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Agent-based modelling and mental simulation for resilience engineering in air transport

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ABSTRACT

Following a discussion of recent reviews, we argue that in resilience engineering (RE) there is a need for more structured modelling approaches for analysis of resilience in sociotechnical systems that can support both qualitative and quantitative studies. In this paper we present agent-based modelling and simulation (ABMS) as an approach towards this end. An agent-based model of a sociotechnical system describes the performance and interactions of its constituent human operators and technical systems in an operational context. In support of RE it can effectively be used to analyse the capability of a sociotechnical system to deal with disturbances and performance variability. We present an RE cycle, which uses qualitative and quantitative ABMS phases for analysis of the adaptive capacity of a sociotechnical system. The focus in this paper is on the qualitative ABMS phase, including the development of a qualitative model and mental simulation using the qualitative model. The model development is supported by a set of model constructs, which represent key aspects of evolution of agents' states and agents' interactions. The mental simulations use reasoning on the basis of the qualitative model to structurally analyse the interactions and dynamics of the performance in the agent-based model. Results of the qualitative ABMS phase can be used to improve the resilience of operations or they may be followed by quantitative ABMS. The approach is presented in detail for aircraft runway approach operations using conventional systems and an advanced aircraft surveillance application system.

1. Introduction

1.1. Resilience engineering

Following the origins of the resilience perspective in ecological studies on prey-predator populations (Holling, 1973), the resilience concept has been adopted in a large number of domains. Various review studies (Francis, 2013; Francis and Bekera, 2014; Hosseini et al., 2016; Martin-Breen and Anderies, 2011) discuss resilience in domains such as ecosystems, socio-ecological systems, socio-economic systems, institutions and governance, social innovation, climate, economy, individual trauma response, psychology, psychiatry, infrastructure, safety management, and organizational science. The resilience concept was introduced in the safety science domain by Hollnagel et al. (2006). For this they coined the term resilience engineering (RE), indicating the ability of a sociotechnical system to adjust its functioning to sustain required operations notwithstanding changes and disturbances, and the 'engineering' of the sociotechnical system to achieve such ability. RE stresses the key role of performance variability by human operators to adjust for changing demands and conditions in the working context. Safety management that uses an RE perspective leads to what Hollnagel (2014) calls Safety-II, entailing a focus that includes everyday actions and outcomes, which can be contrasted with a Safety-I focus on accidents and incidents only. Bergström et al. (2015) studied a selection of 86 peer-reviewed safety-oriented resilience papers along three questions: why do we need resilience, what is resilience, and who realises resilience? It was found that the need for resilience is typically addressed by referring to the complexity of modern sociotechnical systems and their inherent risks. The object of resilience is the capacity to adapt, so as to keep the complex and inherently risky system within its functional limits. The subject of resilience typically is the individual, either at the sharp end or at higher managerial levels.

In a recent RE perspective paper, Woods (2015) discusses four concepts of resilience:

(1) Resilience as rebound, expressing how a system rebounds from disrupting or traumatic events and returns to previous or normal activities.

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(2) Resilience as robustness, expressing the ability of a system to absorb perturbations.
(3) Resilience as graceful extensibility, expressing how a system extends performance when surprise events challenge its boundaries.
(4) Resilience as sustained adaptability, expressing the ability of a system to adapt to future surprises as conditions continue to evolve.

Woods argues that the rebound concept as such provides limited added value, since it needs to be understood what produces a better rebound. For this it needs to be known first what capacities are present before a surprise event arises and how such a surprise event challenges the base capabilities of the system. Woods argues that this implies a shift in focus from the rebound concept to the graceful extensibility and sustained adaptability concepts. With respect to the robustness concept, Woods refers to robust control engineering and indicates that robustness considers a particular system property that is able to withstand a particular perturbation in some sense. As argued above, system brittleness arises when the set of disturbances is not in the system's base capabilities, setting a need for resilience as graceful extensibility and sustained adaptability. In addition, Woods argues that systems that become more optimal in responding to some disturbances tend to become more brittle to other disturbances, addressing the need for system architectures that can sustain the ability to future surprises. In support of graceful extensibility, indicators of system decompensation should be tracked and anticipation of bottlenecks ahead should be stimulated. Sustained adaptability is supported by understanding the effects of changes in a system's life cycle and providing sufficient flexibility to continue to adapt over such longer time scales. In conclusion, a main principle is that a resilient system should be able to well handle surprise events that are outside its design base. How such ability can be achieved is still largely a research subject and new methods are needed for analysis and engineering towards such resilience.

1.2. Modelling for resilience engineering

As ways to assess resilience in various domains, qualitative and quantitative approaches can be distinguished, following a review in (Hosseini et al., 2016). The qualitative approaches include conceptual frameworks and semi-quantitative indices. The conceptual frameworks provide guidelines and best practices for studying resilience in various domains. The semi-quantitative indices are based on expert assessments of different qualitative aspects of resilience, for instance by structured sets of questions that are scored on a Likert scale. The quantitative approaches include general measures for resilience quantification and domain-specific structural-based modelling approaches. As general measures, a broad range of deterministic and stochastic measures are presented in Hosseini et al. (2016), which all somehow describe the decline and recovery of system performance following a disturbance. The structural-based models include optimization models, simulation models and fuzzy logic models, which mostly describe the vulnerability and recovery for disturbances in networks (e.g. transportation, power transmission, communication) and supply chains. Such models tend to describe system performance at relatively high and aggregated system levels, such as network nodes and average consumption, rather than at the level of interacting humans and technical systems in a sociotechnical system. As such they remain at a distance from RE needs.

In RE, typically qualitative approaches are used to assess resilience, and to improve resilience on the basis of such understanding. The results of such studies include guidelines for performing resilience research, qualitative insights into safety occurrences, or qualitative recommendations for design. Typically these studies discuss sociotechnical systems in detail, including interacting humans and technical systems. A well-known qualitative approach is the Functional Resonance Analysis Method (FRAM) developed by Hollnagel (2012). It uses a functional analysis-based approach, wherein functions (e.g. activities, tasks) in an operation are described by six aspects, performance variability of functions is identified, relations between functions and propagation of performance variability that may lead to functional resonance is analysed, and these analysis results are linked to the consequences for the operation. FRAM has been applied for retrospective analysis of incidents and accidents (Herrera and Woltjer, 2010; Paulo Victor Rodrigues, 2011) as well as for prospective analysis in system design (Macchi et al., 2011; Praetorius et al., 2015). It is recognized in Praetorius et al. (2015) that notwithstanding the potential of FRAM to uncover operational complexity given particular events, it is difficult to analyse and model everyday operations that do not include such events, and it may be hard to convey field data into functional models. Also other RE studies often use incidents, accidents or some kinds of non-nominal events as basis for their analysis. Thus, it is often still hard to use RE approaches productively for understanding everyday actions and outcomes, such as advocated in the Safety-II perspective of Hollnagel (2014).

We argue that there is a need in RE for more structured modelling approaches for analysis of resilience in sociotechnical systems that can support qualitative as well as quantitative studies. Support of qualitative studies is needed to align with customary approaches for studying sociotechnical systems and with the vocabulary of their practitioners, such that multidisciplinary contributions to the analysis can be achieved. Furthermore, there are cases in which a qualitative study provides sufficient results and no further detailing towards quantification is needed. Prime reasons for structured modelling and quantification in RE are to better understand complex sociotechnical systems' behaviour, and to develop more specific design requirements. Relations, events and dynamics of sociotechnical systems can be manifold and they can be hard to analyse and understand without structured means. Modelling and simulation provide such structured means for attaining deepened understanding of sociotechnical systems. Given the key contributions of human behaviour and performance variability for resilience (Hollnagel et al., 2006), it is essential that human roles and performance variability are well represented in such modelling and simulation.

1.3. Agent-based modelling and simulation

In this paper we present agent-based modelling and simulation (ABMS) as a structured approach for RE of sociotechnical systems. ABMS is an approach for modelling complex systems by describing the behaviour and interactions of a collection of autonomous decision-making entities, called agents (Bonabeau, 2002; Macal and North, 2010; Van Dam et al., 2013). The overall system behaviour emerges as a result of the individual agent processes and their interactions. ABMS provides a highly modular and transparent way of structuring a model, thus supporting systematic analysis, both conceptually and computationally. ABMS has been used in a wide range of application fields, including molecular physics, cell biology, ecology, epidemiology, social sciences, economy, market analysis, archaeology, anthropology, and transport and traffic (Chen and Cheng, 2010; Macal and North, 2010). In safety studies, ABMS has been used for accident risk assessments (Blom and Bakker, 2012; Everdij et al., 2014; Stroeve et al., 2013a).

