Emergent Behaviour

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6.1 Introduction

In complexity science a property or behaviour of a system is called emergent if it is not a property or behaviour of the constituting elements of the system, though results from the interactions between its constituting elements. In the socio-technical air transportation system these interactions are between human operators, technical systems and procedures, at airlines, airports and air traffic centres. Safety is a clear example of an emergent property of the complex socio-technical air transportation system: it is not a property of any constituting element, though results from the interactions between the constituting elements. Safety as well as other emergent properties and behaviours of the current air transportation system are results from decades of evolutionary development and improvement. For example, each commerical aviation accident is well investigated, the findings of which often leads to various kinds of improvements regarding elements of the air transportation system. Aviation statistics show that the factual result has been a steady increase of air traffic in combination with a steady improvement of safety, e.g. (Roelen & Blom, 2013). Therefore, one may conclude: current aviation works thanks to the implicit use of emergent behaviour.

In order to accommodate further expected growth in commercial air traffic, significant changes to this socio-technical system are in development both in the USA and in Europe. In addition to accommodating much higher future traffic demands, the challenge also is to improve performance across a number of other key performance areas (KPAs), including safety and efficiency (SESAR, 2007a). For such a complex socio-technical system, it is essential to study and understand the effects on emergent properties and behaviours of changes of individual elements and interactions (Bar Yam, 2003; Holmes, 2004; SESAR, 2007b; ComplexWorld, 2012). One of the main needs identified with respect to future air traffic designs is the identification of unknown emergent risks (EUROCONTROL, 2010b). Hazards that were not anticipated before could rise as a result of new concepts, tools, or procedures. Similarly, yet unknown positive emergent behaviour could also be possible. Woods et al. (2010) explain that as much as new paradigms (e.g. airborne self-separation) could give rise to new vulnerabilities, they could also remove existing ones. More generally, new emergent behaviour that is not well understood often leads to poor performance. However, once new emergent behaviour is better understood, it may be possible to realize emergent behaviour that yields better performance. This raises the question how to identify and study emergent behaviour already during the early design stage of future air traffic management. The aim of this chapter is to develop answers to the latter question.

This chapter is organized as follows. Section 6.2 studies emergent properties and behaviour in air transportation. This starts with a review of the various emergence perspectives developed in the literature, followed by an explanation of illustrative emergence examples in air transportation, and concluded with a study of what this means for the identification and analysis of emergence in future air transportation designs. Next, Section 6.3 provides a systematic identification of the key methods required to identify and analyse emergence in future air transportation. Subsequently, Section 6.4 presents an application of these methods to an advanced design. Section 6.5 provides concluding remarks.

6.2 Emergent behaviour in air transportation

6.2.1 Different perspectives on emergent behaviour

Philosophers have long been interested in the concept of emergence, and especially in trying to establish a common definition for this vague yet very useful concept. The use of the notion traces back to Aristotle (350 BC), who referred to it as 'the whole is something over and above its parts, and not just the sum of them all'. Two thousand years later, Mill (1872) used the example of water to illustrate the same idea; the physical properties of water cannot be predicted a priori from knowledge of the properties of hydrogen and oxygen atoms. The term 'emergent' was said to be coined by Lewes (1875), who argued that certain phenomena produce 'qualitative novelty' or material changes that cannot be expressed in simple quantitative terms. Quoting Lewes: 'The emergent is unlike its components insofar as these are incommensurable, and it cannot be reduced to their sum or their difference.'

One fundamental aspect of emergence is that it refers to a property of a system or structure on a higher level of organisation. Bedau (1997, 2008) refers to this as a 'macro-property'. A property of a system is called emergent if it is not a property of any fundamental element of the system: it is a macro-property that cannot be a micro-property. For example, water can have the property of transparency, but an individual water molecule cannot. The difficulty in understanding this is that an emergent property of a system also somehow arises out of the properties and relations of its elements, though often there is no simple explanation. Transparency of water cannot simply be explained by studying individual water molecules, yet it somehow emerges from the properties of these molecules. Much of the literature on emergence has therefore focused on understanding the relations between micro-processes and macro-properties. The study of emergence found renewed interest (it 're-emerged') in the last decades of the twentieth century, with the growth of scientific interest in the phenomenon of complexity and the development of new non-linear mathematical tools (Corning, 2002). This came at the expense of the view of 'reductionism', which implies the ability to understand all phenomena completely in terms of the processes from which they are composed.

A more contemporary interpretation of the reductionist view is 'supervenience', e.g. (Horgan, 1993), (Kim, 1991). A macro property supervenes on a micro property if there cannot be a macro-difference without a micro-difference. For example, there can be no difference in the temperature of a gas without some difference in the behaviour of its molecules. Even though the idea of supervenience seems straightforward, in the literature there are many heated discussions on 'problems' with the concept, e.g. (Kim, 1991).

Another important term in the literature on emergence is 'downward causation'. Several interpretations of the term are in circulation. A 'strong' definition is proposed by Sperry (1964), who states that downward causation makes that the macro properties have power to control the micro processes. Other authors propose 'weaker' definitions; e.g. (Campbell, 1974) states that in downward causation the micro processes are restrained by and act in conformity to macro properties. For this weaker definition, many more examples can be found, in nature and culture, see e.g. (Heylighen, 1995).

Bedau (2008) defines 'nominal emergence' as a notion of a 'macro property' that cannot be a 'micro property'. Subsequently he argues there are three main types of nominal emergence: resultant, weak and strong:

- Resultant emergence is nominal emergence where the macro properties are derivable from the micro processes without simulation. Hence resultant emergence can be fully explained in terms of the micro processes.
- Weak emergence is the notion of a macro property that is derivable from the micro processes, but only by simulation, i.e. by watching how it unfolds in time. The micro-level interactions are interwoven in such a complicated network that the macro properties have no simple explanation; they are 'explanatory irreducible'. Weak emergence may involve downward causation in the sense that the micro properties cannot be explained by micro-micro interactions, but only by objective macro properties that unify an otherwise heterogeneous collection of micro instances.
- Strong emergence is nominal emergence in which the emergent properties are supervenient properties with irreducible macro causal powers. These macro causal powers have effects both at the macro-to-macro level and at the macro-to-micro level; the latter effects refer to downward causation. The irreducibility part explains that the macro properties are autonomous (cannot be derived) from the micro processes. The macro properties do depend on their micro processes, though this is not derivable through simulation.

Bedau's example of strong emergence is 'consciousness', which cannot be derived, not even in principle, from the physical properties of human beings, including their genes, neurological connections and DNA. In lack of other examples, Bedau (2008) argues that although strong emergence has had a prominent place in the philosophical discussions its scientific credentials are poor, whereas weak emergence is consistent with materialism and is scientifically useful. Bedau also proposes to further split up the concept of weak emergence into three types: a) weak emergence that in principle is derivable without simulation but in practice must be simulated; b) weak emergence that in principle is underivable except by finite feasible simulation; c) weak emergence that is underivable except by simulation, but the requisite simulation is unfeasible or infinite. It should be noted that in his argumentation, Bedau applies a deterministic view on the type of simulations considered, which for example precludes Monte Carlo simulation.

