called to be resilient if it has the intrinsic ability to adjust its functioning prior to, during, or following changes and disturbances, and thereby sustain required operations under both expected and unexpected conditions”. In the safety domain, Hollnagel (2014) explains that this resilience engineering view reveals a need to study “what may go right”, rather than the traditional approach of studying “what may go wrong” only. The traditional and novel approaches are referred to as Safety-I and Safety-II respectively.

In the literature several resilience metrics have been developed in various domains, both of qualitative and quantitative nature. The qualitative measures are of two types: **Ecological resilience** and **Engineering resilience**. Ecological resilience is a measure for the amount of disruptions that the socio-technical air transport system can absorb before it leads to significant changes in its KPAs. Engineering resilience is a measure for the duration of the period between the moment of significant reduction in its KPIs and the moment of recovery.

Most resilience metrics are of engineering resilience type, i.e. they address recovery rather than avoidance of significant consequences. Exceptions are the psychological metrics (e.g. Likert scales) for individual human performance (Ahern et al., 2006), and mission risk, such as reach probability for conflict and collision risk in air traffic management (Prandini and Hu, 2008; Blom et al., 2009).

None of the resilience metrics from literature is able to capture the effect of adaptive capacities of a socio-technical system in a separate way from capturing the effects of absorptive and restorative capacities. As has been shown in Section 6.5, an effective way to address this problem is developing a proper model of the socio-technical system considered, and subsequently perform two measurements: one for the full model, and the other for a version of the model in which the adaptive capacities are nullified.

Complexity science provides powerful modelling and analysis means, the most important of which are agent-based modelling and simulation, network flow-based methods, stochastic reachability, and viability theory. When human operators play a key role in the specific resilience aspect to be studied, then agent-based modelling is the logical choice. When the resilience issue to be studied is concerned with propagation of disruption effects through a network, then a network flow-based method is the preferred choice. When both aspects play a role, then a network-flow based approach that uses agent-based architecture might be used. Once a proper agent-based or network-flow based model has been developed this may be used as a basis to mobilise stochastic reachability analysis or viability theory. These complexity science approaches allow making a model of the socio-technical air transportation system considered, and then use this model to assess the effects upon KPIs by increasing the size of disruptions and by varying disruption management strategies in each of the three capacities. The practical working of this approach is demonstrated in Section 5.5 by quantifying the impact of adopting changes in coordination policies by airline operations control (AOC), e.g. by making them more or less adaptive.

In conclusion, this chapter has shown that the complexity science approach towards resilience in future air transportation has significant potential in both strengthening and broadening the resilience engineering approach of Hollnagel et al. (2006, 2009, 2014). It has also been demonstrated that the thinking along a complexity science based approach to resilience yields practical results for the complex socio-technical air transportation system. This great potential of complexity science for the development of air transportation brings with it several valuable directions for follow up research, such as:

- To further develop and apply mission risk metrics that capture the effect of absorptive and adaptive capacities of the socio-technical air transportation system to both separation related and non-separation related disruptions.
- To further develop metrics that are directed to the recovery and adaptation of the socio-technical air transportation system from performance degradation due to disruptions.
- To further the development and application of ABMS for the evaluation of both positive as well as negative impacts of potential resilience improvements in the future designs in Air Traffic Management and Air Transport Operations.
- To further the development of network flow-based modelling and its integration with ABMS for the evaluation of recovery from network wide performance degradation in the air transportation system.
- To further develop the application of reachability and viability theories to the socio-technical air transportation system, by taking advantage of the above mentioned network-flow and agent-based model developments.

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