An agent-based model of a sociotechnical system describes the performance and interactions of its constituent human operators and technical systems working in an operational context. In studying resilience of a sociotechnical system it is key to understand the system's capability to deal with disturbances and performance variability. Such disturbances and performance variability may reflect a wide range of events, conditions or circumstances, and they may be internal to the sociotechnical system, i.e. stem from particular human operators or technical systems, or they may be external, i.e. reflect phenomena in the environment of the sociotechnical system. Human operators and technical systems can express a large variety of behavioural patterns, which are influenced by processes and characteristics of the agent considered (e.g. cognitive and affective aspects), and which depend on interactions between the agents. ABMS offers the possibility to combine a large variety of models for expressing the behaviour and performance variability of the interacting agents in a sociotechnical system. Simulations for ranges of varying conditions can help to unravel the complexity of the sociotechnical system, and to find ways to effectively support its adaptive capacity. As such ABMS is a very promising technique in support of RE.

1.4. Agent-based modelling and mental simulation

We present ABMS as part of a generic cycle for RE, wherein we distinguish two ABMS phases: qualitative ABMS and quantitative ABMS. Qualitative ABMS includes the development of a qualitative agent-based model and it uses this model for reasoning on relations and dynamics of agents' states; this use of the model we call "mental simulation". Quantitative ABMS includes development of a formal model, software implementation and computer simulation; this is the customary type of simulation in ABMS research. In this paper we focus on the principles of ABMS for RE and on the qualitative modelling phase, including mental simulation for evaluation of the model.

Mental simulation is a well-known concept in neuroscience and psychology, which describes the act of imagination and the generation of alternative realities, and which is used for explaining a broad variety of phenomena such as affect, motivation, behaviour and motor control (Markman et al., 2012). This process of self-projection into alternate temporal, spatial, social, or hypothetical realities is considered a distinctively human capacity, which provides meaning in life (Waytz et al., 2015) and which allows humans to participate in a complex sociocultural world (Baumeister and Masicampo, 2010). Mental simulations are also used in engineering and science as ways to reason about interacting and evolving processes, e.g. for mechanical systems (Hegarty, 2004), or for generating new scientific hypotheses and theories (Clement, 2008; Nersessian, 1999). In particular, mental simulation is the cognitive process for building and interpreting thought experiments (Nersessian, 1992), which are described as "... the construction of a dynamical model in the mind by the scientist who imagines a sequence of events and processes and infers outcomes. She then constructs a narrative to describe the setting and sequence in order to communicate the experiment to others...". Such a narrative basically is a linguistic description of the spatial, temporal and causal relationships among events and entities, but it can be enhanced by supporting material, such as diagrams, pictures and maps. Nersessian (1992) discusses experimental evidence which indicates that such model-based reasoning is faster than reasoning with (logical) propositions, as well as evidence that a reader of a narrative spontaneously constructs mental models to represent and reason about the situations depicted by the narrative. In later work (Chandrasekharan et al., 2013), thought experiments are considered to be on a spectrum of simulative model-based reasoning, together with physical models and computational models. Herein it is argued that computational models can provide deeper insights than thought experiments, since they better support examining a wide range of possibilities within the model parameter space. An agent-based model provides a detailed and structured representation of a sociotechnical system, which ultimately is on the computational side of the spectrum for simulative model-based reasoning. During the development of an agent-based model, it is customary to use mental simulations to arrive at narratives on the ways that agents perform and interact, and to reason whether all essential entities and types of performance are represented in the model for the research question posed.

1.5. Objective and structure of the paper

It is the objective of this paper to show that agent-based modelling and simulation is a suitable modelling approach for resilience engineering, and that mental simulation on the basis of a qualitative agent-based model effectively supports attaining insights in the dynamic relations and performance of a sociotechnical system. The approach is illustrated in detail by an air traffic application case for aircraft approach operations towards a runway using conventional systems and an advanced aircraft surveillance application system (ASAS).

Section 2 presents the ABMS-supported RE cycle and it describes the methods for the development of a qualitative agent-based model and for the mental simulations using this model. Section 3 introduces the RE study of the air traffic application case. Section 4 describes the development of a qualitative agent-based model for these air traffic operations, which addresses the performance of interacting human and technical system agents. Section 5 describes the results attained by mental simulation of the qualitative agent-based model for agents' interactions and evolution of agents' states, and implications of these results. Section 6 provides a discussion of the ABMS approach for RE.

2. ABMS approach for resilience engineering

2.1. ABMS-supported resilience engineering cycle

In this paper, ABMS is part of an RE approach (Pinska-Chauvin et al., 2016), which includes the following main steps (Fig. 1):

Step 0. *Scope RE study:* to determine the objectives and scope of the RE study;
Step 1. *Describe operations:* to describe the sociotechnical system and its operations in nominal conditions;
Step 2. *Identify varying conditions:* to identify all kinds of disturbances and performance variability that can influence operations by the sociotechnical system;
Step 3. *Analyse adaptive capacity:* to identify and understand the strategies applied by the sociotechnical system for dealing with the varying conditions;
Step 4. *Improve resilience:* to identify means to improve the resilience of the sociotechnical system. Such changes in the operations may induce a need for another round in the RE cycle.

Prime methods in these steps are workshops with human operators who are experienced in the operations studied. Such workshops contain specific sessions for each of Steps 1–4 (Everdij et al., 2016).

ABMS contributes to the analysis of adaptive capacity in Step 3 of this RE cycle. As a first sub-step (3a) strategies that are applied for dealing with varying conditions are identified and discussed in a workshop with operators. This provides an initial analysis of the adaptive capacity of the sociotechnical system for dealing with the identified varying conditions in the context of the operations. In some cases, such analysis may be sufficient to gain a proper understanding of the adaptive capacity, such that this understanding

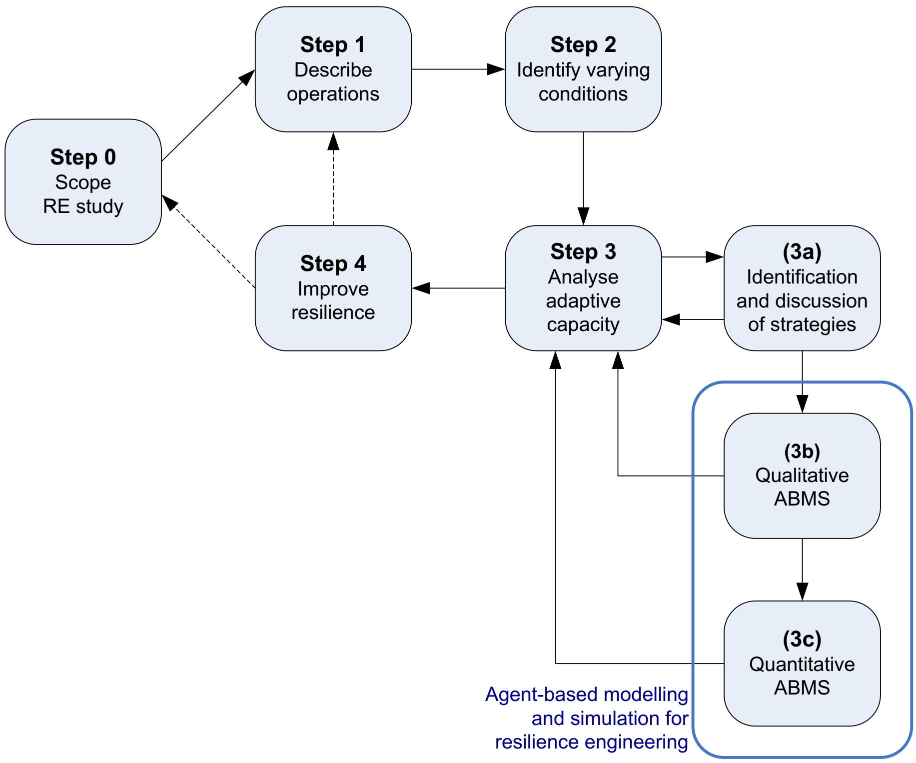

Fig. 1. Steps in an ABMS supported resilience engineering cycle.

suffices for the identification of measures to improve the resilience. In other cases it may be recognized that the complexity of the interrelations and dynamics of the sociotechnical system is too high to attain a sufficient understanding of the adaptive capacity. In these cases ABMS provides a structured means to obtain a more profound understanding of the adaptive capacity of the sociotechnical system. In support of Step 3, we distinguish two phases in ABMS: (3b) qualitative ABMS and (3c) quantitative ABMS.

The qualitative ABMS phase is the first phase, which always precedes the quantitative ABMS phase, but which can also be the sole result of ABMS in support of Step 3. It consists of the following steps:

- *Development of a qualitative model.* The scope of the model development is determined. This scope may focus on particular (more complex) parts of the operation in relation with particular varying conditions. Next the agents and interactions between the agents are determined. For each of the agents it is determined what model constructs are needed to describe the states and behaviour of the agent and details of the model constructs are provided qualitatively.
- *Mental simulation.* On the basis of the developed qualitative model it is reasoned by the model developers what kinds of sequences of agents' interactions exist and in what way performance variables of the model may develop given particular varying conditions. Such mental simulation can serve to provide feedback in the model development process by identifying weak spots in the developed model. The mental simulation also can lead to new insights into the coupling and dynamics of the agents as a basis for recommendations to improve resilience of the sociotechnical system.