Chalmers (2002) includes a notion of 'unexpectedness' or 'surprise' to the definition of emergence, which leads to some alternative definitions for strong and weak emergence. Other authors also refer to the notion of surprise, like Sanz (2004) who defines emergence as 'just systemic behaviour that is difficult to predict in advance.' Bedau (2008) explains that he left the notion of surprise absent on purpose, due to it being rather subjective. Instead, Bedau claims that with his definition of weak emergence in terms of simulation he is presenting objectivist approaches to emergence, though he notes that his classification is not exhaustive.

Zarboutis & Wright (2006) explain that emergence is closely related to 'adaptation': in complexity science, each micro component interacts with its neighbouring ones, and adapts its internal organisation in order to assure the satisfaction of individual criteria. They do this by using local information and usually while being unaware of the properties that emerge at the macro level. The process of micro-to-macro emergence undergoes simultaneously a form of macro-to-micro control that aims to assure that the macro properties are meaningful. The complex system ideally finds a form of 'optimal adaptation', which goes through the balance between emergence and hierarchical control. The notion of adaptation seems to find a balance between micro-to-macro and macro-to-micro causation, by adding various feedback loops.0

Bar-Yam (2004) develops a mathematical theory behind Bedau's strong emergence. Partly based on this, Fromm (2005) places the philosophical emergence views of Bedau and Chalmers within the context of complex multi-agent systems (MAS). This leads to a splitting of Bedau's weak emergence into two types, and to clear scientific credentials of strong emergence. Fromm's Type I emergence corresponds to 'resultant emergence' of Bedau (2008). Fromm's Type II is Bedau's weak emergence with single feedback from the macro property to the micro processes. Fromm's type III is Bedau's weak emergence with multiple macro properties as well as multiple feedbacks between macro-macro and macro-micro. Example of type III emergence typically applies when a multi agent system incorporates intelligent agents (e.g. who can learn). Fromm's type IV emergence is Bedau's strong emergence, though with the novel insight that macro properties may emerge in a complex multi agent system in a hierarchically hidden multi-level way. This makes it feasible that Bedau's strong emergence conditions are satisfied without violating any law of physics. Fromm's examples of strong emergence are Life and Culture. Life as a strong emergent property based on genes, genetic code and nuclei/amino acids. Culture is a strong emergent property based on memes, language and writing systems.

6.2.2. Emergent behaviour in air transportation

Air transportation is a complex system in which several emergent properties, phenomena and behaviours appear (Everdij et al., 2011). This subsection gives some illustrative examples, and tries to classify them in terms of Bedau's 'resultant emergence', 'weak emergence' and 'strong emergence'.

Air transportation is full of **resultant emergence**. These include macro properties that cannot be micro properties, but that can be derived from all the micro properties, without using simulation. Examples include:

- The function of a technical system on-board an aircraft or on the ground. The function of a technical system is a resultant of the fixed roles of the components, but it cannot be fulfilled by these components in isolation.
- Thermodynamic properties such as pressure, volume, temperature, which play a role in airworthiness issues.
- For some air transportation operations, such as procedural management of oceanic air traffic, the risk of an aircraft collision can be predicted without simulations, by making use of information about the parallel route structure, the traffic flows, and the statistics of large deviations by aircraft from their agreed route (Reich, 1966).

In air transportation, an example of **strong emergence** is safety culture in an airline, or in an air traffic control centre. It is an evolutionary product of routine aspects of everyday practice and rules, of management and organisational structures, and of nation-cultural behaviours (Ek et al., 2007; Gordon et al., 2007). Even through simulation, causal relationships in this safety culture have not been revealed (Sharpanskykh & Stroeve, 2011).

Weak emergence is abundant in air transportation. The key reason is that air transportation forms a complex critical infrastructure which involves each of the key interdependencies identified by Rinaldi (2004):

- Physical Interdependency: Two systems are physically interdependent if the state of each depends upon the material output(s) of the other. This for example applies to the many aircraft in a sector and their interdependency on Air Traffic Control (ATC) in this sector.
- Cyber Interdependency: A system has a cyber-interdependency if its state depends on information transmitted through the information infrastructure. This applies for example to the information exchange between entities on the ground and in the air.
- Geographic Interdependency: Systems are geographically interdependent if a local environmental event can create state changes in all of them. This for example applies when a major weather front enforces distant aircraft and air traffic sectors to make large changes in their plans.
- Logical Interdependency: Two systems are logically interdependent if the state of each depends upon the state of the other via some mechanism that is not a physical, cyber, or geographic connection. This applies for example to the explicit involvement of humans (e.g. pilots, controllers) in the critical decision-making processes.

In air transportation these four types of key interdependencies are very well organized, and they induce various types of weakly emergent macro properties and behaviour at various levels and multiple feedbacks. Because of the involvement of human agents (e.g. pilots, controllers), the macro-properties typically are of Fromm's type III. Only in some exceptional events the interdependencies may fail. There are two categories of such exceptional events: 1) 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; and 2) safety-critical behaviour involving one or more aircraft that in rare cases leads to accidents. It should be noted that these two categories are not necessarily mutually exclusive.

Weak emergence examples of exceptional events of category 1) are: phase transitions, and percolation in a network. 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 the liquid phase). Typically, there exists a critical point that marks the passage from one phase to another (e.g. Helbing, 2001). For example, in road traffic a relatively small increase of traffic demand may lead to a sudden decrease in travel velocity as a result of which the total traffic flow may suddenly decrease (e.g. Kerner, 2004). By posing a cap on air traffic flows, this specific kind of phase transition is largely absent in air traffic. Percolation in a network refers to probabilistic, network-wide propagation, between sites or sub-systems, across links in the network. In air transportation, there are several networks where propagation may happen; for example, the spatio-temporal propagation of congestion over airspace sectors (Ben Amor & Bui, 2012; Conway, 2005) or the propagation of the queuing of passengers through the total air transportation system.

Weak emergence examples of category 2) include safety and safety perception. Safety in air transportation is the complement of the macro property safety risk. Safety perception is a weak emergent macro awareness by a human agent (e.g. a pilot or controller) regarding the safety of those flight(s) that fall under his/her responsibility. Both safety risk and safety perception emerge from and influence behaviour at various other macro levels. For example, the propagation of one or more hazards through the socio-technical air transportation system may create 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). Example fatal outcomes of this kind of emergent behaviour are fatal runway incursions (e.g. Linate runway collision in 2001), fatal mid-air collisions (e.g. Ueberlingen mid-air in 2002), loss of control of an en route flying aircraft (e.g. Air France crash in Atlantic Ocean in 2009). Fortunately, most of the time, the exceptional safety-critical behaviour is resolved prior to evolving into an accident.