The quantitative ABMS phase builds upon the qualitative ABMS phase and it consists of the following steps:

- *Development of a formal model.* The qualitative agent-based model is further formalized to arrive at a complete mathematical description of the agent-based model. Parameters in the model are provided with quantitative values. Such parameter values may be uncertain and it can be useful to specify uncertainty bounds.
- *Software implementation.* The formal model is used to develop computer simulation code of the agent-based model, e.g. using general programming languages or a specific agent-based modelling tool (Macal and North, 2010). The performance of the software is verified.
- *Computer simulation.* The software implementation is used for computer simulation of the agent-based model and the simulation results are interpreted by the user. The computer simulation results provide detailed insights into the couplings, dynamics and variability of the agents' performance. The insights thus achieved can be the basis for qualitative or quantitative recommendations to improve the resilience of the sociotechnical system.

The focus of this paper is on the methods and results of the (3b) qualitative ABMS phase and the following two subsections describe the methods of the development of a qualitative model and of the mental simulation using this qualitative model.

2.2. Development of a qualitative agent-based model

2.2.1. Introduction

An agent-based model of a sociotechnical system describes the performance and interactions of its constituent human operators and technical systems working in an operational context. Agents in a sociotechnical system contain boundaries separating internal states and processes from states and processes external to the agent (in other agents/environment). Relations between an agent's internal and external states or processes are represented strictly via the inputs and outputs of the agent considered. This makes it easier to specify models of complex systems that consist of many interacting entities, thereby facilitating effective study of the emergent behaviour of such systems. The particular ways that an agent's states evolve, the implications of an agent's input, and the behavioural patterns and output of an agent can be represented by model constructs. Also events and conditions that make up the environment of the sociotechnical system can be represented by model constructs (see Fig. 2).

The development of a qualitative agent-based model of a sociotechnical system for RE is done along the following steps:

- Scoping of the qualitative agent-based modelling;
- Identification of agents and interactions;
- Identification of model constructs;
- Qualitative description of model details.

These steps are explained next.

2.2.2. Scoping

The scope of the qualitative agent-based modelling refers to the types of operations, the human operators and technical systems, the varying conditions, and the geographical boundaries of the sociotechnical system. Typically, the scope of the qualitative agent-based modelling is a subset of the scope of the overall RE study (as described in Step 1 of Fig. 1). In particular, the scope includes those aspects of the performance of the sociotechnical system for which the results of the analysis in Step 3a are too uncertain and for which it is expected that additional analysis by ABMS can reduce the level of uncertainty.

2.2.3. Identification of agents and interactions

The sociotechnical system in the scope of the study is modelled by a set of agents. In Macal and North (2010) essential characteristics of an agent are considered to be that an agent is a self-contained uniquely identifiable individual, that it is autonomous and can function independently, that it has a dynamic state, and that it has dynamic interactions with other agents that influence its behaviour. In the modelling of a sociotechnical system the agents typically are human operators and technical systems. To restrict the complexity of the overall agent-based model, a group of human operators or a group of technical systems may be considered as a single (aggregated) agent, if it can be considered as a single entity in its behaviour and interactions with other agents. In this modelling step, it is decided what the agents of the studied sociotechnical system are, and which inter-agent interactions exist. This builds upon the understanding of the operations in nominal situations achieved in Step 1, as well as on the knowledge of strategies for dealing with particular varying conditions achieved in Step 3 of the RE cycle.

2.2.4. Identification of model constructs

A model construct is a generic model describing particular aspects of the ways that agents behave and evolve in interactions with other agents and conditions in the environment. Model constructs are also used to describe evolutions in the environment of the agents. Model constructs are high-level archetypes and within specific applications, modelling details need to be specified at a later stage (see Section 2.2.5).

For the identification of model constructs it needs to be understood, which key aspects of the entities in the sociotechnical system drive their behaviour and contribute to the uncertainty in the overall performance, for the conditions in the scope of the ABMS study. Such understanding can be achieved in the initial analysis of the adaptive capacity of Step 3a and this also forms the basis for the scoping of the ABMS study.

Next, this knowledge is used to identify the set of model constructs that can best represent the key behavioural aspects of the agents in the model. This identification requires an understanding of types of agent-based models, their background, and the ways that they are applied in ABMS. Notwithstanding the systematic background knowledge that is used, to a certain extent the

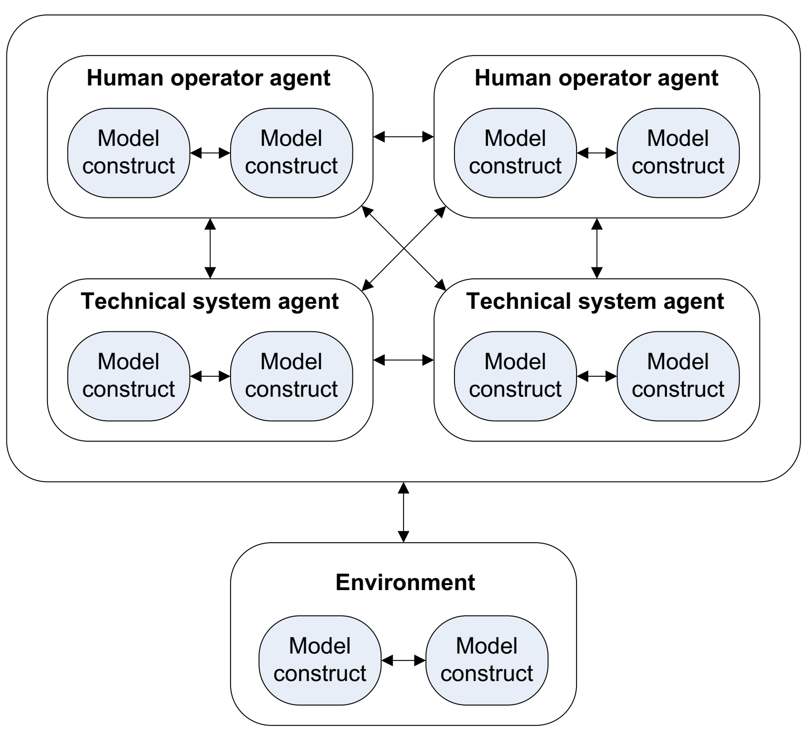

Fig. 2. Generic overview of an agent-based model, consisting of human operators and technical systems in an environment. Agents are represented by a combination of model constructs that represent aspects of the agents' behaviour and interactions.

identification of model constructs is also a creative process, which builds upon the experience and preferences of the modeller. As such, there is no unique set of model constructs for a particular problem. Also, if no suitable model construct exists to represent a particular aspect of the sociotechnical system, a new model construct can be developed to this end.

As a basis for the identification of model constructs, the ABMS literature provides a large variety of agent models (Macal and North, 2010), including for modelling of sociotechnical systems (Van Dam et al., 2013) and social interactions (Sun, 2006). In support of RE in air traffic management (ATM), Stroeve et al. (2013b) developed a library of model constructs for agent-based modelling. This set contains 38 model constructs, which were identified in the ABMS literature and which were evaluated for their capability to support the modelling of a broad range of conditions and events that may contribute to unsafe situations. These model constructs include quite generic ones, e.g. describing how situation awareness may evolve or generic tasks are scheduled and performed, as well as quite detailed and specific ones, e.g. about confusion, group emotion, and goal-oriented attention. For studying resilience in air transport, this library provides a useful starting point for the identification of model constructs.

2.2.5. Qualitative description of model details

In this step, the details of the model constructs are determined at a qualitative level for all agents in the use case. The specifically required model details depend on the model construct considered. The list below provides an overview of the types of details that may be specified in this stage.

- State variables, such as the position and speed of an aircraft, or the situation awareness of an air traffic controller about the position of an aircraft;
- Mode variables, describing an operating mode of a technical system (e.g. some normal working mode, or a failure mode), or of an human operator (e.g. tactical or opportunistic contextual control mode);
- Types of tasks that a human operator may perform;
- Types of behaviour that an agent may show;
- The way that a model construct is influenced by other model constructs within the same agent (intra-agent input);
- The way that a model construct influences other model constructs within the same agent (intra-agent output);
- The way that a model construct is influenced by model constructs of other agents (inter-agent input);
- The way that a model construct influences model constructs of other agents (inter-agent output).

All these aspects are provided qualitatively using textual descriptions. Quantification of the agent-based model is not done in this step, but only in Step 3c of the RE cycle (not detailed in this paper).

2.3. Mental simulation

The developed qualitative agent-based model provides a structured representation of the sociotechnical system for a particular operational context. Such structured representation helps to improve the understanding of the complexity of the relations and dynamics of the sociotechnical system. The development of the qualitative model as such is a first way to support this understanding. As a second and more illustrative way, mental simulation employs reasoning on the basis of the developed qualitative agent-based model.

We next discuss two types of mental simulation, which focus on the interactions in the agent-based model and on its dynamics, and we discuss the use of the mental simulation results in the RE cycle.

2.3.1. Analysis of interactions

As a first type of mental simulation, the qualitative agent-based model can be used for structured reasoning about the interactions between the agents' models in the contextual conditions of the operation that are in the scope of the qualitative ABMS phase. Such analysis can focus on interactions during operations that are considered to be normal, or on interactions following some varying condition of interest. It consists of the followings steps.

- As a starting point, an initial condition of agents should be formulated. This initial condition specifies the states and modes of the agents at the start of the mental simulation.
- One or several triggering events or occurrences of varying conditions are specified, which describe conditions of interest for studying the adaptive capacity of the sociotechnical system. If such event/condition occurs at the start of the simulations, it extends the initial condition, otherwise its timing during the scenario is specified.
- Next it is argued what the main changes are in the states and modes of the agents' models following the initial condition. This argumentation is structured by listing sequences of triggers and resulting actions in the agents. Such trigger-action pairs can be internal to an agent (e.g. an observation leading to a decision to coordinate) or it can impose an interaction between agents (e.g. a communication act leading to a change in situation awareness). As such this exercise provides instantiations of sequences of interactions that may occur in the agent-based model. As the state space of the overall model can be extensive, this argumentation is done for the states that are judged to be most relevant for the situation studied. By making such judgments during the simulations, mental simulations differentiate from computer simulations, wherein the overall state space is simulated and wherein only after the simulations the most relevant state transitions are identified.
- A case of multiple varying conditions leads to multiple instantiations of interaction sequences that need to be accounted for, e.g. a bad weather condition versus a bad weather condition in combination with a technical failure.

The ways that the results of such mental simulation can be used in the RE cycle is discussed in Section 2.3.3 and a detailed illustration for the air traffic application is presented in Section 5.1.

2.3.2. Analysis of dynamics

As a next type of mental simulation, the qualitative agent-based model supports structured reasoning about dynamic relations between states and modes of agents. This can most effectively be done in follow-up to the analysis of interactions as explained above, since the types of interactions need to be understood in order to reason about the dynamic effects. It consists of the following steps.

- As a starting point of the analysis it is decided what states or modes need to be studied in detail to support the understanding of the adaptive capacity. These may be key states identified in the analysis of interactions (Section 2.3.1) or other relevant indicators of the overall system performance. It can be especially useful to reason about some aggregated values of states, such as averages of states over ranges of instantiations of the agent-based model.

- An initial condition of the agents' states and modes is specified.
- One or several triggering events or occurrences of varying conditions are specified, which extend the initial condition or occur at a later stage.
- It is qualitatively argued how the relevant states change in time due to the interactions in the agent-based model. The results of this reasoning about the agent states are described in narratives and can be illustrated by graphs as function of time. These graphs provide qualitative indications of the variation in the selected (aggregate) state variables, which are supported by the argumentation of the elements in the agent-based model that are expected to give rise to them. It can be useful to compare the qualitative graphs for several cases, e.g. a new versus an old operation, or an operation in condition 1 versus condition 2. Also in this type of mental simulation, the dynamics of the complete state space are not described in detail, but rather it is judged during the mental simulation what the most relevant state dynamics are.
- In the case of multiple varying conditions, above process needs to account for the triggers they induce for the state dynamics.

The use of this type of mental simulations in the RE cycle is discussed next and a detailed illustration for the air traffic application is presented in Section 5.2.

2.3.3. Use of mental simulation results in the RE cycle

Performing mental simulation requires a good overview and understanding of the qualitative agent-based model, as well as sufficient knowledge about the application field. In addition, experience in agent-based computer simulations or multidisciplinary systems engineering supports meaningful reasoning about the qualitative agent-based model. These requirements typically imply that the prime executors of mental simulations are scientists of the multidisciplinary model design team. Nevertheless, also other independent researchers with a suitable background should be able to understand the model and to execute the mental simulations. This would require some additional effort to understand the overall model, but has the added value of an independent view and interpretation of the model.

Results of the mental simulations can be discussed with operational experts, for instance with the experts who contributed to the identification and discussion of strategies in Step 3a of the RE cycle. The objective of such discussion in Step 3 of the RE cycle is to get feedback from the operational experts on their view of the validity of the mental simulation results. Do they agree with the presented behaviour and interactions of the agents? Do they think that particular key aspects or interactions are missing in the simulation results? Do they understand and agree with the resulting dynamics? Feedback to these types of questions can lead to several types of conclusions in the context of the RE cycle:

- It can support the identification of missing aspects in the agent-based model, e.g. particular agents, behavioural aspects or agent interactions. This may require an update of the qualitative agent-based model and of the mental simulations, followed by another feedback round of operational experts.
- It can lead to the conclusion that all key elements of the sociotechnical system are well represented in the agent-based model, but that the methods of mental simulation are not sufficiently sophisticated to understand the dynamic and stochastic implications of the agents' behaviour and interactions with sufficient certainty. Following this conclusion, it can be decided to further develop the agent-based model towards a formally specified and quantified model, which is evaluated using computer simulations in Step 3c of the RE cycle.
- It can lead to the conclusion that the mental simulations provided sufficient insights into the adaptive capacity. The thus achieved insights can be used in Step 4 of the RE cycle as a basis to identify measures to improve the resilience of the sociotechnical system.

3. Studying the resilience of an air traffic operation

3.1. Air traffic operation

The air traffic application case of this paper considers the approach of multiple traffic streams towards a single runway. A schematic overview of the air space organization is shown in Fig. 3. Aircraft enter via sectors S1 or S2, heading towards waypoints W1 or W2, respectively. The two traffic streams merge at W3 in the ARR (Arrival) sector. The last part of the approach and landing on the runway is controlled in the TWR (Tower) sector. Each sector is under the control of a single air traffic controller, who is responsible for safe and efficient traffic through the sector. Prime means for this are radar surveillance systems and radio-enabled voice communication between pilots and controllers. In conventional air traffic control, pilots are given instructions to adhere to particular speeds or to use series of heading directions (vectoring) such that separation between aircraft is maintained in the sequence and during merging. There is a joint supervisor for the controllers working in sectors S1, S2 and ARR, and there is a supervisor for the TWR sector.

The future operation studied uses an aircraft surveillance applications system (ASAS) to enable airborne spacing (ASPA) for sequencing and merging. Pilots can get an instruction by the S1, S2 or ARR controller to use ASAS to maintain a particular spacing with respect to a target aircraft in front of them. If the target aircraft is on the same route, ASAS is used for sequencing only (e.g. aircraft 3 uses aircraft 2 as a target for sequencing in Fig. 3). If the target is on the merging route, ASAS is used for merging first and sequencing next (e.g. aircraft 4 uses aircraft 3 as a target for merging and sequencing in Fig. 3). Following the controller instruction the pilots first use ASAS to find out whether the requested airborne spacing is acceptable, and if so, they affirm the controller's request and initiate the airborne spacing operation. Now ASAS continuously tracks the spacing with respect to the target aircraft and it adjusts the aircraft speed (within limits) to attain and maintain the requested spacing. Although the spacing is maintained by ASAS under the pilots' supervision, the controller is still the person responsible for guarding the separation minima.

3.2. Workshop-based resilience analysis

The operations outlined in the previous section were studied for conventional and ASAS approach operations at a large European airport. Resilience of these operations was studied by a workshop-based analysis following a first cycle of Steps 0–4 as described in Section 2.1. As such, workshop sessions with air traffic controllers and airline pilots were used as the prime means to describe current and future operations, identify varying conditions, identify strategies to deal with the varying conditions, and to identify means to improve the resilience of the sociotechnical system (Everdij et al., 2016). This approach led to qualitative interpretations of the adaptive capacity by structuring of the workshop discussions with the operational experts. It was recognized in the study that the analysis of the adaptive capacity may benefit from additional more detailed analysis approaches, such as agent-based modelling and simulation. The development of a qualitative agent-based model for these operations and results of mental simulation for these models are presented next in Sections 4 and 5, respectively.

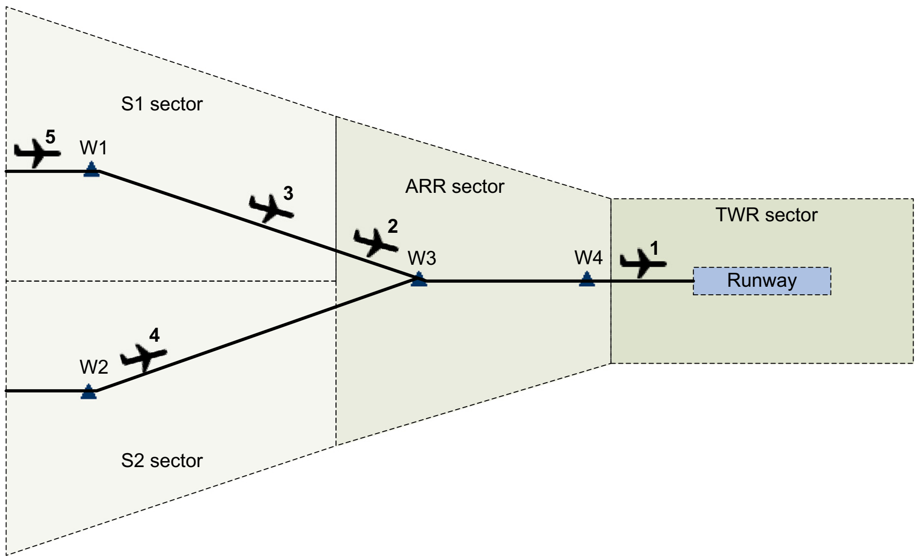

Fig. 3. Schematic top view of air traffic routes approaching a runway with a sample of aircraft.