An example of such exceptional safety-critical behaviour that is identified by simulation is described by Stroeve et al. (2013). A concept of operations is considered in which frequent active runway crossings take place on a departure runway in good visibility conditions. To limit potential risks related to such operation, the concept included a runway incursion alerting system to warn the air traffic controller in situations in which a departing and a crossing aircraft simultaneously make use or start making use of the runway. According to early safety assessments using traditional approaches such as fault trees and event trees, the alerting system would provide a significant risk reducing effect. However, according to Monte Carlo simulations of a dynamic risk model of the actors, systems and interactions, the risk decreasing contribution of the alerting system and the air traffic controller in the same concept appeared small. The key new insight obtained from the simulations was that in most situations in which the alerting system enables the air traffic controller to warn the pilot, the pilot of one of the involved aircraft has already identified and started to solve the conflict themselves. If in time-critical situations the conflict would not be detected by the pilots, then it would often not be resolved via the alerting system either, e.g., because of a late alert, delay in the communication line between controller and pilots, or a late or inappropriate reaction of the controller or pilot.

The described effect was discovered only after developing and simulating a dynamic risk model that covered the totality of interactions of components including their variability in performance over time. The complexity of air transport operations involves a combinatorial explosion of the many events that may occur in a dynamic way and the many involved uncertainties, such that certain aspects of safety risk can only be studied through simulation. The human mind is simply not able to grasp the many combinations of events occurring later or earlier than average, or resolutions of situations that are implemented in another way, not even when supported by graphical tools such as tree-based schemes or analytical equations. The Monte Carlo simulations made it possible to identify how the operation evolves through time in a dynamic way, addressing to a larger extent the combinatorial explosion and allowing specific behaviour to emerge.

6.2.3. Identifying emergence in future air traffic design

The challenge posed by SESAR and NEXTGEN is to make significant changes in air transportation. SESAR (2006) has formulated strategic objectives of increasing capacity by a factor 2, economy by a factor 2, and safety by a factor 10. In order to realize these challenging objectives, significant changes in the air transportation infrastructure are foreseen, e.g. the Cyber Interdependency will be strengthened by the System Wide Information Management (SWIM), the Physical Interdependency will be strengthened by Trajectory Based Operations (TBO), and the Logical Interdependency will be strengthened by changing the role of human (pilots and controllers). These kinds of changes may lead to significant changes in emergent behaviours in air transportation.

Following Bedau (2008), simulation is needed to capture yet unknown weak emergence. There are three established types of simulation tools available:

- Human-in-the-loop simulation; this works well for the identification of weak emergent behaviour that happens under normal conditions. For example to identify that a pilot or controller tends to use a technical system or procedure in a different way than intended by the developers.
- Network flow-based simulation: this works well for identifying how specific propagation patterns in the air transport network change as a result of a new design. For example to identify the impact of the design change on the traffic flows in case of a significant disturbance, such as a bad weather condition (e.g. Gong et al., 2012).
- Agent Based Modelling and Simulation: this works well in case of many interacting agents, in particular if these agents have intelligence, e.g. pilots and controllers. Shah et al. (2005) explain that ABMS can identify emergent behaviour in air transportation in which human agents play a key role. Monechi et al. (2013) use ABMS to identify phase transitions when the capping of traffic flow in a sector is omitted.

The problem is that these three simulation tools cannot capture emergent behaviours of exceptional safety critical events, nor can they be used to analyse the safety risk of a novel design. The gap between these established simulation approaches and what is required is depicted in Figure 6.1. At the bottom of the safety pyramid there are the controller and pilot actions, which may happen in the order of 10 to 100 events per flight hour. These events are well analyzed by human-in-the-loop (HITL) simulation and ABMS. However, HITL and ABMS leave weak emergent behaviour unexplored that happens along the flank and at the top of the safety pyramid. Halfway the flank, there are incidents happening in the order of once per 10 thousand flight hours. Just below the top there are accidents, which happen in the order of once per ten million flight hours. At the top you have mid-air collisions which may happen in the order of once per billion flight hours. The ratio between the event frequencies at the top versus those at the bottom are in the order of 10 to the power 10. This is abridged by Agent-based Safety Risk Analysis, which is explained in the next section.

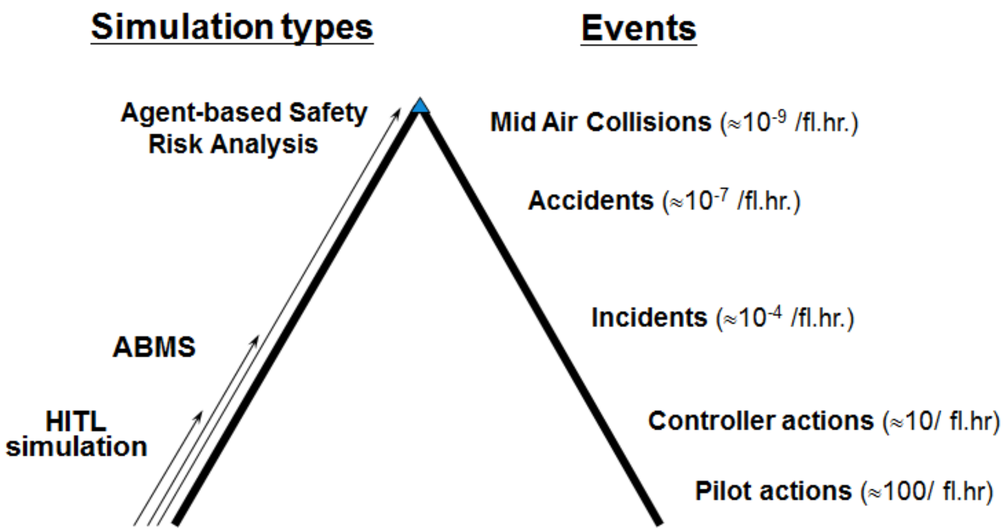

Figure 6.1. Complementary simulation tools are required to evaluate weak emergent behaviour along the flank and at the top of the safety pyramid (Heinrich, 1931) in air transportation; adapted from Blom (2013).

6.3 Agent-based emergent behaviour analysis

6.3.1 ABMS of complex socio-technical systems

ABMS is increasingly recognized as a powerful approach to understanding complex socio-technical systems exhibiting emergent behaviour (Holland, 1998). ABMS has the capability to identify and learn understanding known and unknown emergent behaviours (Chan et al., 2010). 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 agent-based approach in domains that are functionally or geographically composed of autonomous subsystems, where the subsystems exist in a dynamic environment, and these subsystems interact. According to Burmeister et al. (1997), agent-based modelling can be used to structure and appropriately combine the information into a comprehensible form. For a large complex system such as a traffic system, agent-based modelling provides the tools for analysing, modelling, and designing the whole system in terms of its subsystems, each with its own set of local tasks and capability. The integration of the subsystems can then be achieved by modelling the interactions among the subsystems. So agent-based modelling provides abstraction levels that make it simpler and more natural to deal with the scale and complexity of problems in these systems. Agent components can be described at a high level of abstraction, yet they support a systematic compositional modelling approach. Burmeister et al. (1997) conclude that agent-based modelling reduces the complexity in systems design by making available abstraction levels that lend themselves to a more natural way of modelling. In the same vein, Jennings (2000) outlines that ABMS and complex system development requirements are highly compatible. He shows that agent-based modelling 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 of modelling complex systems through abstraction; and c) they capture the interactions and dependencies.

Because ABMS is applied in many different domains, multiple definitions for an agent are in use in different domains. Among the various definitions in the literature for an agent are:

- “An agent is an autonomous system situated within a part of an environment, which senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future” (Franklin & Graesser, 1997);
- “An agent is a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its delegated objectives” (Wooldridge, 2009);
- “An agent is anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators” (Russel & Norvig, 2010).

In the context of air transportation, in particular where different actors, hardware, and software are interacting elements of a complex socio-technical system, we consider agents as entities that are able to perceive and act upon (part of) their environment (see Figure 6.2). These agents may be humans, systems, organizations, and any other entity that pursues a certain goal. For instance, an air traffic controller can be viewed as an agent perceiving his/her environment (displays, alerting systems, runway availability, etc.) and acting upon this environment (e.g. through communicating with other agents like pilots/ other controllers, or turning off runway stop-bars remotely). The environment of agent *i* is understood as all surrounding of agent *i*.

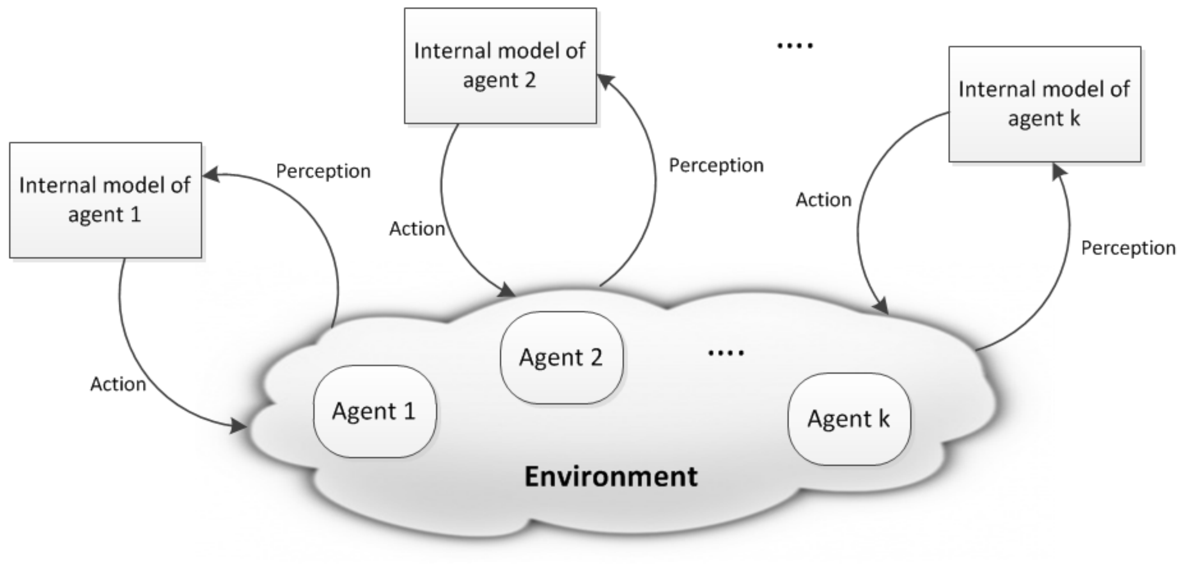

Figure 6.2. Agent-based model

6.3.2 Agent-based modelling of hazards

Traditional safety approaches assume well defined cause-effect links that propagate the effects of events contributing to the safety risk (e.g. sequential or epidemiological safety models). Recent views indicate that such models may not be adequate to represent the complexity of modern socio-technical systems (Hollnagel & Woods, 2005; Hollnagel et al., 2006). Instead, ABMS forms a logical choice for the safety-risk analysis from a socio-technical perspective (Blom et al., 2001a,b, 2006; Stroeve et al., 2009). By having distinguished a number of agents and their interactions, the overall process can be analysed as emerging from the individual agent processes. This not only provides a transparent way of structuring the model, which supports the analysis both conceptually and computationally, but also makes the model easier to maintain, resulting in local model refinements instead of global changes. Stroeve et al. (2013) made a systematic comparison of the agent-based approach against a sequence based approach for a runway crossing operation. This study revealed many advantages of the former approach, including considerable differences in the risk results obtained. The main disadvantage is that agent-based safety risk analysis requires computational modelling expertise that differs from the expertise of traditional safety analysts.

In safety risk analysis the developed multi-agent model of the ATM concept considered is coded in a computer language which includes the possibility to generate random numbers. The generation of these random numbers allows a computer to run a large number (say N) of different simulations with the agent-based model of the operation considered. This is known as Monte Carlo (MC) simulation. By counting the number C of crashes over all these N runs, one gets an estimated crash probability of C/N per run. One of the clear advantages is that MC simulation provides a much more powerful approach in handling the combinatorially many possible event sequences. In a classical risk assessment approach, the analyst needs to identify the possible event sequences *prior* to systematic quantification of risk. However, with MC simulation, there is no need to first identify the possible event sequences. Instead, the agent-based model is MC simulated to assess the probabilities with which particular event sequences and outcomes occur. MC simulation has another advantage: for the catastrophic outcomes of a simulation run, one can look back and see how the trajectories evolved prior to the crash. By doing so for a sufficient number of MC simulated crashes, one can gain insight what exactly happens along the slope of the safety pyramid.

Along the slope of the safety pyramid, all kinds of hazards and non-normal events play important roles. Recently a systematic study has been completed regarding the agent-based modelling of the various kind of such hazards (Bosse et al., 2013), and it has been analyzed how important the various sub-models are in terms of the percentage of hazards that can be captured (Blom et al., 2013). Table 6.1 presents the resulting top 5; the full list is much longer, though the first five already reveal a remarkable aspect of agent-based modelling in air transportation.