4. Development of a qualitative agent-based model

This section shows the development of a qualitative agent-based model along the steps of Section 2.2 for the operation described in Section 3. Section 4.1 describes the scope of the agent-based modelling. Section 4.2 provides an overview of the agents and their interactions. Section 4.3 presents the selection of the model constructs. Section 4.4 presents the models of the human agents. Section 4.5 presents the models of the technical system agents. Section 4.6 presents the models of the environment of the sociotechnical system.

4.1. Scope

It was decided to include the conventional approach operation as well as the future ASAS approach operation in the scope of the agent-based modelling study. This provides the opportunity to compare results of both cases. With respect to the human operators, all air traffic controllers, supervisors and airline pilots operating in the airspace sectors, as discussed in Section 3.1, are included in the scope. For the technical systems, the air traffic control (ATC) communication systems, ATC surveillance systems, the communi cation-navigation-surveillance (CNS) systems of the aircraft, the ASAS systems of the aircraft, and the aircraft as flying entities themselves are in the modelling scope. The geographical boundaries of the model reflect the aircraft entry in sectors S1 or S2 and the aircraft exit when they pass the runway threshold. The varying condition in the scope of the modelling is a situation of sudden and unexpected bad weather at the airport, which deteriorates the runway condition and therefore leads to the need to reduce the runway capacity.

4.2. Agents and interactions

Fig. 4 shows an overview of the identified agents and interactions in the agent-based models of the conventional and ASAS cases. It represents a sequence of aircraft and the air traffic control provided by the controllers during the aircraft approaches. Within each aircraft we distinguish the pilots as an aggregated agent, the aircraft flight performance (position, speed, heading, etc.), the aircraft CNS system, and the ASAS system. The controllers use ATC communication systems and ATC surveillance systems as prime technical systems. Supervisors in the tower and S1/S2/ARR control room decide on modes of operations and interact with the controllers. The integrated set of these agents is considered as the sociotechnical system. It exists in an environment, consisting of airspace and weather in the current model instantiation.

4.3. Selection of model constructs

As a basis for the identification of model constructs for the air traffic application case we used a library of 38 agent-based model constructs that was developed in support of RE in ATM (Stroeve et al., 2013b). For each of these model constructs we described its potential role in an agent-based model for the use case and we assessed whether the model construct is needed. A leading argument in this assessment was that in this development stage the overall agent-based model should not be overly complex, but the main interactions and behavioural aspects of the sociotechnical system should be represented.

As a result of this assessment, a set of 11 model constructs was chosen for modelling of the application case. These model constructs are introduced is the list below. More details on the way that they are applied and integrated in the use case are provided in Sections 4.4–4.6.

- *M1: Multi-agent situation awareness.* Situation awareness (SA) is a well-known and much discussed human factors concept for the perception of elements in the environment, their interpretation and the projection of the future status (Endsley, 1995). In agent-based modelling, ascription of mental qualities (e.g. beliefs, desires) to technical systems is seen as useful for analysis of complex systems (Wooldridge and Jennings, 1995). For analysis of safety risks in complex sociotechnical systems, Stroeve et al. (2003) developed the multi-agent SA model construct to describe the development of states of humans and technical systems with regard to their perception, interpretation and future projection of their multi-agent environment. Observation, communication and reasoning processes of the agents drive such state development.
- *M2: Task identification.* This describes the ways that the operator identifies the tasks that need to be performed at a particular time instance.

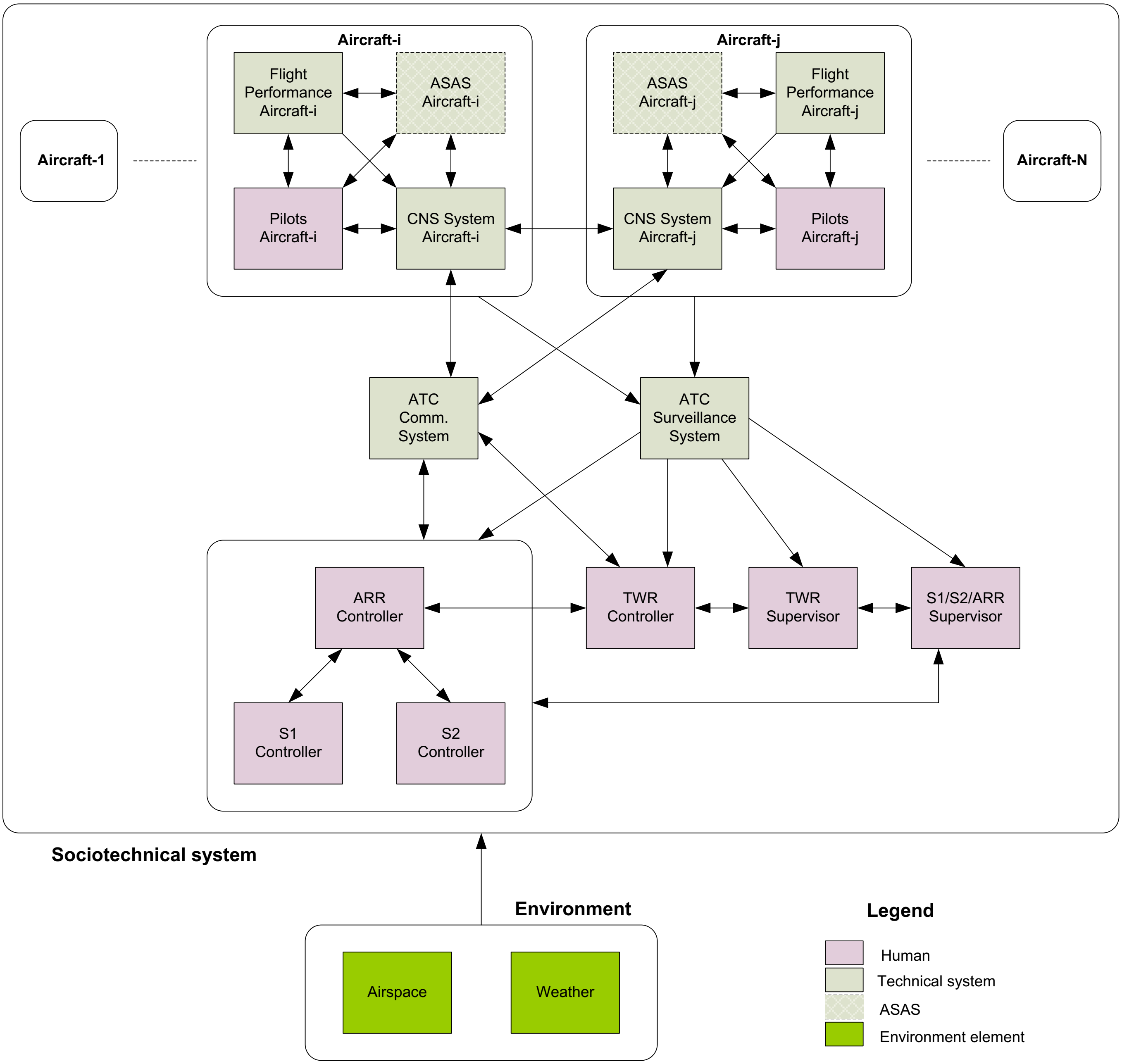

Fig. 4. Interactions in the agent-based models for the conventional case (without ASAS elements) and for the ASAS case (all elements).

- *M3: Task scheduling.* This describes which tasks may be performed concurrently, as well as priority among the tasks that cannot be performed concurrently (Blom et al., 2001).
- *M4: Task execution.* This describes the performance of a human operator with regard to the execution of a specific task, including task-specific performance characteristics.
- *M5: Contextual control mode.* This model construct considers that humans can function in a number of contextual control modes, such as Strategic, Tactical, Opportunistic and Scrambled (Hollnagel, 1993). The contextual control mode may depend on human performance aspects such as the range of tasks to be done and the situation awareness of the human. It influences human performance aspects such as the planning horizon and the accuracy of task performance.
- *M6: Task load.* This model construct describes the number and complexity of tasks that need to be performed, as considered in the task scheduling process. The task load influences the contextual control mode of the human operator. At a more detailed level, the task load may also describe the resources required by tasks at the level of visual, auditory, cognitive and motor performance.
- *M7: Decision making.* This model construct describes decision making by agents on the basis of the situation awareness and decision rules or processes.
- *M8: System mode.* This model construct describes the behaviour of a technical system by different modes. These modes are discrete states for the functioning of technical systems, e.g. failure conditions and system settings. Mode changes may be deterministic or probabilistic and they may depend on the functioning of other agents.
- *M9: Dynamic variability.* This model construct describes the variability of states of agents due to dynamic processes, e.g. the movements of an aircraft according to differential equations relating states such as position, velocity, acceleration and thrust.

- *M10: Stochastic variability.* This model construct describes the stochastic variability in the performance of human operators and technical systems, e.g. variability in task duration or system accuracy. This stochastic variability also includes large deviations from normal or intended practices in human performance, which may be labelled as 'errors' in hindsight (Dekker, 2005). The level of stochastic variability may be influenced by the contextual control mode.
- *M11: Contextual condition.* This model construct describes the context of the operation, such as weather, route structure, environmental conditions and airport infrastructure.

4.4. Human agents models

The human agents in the models are S1 Controller, S2 Controller, ARR Controller, TWR Controller, Supervisor S1/S2/ARR, Supervisor Tower, and Pilots Aircraft. These human agents are all modelled by the same set of model constructs as shown in Fig. 5; these are all the model constructs identified in Section 4.3 except M8 and M11.

Multi-agent situation awareness (M1) is a key modelling construct, which represents the situation awareness of a human agent with respect to other agents and the environment of the agent. The situation awareness is updated by task execution (M4), e.g. communication, observation, or by decision making (M7), and vice versa, task execution and decision making depend on the agent's situation awareness. During task execution, input of other agents or elements in the environment may be obtained and output may be sent to other agents or elements in the environment. The identification and scheduling of tasks' execution is represented by four modelling constructs:

- Task identification (M2), which determines whether a task should be done, triggered by some internal timing mechanism, by the agent's situation awareness, or by an external cue;
- Task scheduling (M3), which determines when a particular task is performed;
- Task load (M6), which represents the load of the identified tasks; and
- Contextual control mode (M5), which represents the control mode of the human agent and which influences the scheduling and execution of tasks.

The remaining model constructs represent the dynamic performance of the agent (dynamic variability, M9), and stochastic/random elements in the behaviour of the agent (stochastic variability, M10).

To provide more insight into the application of the model constructs in the human agents, Tables 1 and 2 present details for the ARR controller agent. Similar models were developed for the other human agents. The basis for the task-related model constructs M2, M3 and M4 are a number of tasks that the ARR controller can perform in the context of the approach operations. Table 1 shows these tasks and for each task it is indicated whether it can be used in the ASAS or conventional cases, what the trigger is for task identification (M2), what the task priority is and whether a task can be

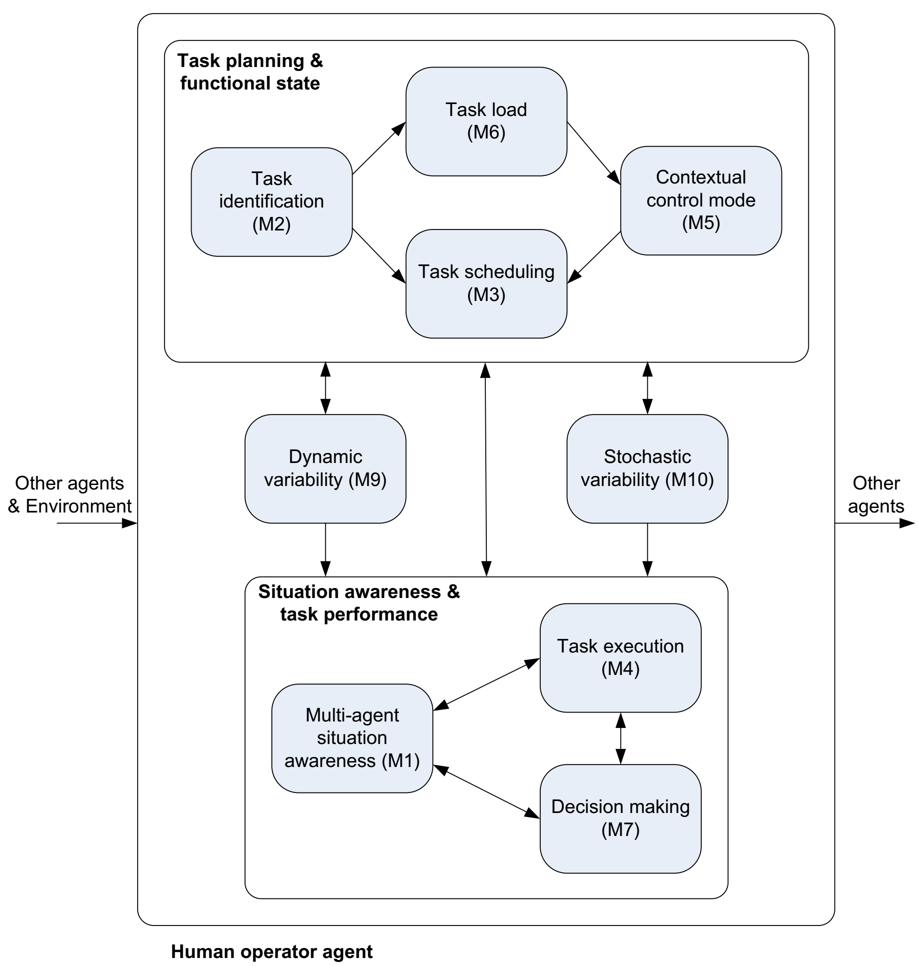

Fig. 5. Model constructs of a human operator agent and their interactions.

Table 1
Modelled ARR controller tasks and the related model constructs M2, M3 and M4. For each task the following aspects are indicated: whether it can be used in the ASAS and/or conventional case (yes/no); what the trigger is for task identification; what the task priority is (1 = highest priority); whether a task can be done concurrently (yes/no); what is done in task execution.

Task		Case		M2. Task identification	M3. Task scheduling		M4. Task execution
No	*Description*	*ASAS*	*Conv*	*Trigger*	*Priority*	*Concurrency*	
A	Decide on initiation of ASPA operation	y	n	When aircraft has passed a particular point; regular re-evaluation until decision reached	11/12	y	Update SA about initiation of ASPA operation
B	Provide ASPA clearance to aircraft-i: merge or remain behind	y	n	When it was decided in Task A	11/12	n	Communicate ASPA clearance to aircraft-i
C	Communicate termination of ASPA operation to multiple aircraft	y	n	When told so by supervisor (in Task D)	6	n	Communicate termination of ASPA to a sequence of aircraft, starting with the aircraft that is closest to the entry of the ARR sector
D	Coordinate with supervisor about separation and possibly ASPA end	y	y	When initiated by supervisor	5	n	Update SA about separation standard and possibly ASPA termination
E	Handover from S1 or S2 controller	y	y	When initiated by S1 or S2 controller	13/14	n	Communicate with handed over aircraft-i
F	Handover to TWR controller	y	y	When aircraft is 6 NM from runway	13/14	n	Instruct aircraft-i to contact TWR
G	Terminate ASPA operation for single aircraft	y	n	When aircraft reports problem or when separation conflict is detected	3	n	Update SA about termination of ASPA for single aircraft and communicate to aircraft
H	Monitor traffic situation and spacing	y	y	When aircraft is handed over, regular tracking of each aircraft	4	y	Monitor traffic situation and spacing between aircraft in the sequence
I	Decide on aircraft control in normal control situation	y	y	When monitoring (task H) is done	7	y	Update SA about planned control action
J	Decide on intervention (heading, speed and/or altitude) in case of separation conflict	y	y	When separation conflict is detected	1	y	Update SA about planned intervention action
K	Provide navigation clearance (route, waypoints) to aircraft-i	y	y	When it was decided in Task I	8/9/10	n	Communicate navigation clearance to aircraft-i
L	Provide heading, speed or altitude instruction to aircraft-i in normal control situation	y	y	When it was decided in Task I or Task J	8/9/10	n	Communicate heading/speed/altitude to aircraft-i in normal situation
M	Provide heading (vector), speed or altitude instruction to aircraft-i in separation conflict	y	y	When it was decided in Task I or Task J	2	n	Communicate heading/speed/altitude to aircraft-i in separation conflict
N	Provide vector back to route to aircraft-i	y	y	When it was decided in Task I	8/9/10	n	Communicate vector back to route to aircraft-i

done concurrently with other tasks (M3), and what the implication of task execution is (M4). For all model constructs, Table 2 shows their main performance aspects (e.g. situation awareness components, contextual control modes, task load influences), their input/output relations within the agent, and their input/output relations with other agents.