Table 6.1. Top five ranking sub-models in capturing hazards and non-nominal effects; from Blom et al. (2013)

Top 5 sub-models	% of hazards
Multi-Agent Situation Awareness Differences	41.4%
Technical System Modes (Configurations, Failures)	19.9%
Basic Human Errors (Slips, Lapses, Mistakes)	18.0%
Human Information Processing	14.3%
Dynamic Variability (e.g. Aerodynamics)	8.6%

To start with the fifth one: dynamic variability applies to 8.6% of the hazards. This sub-model captures for example the dynamic movement of aircraft, e.g. in the form of a set of differential equations. This sub-model is often used in various aviation simulation studies. The fourth highest ranking sub-model is the human information processing model (Wickens & Holland, 2000) at 14.3%. Also this model is often used in aviation, e.g. for simulation of human performance (Corker et al., 2008; Foyle & Hooey, 2008). At the third place are human slips, lapses and mistakes (Reason, 1990), at a percentage of 18%. These basic human error models are widely used in classical risk analysis across all safety-critical domains, including nuclear and chemical industries. The second place, at 19.9%, is for technical system modes. These include both system configurations and system failures. These sub-models also are widely used in classical safety risk analysis.

The highest ranking sub-model is 'Multi-Agent Situation Awareness (MA-SA) differences' at 41.4%, which is more than twice the percentage of number 2. The MA-SA sub-model (Stroeve et al., 2003) is an extension of the Situation Awareness model of (Endsley, 1995). The extension allows capturing the possibility that agents in the socio-technical ATM system may build differences in situation awareness while they have no means to recognize that these differences exist. This is comparable to what happens in the game of 'Chinese whispering'[1]. In contrast to Chinese whispering, not only human agents contribute to this propagation, but technical system agents as well. Fortunately these multi-agent SA differences do not often sneak unnoticed into the current ATM system. However, if they do, this may lead to very risky propagation of these differences to other agents as well.

A simple example of multi-agent SA difference propagation in ATM is a phenomenon that is known as 'Level bust'. For example, a pilot of aircraft A receives an instruction from his/her air traffic controller to climb to an altitude level of 31 thousand feet. Assume that the pilot of aircraft A mishears the instruction as 32 thousand feet and enters this into his/her flight management system (FMS). Then the FMS will level-off aircraft A at 32 thousand feet instead of the 31 thousand feet that is expected by the air traffic controller. The air traffic controller may have previously instructed another aircraft B to fly at a level of 32 thousand feet near the intended level-off point of aircraft A, and is now forced to give this aircraft B an instruction to deviate to, say, 33 thousand feet, to avoid a potential collision. In this example the SA difference sneaks in during the communication between the pilot of aircraft A and the air traffic controller. Then this propagates to an SA difference between the controller and the FMS of aircraft A. In the current ATM system the propagation of these SA differences is only noticed when aircraft A does not level off at 31 thousand feet. At such a late moment there is little time left to avoid a potential collision.

Although the above 'Level bust' example is well known in ATM, the idea to capture this phenomenon through multi-agent SA difference propagation modelling is not. Moreover, this kind of multi-agent SA difference propagation appears to apply in a significant percentage of the commercial aviation accidents. Hence, by capturing the multi-agent SA differences propagation in an agent-based model, it is expected that this allows to predict such kind of risky situations in a future air transportation design.

6.3.3 Integration of mathematical methods

Because the time scales of events at the top and bottom of the safety pyramid are widely separated, a straightforward MC simulation of an agent-based model might take a life time. A way out of this problem is to integrate agent-based modelling and simulation with the power of dedicated mathematical tools. This kind of integration of MC simulation and mathematics has become popular in financial mathematics and in particle physics. However, integrating agent-based modelling with mathematics for safety risk analysis is an innovative development. Table 6.2 provides an overview of mathematical tools that have found useful integration with ABMS.

At the top of the listing in Table 6.2 is Stochastically & Dynamically Coloured Petri Nets (SDCPN) (Everdij & Blom, 2005, 2010). This mathematical formalism allows developing a model specification which assures that there is a one-to-one connection between the agent-based model and certain basic stochastic process properties. First of all, an SDCPN-based model supports a one-to-one relation with the evolution equations of Fokker-Planck-Kolmogorov (Bect, 2010; Krystul et al., 2007) and with the theory of probabilistic

[1] Chinese whispering is a game in which the first player whispers a phrase or sentence to the next player. Each player successively whispers what that player believes he or she heard to the next. The last player announces the statement to the entire group. Errors typically accumulate in the retellings, so the statement announced by the last player differs significantly, and often amusingly, from the one uttered by the first.

reachability analysis for stochastic hybrid systems (Blom et al., 2007, 2009; Bujorianu, 2012; Prandini & Hu, 2006).

Table 6.2: Mathematical methods integrated with ABMS.

Stochastically & Dynamically Coloured Petri Nets (SDCPN)
Fokker-Planck-Kolmogorov Evolution
Importance Sampling
Conditional MC Simulation
Interacting Particle System
Sensitivity/Elasticity Analysis
Uncertainty Quantification

SDCPN provides formalisms for specifying and composing interacting infrastructure networks hierarchically, their stochastic analysis and MC simulation. SDCPN consists of places (drawn as circles) and transitions (drawn as squares), which are connected by arcs (drawn as directed arrows). The places represent discrete states; a token (drawn as a coloured dot) in a place represents that discrete state to be currently active. The colour of the token assumes values from a Euclidean state space, its value evolving as the solution of a stochastic differential equation and influencing the random time period between enabling and firing transitions. The transitions remove tokens from places and produce new tokens for places with attached colours that are random functions of the removed tokens and colours in the direction of the arcs, representing random and dynamic jumps between discrete states. Also, it has been proven by Everdij & Blom (2005, 2010), that an SDCPN-generated process (e.g. through Monte Carlo simulation) is mathematically equivalent to a generalized stochastic hybrid process (GSHP), e.g. (Bujorianu, 2012). Therefore, SDCPN generated processes inherit the stochastic analysis power of GSHP, one of which is the strong Markov property (Krystul et al., 2007). These powerful relations provide a sound mathematical basis for accelerated convergence of MC simulations.

In Table 6.2, examples of accelerated MC simulation techniques are importance sampling, conditional MC simulation, and interacting particle system (IPS). Importance sampling is a widely used technique for rare event simulations, e.g. (Asmussen & Glyn, 2007; Bucklew, 2004). Conditional MC simulation consists of decomposing catastrophic risk simulations into a sequence of conditional MC simulation problems and combining the results of these conditional simulations into the assessed risk value. The IPS approach supports probability estimation of a rare event by introducing a sequence of intermediate event conditions that are always preceding the event of interest. The rare event probability is determined as the product of conditional probabilities of reaching these intermediate events. The conditional probabilities are estimated by simulating in parallel several copies of the process, i.e., each copy is considered as a particle following the trajectory generated by the process dynamics (Blom et al., 2007). Cérou et al. (2006) have proven that under certain conditions this IPS approach yields unbiased risk probabilities, which distinguishes IPS from the popular Restart method (Villén-Altamirano & Villén-Altamirano, 2002). The main condition that is required to ensure unbiased estimation is that the simulated process must have the strong Markov property. As has been explained above, by developing a model in terms of SDCPN semantics, the generated stochastic process satisfies this strong Markov requirement.

Uncertainty is inherent to safety risk analysis. Mathematical tools for uncertainty analysis are sensitivity/elasticity (log sensitivity) analysis and uncertainty quantification. In order to assess the bias and uncertainty in the model-based assessed risk level, Everdij et al. (2006b) developed the following stepwise approach:

1. *Identify potential differences between model and reality.* This concerns differences between: i) the values assumed in the SDCPN simulation and the real parameter values; ii) differences between SDCPN structure assumed and structure in reality; iii) differences due to hazards that are not modelled by the SDCPN; and iv) differences between the operational concept assumed in the SDCPN and the real operation.
2. *Assess the size/probability of the differences.* For each parameter value, a bias factor and a corresponding uncertainty interval are assessed. For other types of differences, a value is assessed for the probability that the difference applies in the case considered.
3. *Assess the elasticity (log-sensitivity) of assessed risk level for changes in parameter values.* Additional Monte Carlo simulations are conducted with the SDCPN in order to assess the elasticities (log-sensitivities) of the SDCPN assessed safety risk to changes in its parameter values.
4. *Assess the effect of each potential parameter value difference on the risk outcome.* The bias and uncertainty intervals of each parameter value are combined with the risk elasticities.
5. *Assess the effect of the non-parameter differences.* For the non-parameter types of differences, a conditional risk bias given the difference exists is assessed and this is combined with the probability that the difference exists (step 2).
6. *Determine the joint effect of all differences.* The joint effect of all differences on the bias and uncertainty interval of the risk is determined.

The integration of the above described mathematical techniques within agent-based modelling and simulation has been shown to be highly effective in air traffic management safety risk analysis (Stroeve et al., 2013), which has recently been recognized by the FAA and EUROCONTROL as a valuable approach in evaluating advanced ATM developments (EUROCONTROL/FAA, 2014; Fota et al., 2014).

6.4 Case study: airborne self-separation

6.4.1 Advanced Autonomous Aircraft (A3) operation

This section aims to illustrate the application of agent-based safety risk analysis to an advanced airborne self-separation design. The idea of airborne self-separation (or free flight) is that pilots are enabled to handle separation management by using an Airborne Separation Assistance System (ASAS). Although free flight has been researched well since its ‘invention’ (RTCA, 1995), all these years a dividing dispute has gone on between two schools of researchers. One school believes that the emergent behaviour and properties of free flight are such that it can safely accommodate high traffic demand. The other school believes the opposite. Positive pilot findings (Ruigrok & Hoekstra, 2009) during HITL simulations of free flight have not resolved this dispute. In order to decide this basic dispute there is a need for a systematic understanding of rare emergent behaviours and the safety macro properties of free flight. In order to help resolving this dispute, Blom & Bakker (2011, 2012, 2013, 2014) have conducted an agent-based safety risk analysis of an advanced airborne self-separation design; this forms the background of the case study presented in this section.

The airborne self-separation design considered is the Advanced Autonomous Aircraft (A3) design (Cuevas et al., 2010; Gelnarova & Casek, 2009). This A3 design is largely based on an advanced free flight design of NASA (2004), which was later published in a conference paper (Wing & Cotton, 2011). The related NASA design has been shown to work well in pilot-in-the-loop simulations (Consiglio et al., 2010). The A3 design has a four layered architecture:

- Strategic flow control layer
- Trajectory Based Operation (TBO) layer
- Tactical conflict resolution layer
- Collision avoidance layer

The strategic flow control layer assumes a centrally organized control of air traffic flows such that local traffic demands will stay below certain limits that can safely and efficiently be accommodated by the next layers. In the Trajectory Based Operation (TBO) layer, each aircraft determines a 4D trajectory plan that is aimed to be conflict-free from the 4D trajectory plans of other aircraft. This 4D trajectory plan is broadcast to all other aircraft. As long as there are conflicts between 4D broadcast trajectory plans, the aircraft involved will be triggered to iterate until the overall situation is conflict-free. The tactical conflict resolution layer aims to resolve any short term conflicts through tactical course changes. This is needed if for some strange reason an aircraft deviates too much from its 4D trajectory plan, or if the iteration to conflict-free 4D trajectory plans has not been completed in time, for example. The collision avoidance layer works as a last resort in case a serious conflict is unavoidable, though a collision can still be avoided through a rapid climb or descent.

Each of these layers involves many interacting micro processes with involvement of all flights concerned. This leads to macro behaviour at each of these four levels, i.e. behaviour that cannot be observed at the micro process level. Hence there is flow control induced macro behaviour at a strategic level, TBO induced macro behaviour at the medium term planning level, tactical conflict resolution macro behaviour at the short term level, and airborne collision avoidance macro behaviour at the last resort level. Moreover at each level humans play a key role in the decision-making, and there also is feedback from the macro behaviour at one level to the micro-behaviour at another level. This makes the A3 concept design a nice example of Fromm's Type III emergent behaviour.

Of these four layers, the first and the last one exist in current ATM, but the two layers in the middle differ a lot from current ATM. For this reason it was decided to perform an agent-based safety risk analysis for these two middle layers. Figure 6.3 gives a high-level overview of the agent-based model developed, which shows the relevant agents in these two layers, as well as their main interactions. These interactions include deterministic and stochastic relationships, as is appropriate for the agents considered. The agent-based model has been developed in a hierarchical way. For each aircraft there is an agent representing the aircraft itself, an agent representing the guidance, navigation and control (GNC), an agent for the ASAS, an agent for the pilot flying (PF), and an agent for the pilot not flying (PNF). Common for all aircraft is an agent representation for global communication, navigation and surveillance (CNS) and one for the environment. It should be noted that from a multi-agent perspective the two middle layers are not recognizable as separate architectural layers.

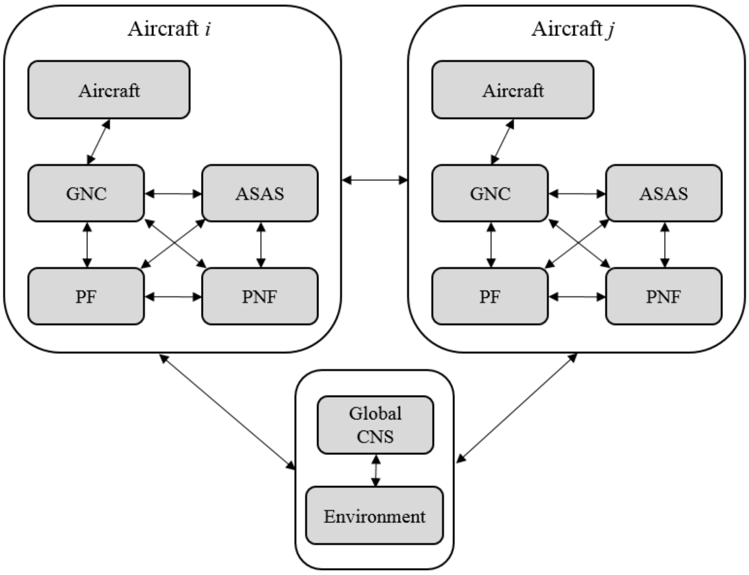

Figure 6.3. Agents in the TBO and tactical conflict resolution layers in A3; from Blom (2013).