In general, the multi-agent situation awareness model describes what kinds of aspects of the overall sociotechnical system each human agent may be aware of, and how this dynamic knowledge state can be influenced by other agents. Application of the task-related model constructs is based upon identification of the tasks done by the humans in the operations considered. In the model development, 13–14 tasks were identified for the main operators in the operation (S1, S2 and ARR controllers and pilots), whereas 4–5 tasks were considered sufficient for the supervisors and tower controller models. As next aspects of the task analysis, it was argued what the triggers are for identification of each of the tasks, what the priorities are in the sets of tasks, and what tasks can be done concurrently with other tasks. Finally, it was argued what the impact is of task execution. In a multi-agent environment, task execution often implicates an effect of one agent on another agent, for instance by communication, observation, or setting of technical system parameters. These kinds of actions typically imply updating of situation awareness of agents in the multi-agent environment. Such updated situation awareness components can be, in their turn, triggers for task identification by the agent considered, and they are input for the decision making model construct. By such situation awareness-based interactions between agents, the multi-agent situation awareness construct is key for analysis of information flows in the sociotechnical system and it forms the link with the task-related performance of the human agents. Next, aspects such as number, duration, complexity and frequency of tasks identified by a human agent effectuate the task load. The task load is considered to be a key input parameter of the contextual control mode of a human agent and this control mode has effect on the task scheduling and task execution. Finally, many model constructs, such as task and decision making related constructs, include dynamic and stochastic variability, such as variability in task durations or noise or errors in observations, and these are explicitly represented in the agent-based model.

4.5. Technical system agents models

4.5.1. ASAS agent

The ASAS agent is part of the ASAS case only. Its model constructs are shown in Fig. 6. They represent the situation awareness (M1) of an ASAS agent about the position, speed and type of the ownship and of the target aircraft, the control actions performed by the ASAS system (decision making, M7), and system modes (M8), such as sending and receiving information to the aircraft and pilots. Details of the performance and the input-output relations in the agent-based model are shown in Table 3.

Table 2
Instantiation of model constructs for ARR controller agent: specific aspects, input/output relations within the agent, input/output relations with other agents. Some elements apply to the ASAS case only.

M1. Multi-agent situation awareness		
SA components		• General control mode: ASPA on/off ∗ASAS case only∗
		• List of aircraft under control
		• ASPA mode of each controlled aircraft-i: on / off ∗ASAS case only∗
		• 3D position of each controlled aircraft-i
		• Speed of each controlled aircraft-i
		• Track of each controlled aircraft-i
		• Instruction/clearance to each controlled aircraft-i: remain behind aircraft-j/merge behind aircraft-j/fly a vector/fly a speed/descend to and/or maintain altitude/fly a published procedure
Intra-agent	Input	• M4 Task execution: executing a task, e.g. a monitoring task, may lead to an update of SA
		• M7 Decision making: reaching a decision leads to an update of SA
	Output	• M2 Task identification: recognition based on SA that a task needs to be done
		• M4 Task execution: task execution influenced by SA, e.g. sending a particular message
		• M7 Decision making: decision making based on SA
Inter-agent	Input	• ATC Surveillance Systems: aircraft position/speed/track
		• Pilots aircraft-i: ASPA mode ∗ASAS case only∗
		• Supervisor S1/S2/ARR: general control mode ASPA ∗ASAS case only∗
	Output	No direct effects on other agents, since this is always done via the agent's task execution
M2. Task identification		
Task triggers		See Table 1
Intra-agent	Input	• M1 Multi-agent situation awareness: SA of controller can be a trigger for a task
		• M10 Stochastic variability
	Output	• M3 Task scheduling: notification that a task needs to be done
		• M6 Task load: keeping track of the number and types of tasks to be done
Inter-agent	Input	• Supervisor S1/S2/ARR: incoming message
		• Pilots aircraft-i: incoming message
	Output	No direct effects on other agents
M3. Task scheduling		
Scheduling aspects		See Table 1
Intra-agent	Input	• M2 Task identification: a task is scheduled after it has been identified
		• M9 Dynamic variability
	Output	• M4 Task execution: task scheduling determines when a task is executed
Inter-agent	Input	None
	Output	No direct effects on other agents
M4. Task execution		
Execution effects		See Table 1
Intra-agent	Input	• M1 Multi-agent situation awareness: task execution may depend on the situation awareness of the ARR controller
		• M3 Task scheduling: task scheduling determines when a task is executed
		• M5 Contextual control mode: the control mode may affect the way that a task is performed
		• M7 Decision making: more complicated tasks may need dedicated decision making
		• M9 Dynamic variability
		• M10 Stochastic variability
	Output	• M1 Multi-agent situation awareness: situation awareness of controller may be updated following task execution
		• M7 Decision making: decisions made may influence the task execution
Inter-agent	Input	None
	Output	• Pilots aircraft-i: outgoing messages
M5. Contextual control mode		
Control modes		• Opportunistic
		• Tactical
Mode switches		• Switch from tactical to opportunistic if task load is higher than a threshold
		• Switch from opportunistic to tactical if task load is lower than a threshold
Intra-agent	Input	• M6 Task load: the task load influences the control mode
	Output	• M9 Dynamic variability: the control mode influences task duration
		• M10 Stochastic variability: the control mode influences stochastic variability in task execution
Inter-agent	Input	None
	Output	None
M6. Task load		
Task load influences		• Number of tasks to be performed
		• Frequency of each task to be performed
		• Expected duration of each task to be performed
		• Novelty, complexity, difficulty of tasks to be performed
Intra-agent	Input	• M2 Task identification: the number, durations and types of tasks to be done determine the task load
	Output	• M5 Contextual control mode: the task load influences the control mode
Inter-agent	Input	None
	Output	None
M7. Decision making		
Related tasks		• Task A: decide on initiating ASPA operation
		• Task G: decide on terminating ASPA operation
		• Task I: decide on how to move aircraft safely and efficiently
		• Task J: decide on intervention (vector, speed, or altitude to be provided) in case of a separation conflict

Intra-agent	Input	• M1 Multi-agent situation awareness: decision making is based on the situation awareness • M4 Task execution: decision making may be called upon during task execution • M9 Dynamic variability • M10 Stochastic variability
	Output	• M1 Multi-agent situation awareness: decision making updates the controller's situation awareness • M4 Task execution: task execution is influenced by the decision making
Inter-agent	Input	None
	Output	None
M9. Dynamic variability		
Examples		• Duration of task execution • Duration of decision making
Intra-agent	Input	• M5 Contextual control mode: the control mode can influence the speed of task execution, e.g. higher speed in case of opportunistic control mode
	Output	• M3 Task scheduling: dynamics of task scheduling • M4 Task execution: dynamics of task execution • M7 Decision making: dynamics of decision making
Inter-agent	Input	None
	Output	None
M10. Stochastic variability		
Examples		• Variation in observed spacing during monitoring (Task H) • Variation in decision on intervention strategy (Task J) • Controller communicates to merge behind wrong aircraft (Task B) *ASAS case only*
Intra-agent	Input	• M5 Contextual control mode: the control mode influences stochastic variability, e.g. a higher probability of a deviation in task execution in the opportunistic control mode
	Output	• M2 Task identification: stochastic variation in task identification • M4 Task execution: stochastic variation in task execution • M7 Decision making: stochastic variation in decision making
Inter-agent	Input	None
	Output	None

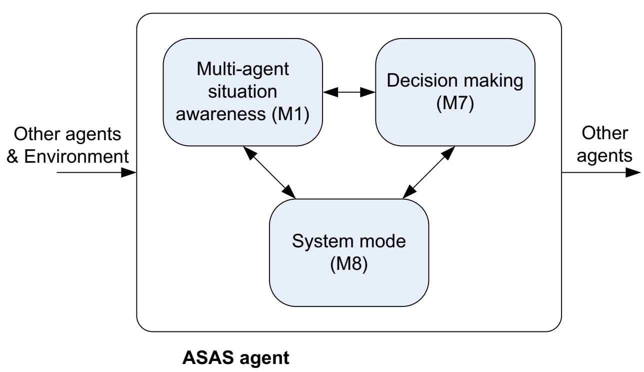

Fig. 6. Model constructs of an ASAS agent and their interactions.

4.5.2. Aircraft flight performance agent

The model constructs of an aircraft flight performance agent (Fig. 7) represent the aircraft movements and related aircraft system modes. The dynamic variability construct (M9) represents variations in aircraft movement states (position, speed, heading) and these interact with intra-agent system modes. The system mode construct (M8) represents flight control modes for flying speed profiles, heading profiles, and/or altitude profiles. It has intra-agent interactions with the dynamic variability construct and it has inter-agent interactions with the pilots, ASAS and CNS agents of the own aircraft.