Following the development, implementation and verification of this agent-based model in computer code, MC simulations of the operations using the two middle layers have been conducted. Figure 6.4 shows a top view of an example outcome of a single MC simulation run for a scenario of eight conflicting aircraft. Opposite aircraft in this scenario start at distances of 135 Nautical miles (Nm) from each other; the straight lines for each of these aircraft to their respective destinations meet each other in the centre. Without a properly working ASAS system this would be unsafe.

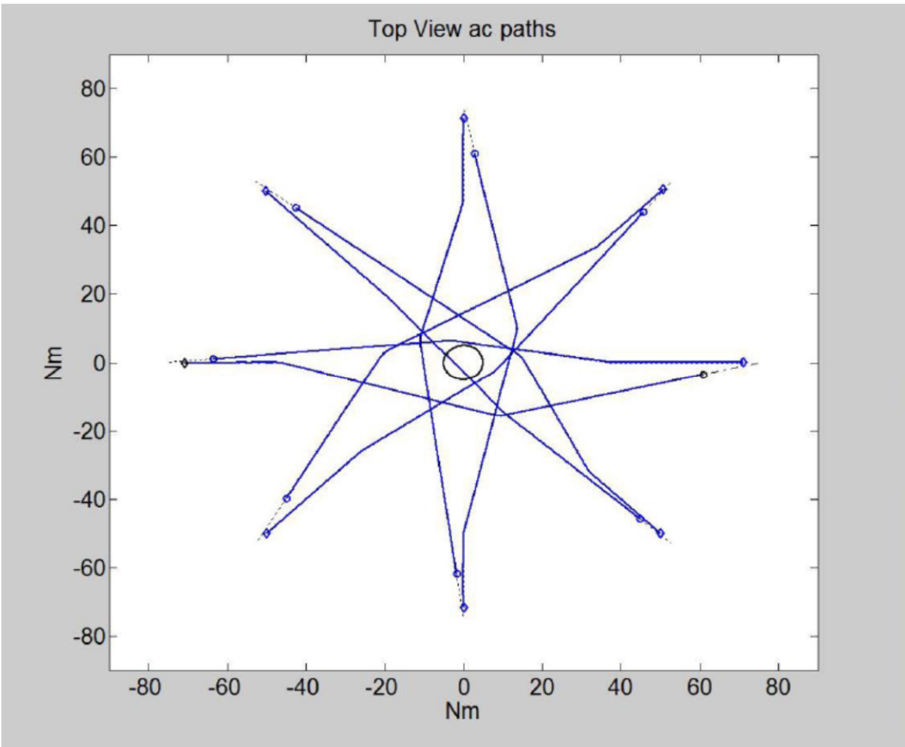

Figure 6.4. Example of eight encountering aircraft trajectories realized under the A3 design. The aircraft started at the locations of the diamonds, and stopped

shortly before reaching the opposite diamond. The circle in the middle has a diameter of 10 Nm (18.5 km); from Blom (2013)

4.2 Rare event Monte Carlo simulations

The key rare event Monte Carlo simulation results of Blom & Bakker (2011, 2012, 2013, 2014) are obtained for dense random traffic scenarios for a situation of multiple times the traffic demand in a busy en-route sector on a busy day in 2005. In order to accomplish this through MC simulation of a limited number of aircraft, use has been made of a Periodic Boundary Condition, e.g. (Rapaport, 2004). The key outcome of these rare event MC simulation results is given in Figure 6.5. The curve in this figure shows the occurrence probabilities per flight hour of realizing miss distance values ranging from 6 Nm down to 100 m. The curve starts at a miss distance value of 6 Nm at a probability value of 1, and then goes down when the miss distance gets smaller. The curve in Figure 6.5 consists of four parts:

- The first part is a horizontal line from 6 Nm till 5.3 Nm at probability level of 1.
- The second part of the curve covers the steep slope between 5.3 Nm and 4.3 Nm.
- The third part of the curve is an almost horizontal line from 4.3 Nm till ~1 Nm.
- The fourth part of the curve bends down between ~1 Nm and 100 m miss distance.

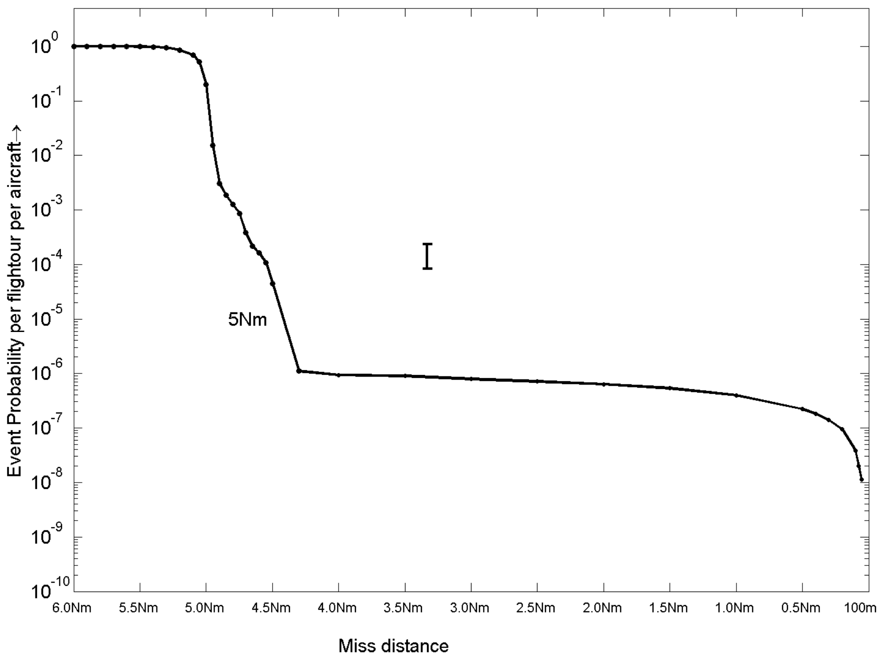

Figure 6.5. Estimated event probability per aircraft per flight hour for random traffic under A3 model control at traffic demand of 3x high en-route traffic demand in 2005; from Blom and Bakker (2012). The bracket I shows the frequency of underscoring 3.33 Nm in current en route traffic (NATS, 2011).

During the first and third parts of this curve the event probability per flight hour hardly decreases with the miss distance. Only during the second and fourth parts of the curve the event probability is clearly going down. The reduction during the fourth part is known as the 'Providence' factor in mid-air collision risk. The fixed level of the third part reflects the limited dependability of the ASAS supporting technical system. By far the largest factor of reduction happens during the second part of the curve; this is due to the Tactical conflict resolution layer. At 5.3 Nm the second part of the curve starts bending down, then goes through a rapid downfall around 5.0 Nm, and subsequently continues to go rapidly down until the ASAS supporting dependability level has been reached.

Figure 6.5 also shows a reference point in the form of a bracket I representing the frequency of current events in controlled UK airspace for which the miss distance between aircraft underscores 66% of the applicable minimum separation criteria (NATS, 2011). For the 3× highest density in 2005, the A3 design is doing much better than the bracket I for current operations, in Figure 6.5.

It should be noted that the curve in Figure 6.5 does not show a direct contribution of the TBO layer. This raises the question whether the tactical layer can do the above without a proper working TBO layer. In order to verify this, the rare event MC simulation has been repeated for a situation in which the TBO layer is not properly working. The sharp second part of the curve in Figure 6.5 appeared to completely disappear, and instead a slowly decreasing second part in the curve remained (Blom & Bakker, 2013). This shows that an effective working TBO layer is a prerequisite for the Tactical conflict resolution layer to realize the very sharp second part in the curve of Figure 6.5.

In ATM, standing practice is to take care that the distance between centrelines of 4D plans does not become smaller than the minimum horizontal separation criterion (which is 5 Nm) plus an extra buffer of several Nm's for typical navigational deviations from the centreline of a 4D plan. However, the curve in Figure 6.5 has been obtained for situations in which the distance between centrelines of 4D plans is equal to the minimum horizontal separation criterion of 5 Nm, i.e. there is no extra buffer. This means that for the A3 design everything works well without the need for an extra buffer for typical navigational deviations.

While the accuracy of wind forecasts has improved in recent years, it is known that large errors can occur occasionally, which are known to significantly affect the performance of trajectory prediction tools (Paglione & Ryan, 2007). Blom & Bakker (2012, 2014) have shown the impact upon the risk curve in Figure 6.5 of systematic wind field prediction errors of up to 30 m/s (60 knots); this slightly reduces the sharp downfall between 5 Nm and 4 Nm and moves the curve 1 Nm closer to the frequency bracket I for current operations. However, this is much better than the 3Nm reported by Consiglio et al. (2009) for the TBO layer alone, which means that the combination of the TBO layer and the Tactical conflict resolution layer handles wind field prediction errors of 30 m/s far better than what the TBO layer can do alone.

Blom & Bakker (2013, 2014) have also verified whether any phase transitions occur if traffic flow is steadily increased from 3x to 6x high 2005 en route traffic demands. The finding was that no phase transition happens.

Finally, Blom & Bakker (2012, 2014) have provided a comparison against future required target level of safety values has been provided. This shows that the airborne self-separation TBO concept has the potential to realize SESAR very high future safety targets. The tactical layer appeared to work unexpectedly well in managing uncertainties that are not timely resolved by the TBO layer. This is a very positive emergent behaviour that clearly goes beyond the expectations of the A3 designers.

6.5 Conclusions

In complexity science, a property or behaviour of a system is called 'emergent' if it is not a property or behaviour of the constituting elements of the system, but rather results from the interactions between them. This chapter studied commercial air transportation from the perspective of emergence. In order to accommodate the expected growth in commercial air transportation, both in the USA and in Europe, significant changes to its socio-technical system are being developed, including possible changes in the roles of pilots and controllers. For such complex socio-technical designs, it is essential to study and understand the effects of the novel interactions between the many individual elements, in order to be able to identify and address their positive and negative emergent properties and behaviours.

In Section 6.2, challenges have been identified regarding the identification and analysis of emergent behaviours of a novel air transportation design. This has been accomplished in three steps. First, an outline has been given of different perspectives of emergence in the literature. This started by explaining that an emergent property is a macro-property that cannot be a micro-property. Next, it was outlined that in the literature different types of emergence have been identified, ranging from resultant emergence that can be predicted through analysis, through weak emergence that can be predicted through simulation, to strong emergence which cannot even be predicted through simulation. Commercial air transportation displays various examples of each of these three types of emergence, such as resultant emergence from complex technical systems in an aircraft, safety culture as a strong emergence example, and many socio-technical system examples of weak emergence, the most demanding of which are rare emergent behaviours that happen along the flank and at the top of the air transportation safety pyramid presented.

This chapter identified several methods of analysing weak emergence in a future air traffic design, including the safety risk property. Since human operators (e.g. pilots and controllers) continue to play a key role in such designs, agent-based modelling and simulation (ABMS) has been identified as the key approach. It was also determined that ABMS is in need of two complementary approaches: 1) a systematic agent-based modelling of hazards and disturbances; and 2) a combination of ABMS with rare event Monte Carlo simulation methods. Various sub-models play a significant role here, in particular one that addresses differences in situation awareness between different agents. All sub-models are to be integrated and rare event Monte Carlo simulations are to be used to analyse macro properties that happen at various frequencies along the slope of Heinrich's (1931) safety pyramid.

The agent-based safety risk analysis approach has been demonstrated for an advanced airborne self-separation socio-technical design. Since its invention under the name 'free flight', this kind of application has led to a dispute between two schools of researchers. One school believes that free flight brings positive emergent behaviours. The other school believes the opposite. The specific free flight design evaluated has a four-layered architecture, including a strategic flow control layer, a trajectory-based operation (TBO) layer, a tactical conflict resolution layer, and a collision avoidance layer. Each of these layers involves many interacting micro processes that lead to macro behaviour at each of the four layers. It has been explained how an agent-based model was developed for the TBO and tactical conflict resolution layers and their interactions. Subsequently, this model was used to conduct rare event Monte Carlo simulations. The results clearly show that the advanced airborne self-separation design yields various positive emergent behaviours. The findings clearly support the school of believers in free flight.

In conclusion, emergent behaviours that can be predicted are of use in the design of a future socio-technical ATM system. It has also been demonstrated that weak emergent behaviour of future designs can be identified and analysed by the application of ABMS in combination with agent-based hazard modelling and rare event Monte Carlo simulation. This opens valuable directions for follow-up research:

- to further develop ABMS tools for application in the socio-technical air transportation system;
- to further develop and incorporate agent-based hazard modelling and rare event Monte Carlo simulation in above-mentioned ABMS tools;
- to use the above tools for the evaluation of emergent behaviours of future ATM designs along the flank and at the top of the air transportation safety pyramid.

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