4.5.3. Aircraft CNS agent

The model constructs of the communication, navigation and surveillance (CNS) systems of an aircraft (Fig. 8) represent the agent's situation awareness, communication and other working modes of the CNS system, and the dynamic and stochastic variability in the performance of the CNS system. Situation awareness components in M1 include the 3D positions, speeds and headings of the own and other nearby aircraft, and the identity of these other aircraft. The multi-agent SA construct interacts with system modes in the same agents, which influence the SA updating process, and it interacts with the pilots, ASAS and aircraft flight performance of the own aircraft, with the CNS and aircraft flight performance of other nearby aircraft, and with the ATC communication and surveillance systems. The system modes (M8) represent working modes for aircraft communication, navigation and surveillance systems, including failure modes. They interact with the multi-agent SA construct of the same agent. The dynamic variability construct (M9) signifies the time-dependency in the situation awareness updating processes and the switching in system modes. The stochastic variability construct (M10) signifies random aspects in SA updating (e.g. noise in observations/communications) and in system mode switching.

4.5.4. ATC surveillance system agent

The model constructs of the ATC surveillance system are also represented by Fig. 8. In the context of the ATC surveillance, the multi-agent SA construct (M1) represents the position, speed, heading and identity of the aircraft, the system modes influence the updating process, it receives input from with the aircraft flight performance (primary radar) and CNS system (secondary radar) of the aircraft, and it provides surveillance data to the controllers and the supervisors. The system modes (M8) represent modes of the surveillance system, including failure modes. The dynamic variability construct (M9) signifies the dynamics of the situation awareness updating. The stochastic variability construct (M10) signifies noise in SA updating and random aspects in system mode switching.

4.5.5. ATC Communication agent

The model constructs of the ATC Communication agent (Fig. 9) represent system modes of the ATC communication system, such as the functioning of the voice and datalink communication capabilities, as well as the dynamic and stochastic variability of communication message handling. The interactions are with the controller agents and the CNS systems of the aircraft.

4.6. Environment models

Elements of the environment of the agents in the sociotechnical system are represented by the model construct contextual

Table 3
Instantiation of model constructs for ASAS agent: specific aspects, input/output relations within the agent, input/output relations with other agents.

M1. Multi-agent situation awareness		
SA components		• Control mode: ASPA on/off of own aircraft-i • 3D position and track of own aircraft-i • Speed vector of own aircraft-i • Type of own aircraft-i • 3D position and track of target aircraft • Speed of target aircraft • Type of target aircraft • ASPA manoeuvre parameters (target aircraft identity, target aircraft intended flight path information, ASPA manoeuvre type, assigned spacing goal, achieve-by point, planned termination point) • ASPA execution parameters (interval management speed, predicted spacing interval, measured spacing interval, unable to continue and failure flags from the ASAS system)
Intra-agent	Input	• M7 Decision making: reaching a decision leads to an update of the SA • M8 System mode: reception of messages
	Output	• M7 Decision making: reaching a decision leads to an update of the SA • M8 System mode: sending of messages
Inter-agent	Input	None
	Output	No direct effects on other agents, as messages are received and sent via system modes.
M7. Decision making		
Types of decisions		• Deciding/advising whether ASPA operation can be initiated/terminated • Control algorithm generating interval management speeds to achieve and/or maintain required spacing with target aircraft
Intra-agent	Input	• M1 Multi-agent situation awareness: decision making is based on the situation awareness • M8 System mode: reception of messages
	Output	• M1 Multi-agent situation awareness: decision making updates system's situation awareness • M8 System mode: sending of messages
Inter-agent	Input	None
	Output	None
M8 System mode		
Types of system modes		• Send interval management speed to aircraft speed control system • Receive aircraft data: receive data from own aircraft and target aircraft (via CNS System) • Receive ASPA manoeuvre parameters from pilot • Provide ASPA manoeuvre and execution parameters for display to pilot
Intra-agent	Input	• M1 Multi-agent situation awareness • M7 Decision making
	Output	• M1 Multi-agent situation awareness: decision making updates system's situation awareness • M8 System mode: sending of messages
Inter-agent	Input	• CNS of own aircraft-i • Pilots of own aircraft-i • Aircraft evolution of own aircraft-i
	Output	• CNS of own aircraft-i • Pilots of own aircraft-i • Aircraft evolution of own aircraft-i

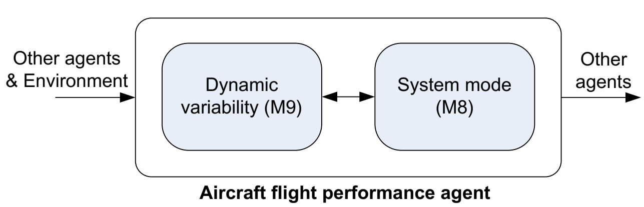

Fig. 7. Model constructs of an aircraft flight performance agent and their interactions.

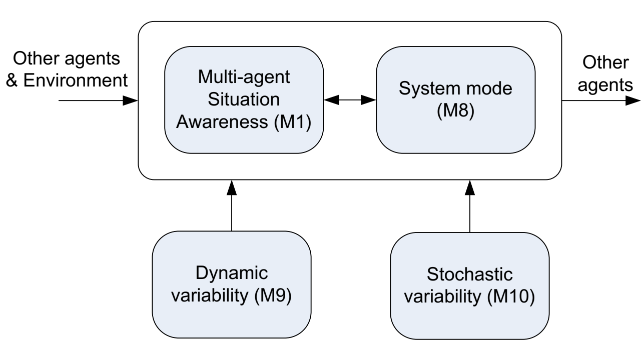

Fig. 8. Model constructs of Aircraft CNS System agent, as well as of ATC Surveillance System agent, and their interactions.

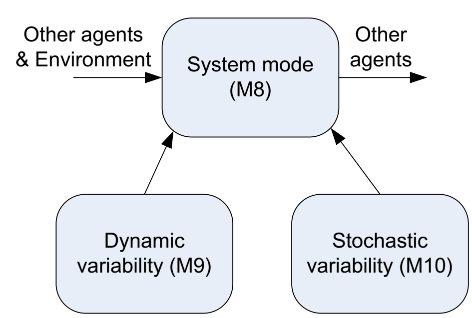

Fig. 9. Model constructs of an ATC communication agent and their interactions.

condition (M11, Fig. 10). In the current model instantiation, simple models are used for the airspace and the weather. The airspace model represents the fixed structure of the airspace, such as the locations of waypoints and of the runway (see Fig. 3). The weather model represents the weather condition at the airport by two modes for good weather and bad weather, and it uses stochastic switches between these modes.

5. Mental simulation of the agent-based model

The qualitative agent-based model presented in Section 4 is used for mental simulation according to the approach described

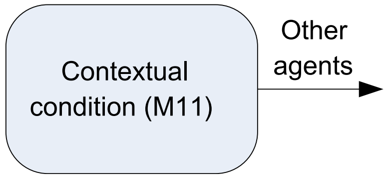

Fig. 10. Model construct of environment.

in Section 2.3. The mental simulations have been performed by the developers of the qualitative agent-based models, who have a vast experience in ABMS for air traffic applications and related human factors. The mental simulation is presented for the situation where the weather at the airport suddenly and unexpectedly changes from good to bad, in both the conventional and ASAS cases. It is known from the workshop with controllers and pilots that the strategy used in such sudden weather deterioration is to reduce the runway capacity. To achieve the associated increase in spacing between the aircraft, the controllers use a vectoring strategy, where they instruct aircraft to deviate from the standard approach route according to aircraft specific directions (vectors) chosen by the controller. In order to apply the vectoring strategy, the controllers first need to cancel the airborne spacing (ASPA) operation in the ASAS case.

The analysis of interactions is presented in Section 5.1, the analysis of dynamic relations is presented in Section 5.2, and the use of the mental simulation results in the RE cycle is presented in Section 5.3.

5.1. Analysis of interactions

The initial condition of the mental simulation considers a stream of aircraft that are on approach to the runway with aircraft spacing that is commensurate with good weather. In the conventional case the aircraft spacing is maintained by the controllers using speed and vectoring instructions, whereas in the ASAS case the ASPA operation is applied to maintain the aircraft spacing. These initial conditions are extended with a sudden and considerable change in the weather at the airport, which is the varying condition studied. Table 4 shows the nominal interactions between the agents following these initial conditions for both cases (see also Fig. 4). In particular, it shows the actions of the agents and the triggers of these actions, which may be either internal or external to the agent considered. The interactions listed are the nominal actions following the initial varying condition, meaning that they do not consider other varying conditions (e.g. system failures) that may change the interactions.

In short, the following interactions occur in response to a sudden weather deterioration at the airport. If the weather suddenly deteriorates (1), the tower supervisor can decide to change the runway capacity (2). The tower supervisor coordinates with the S1/S2/ARR supervisor (3) and informs the tower controller (4). Upon this, the S1/S2/ARR supervisor may decide to adapt the airspace capacity and to cancel the ASPA operation (5), and to inform the S1/S2/ARR controllers about this decision (6).The tower controller updates the situation awareness about the runway capacity and separation standard (7). The ARR controller (8), the S1 controller (9), and the S2 controller (10) update their situation awareness about the ASPA cancellation and the new separation standard. Subsequently in the ASAS case only, these controllers use their ATC communication system to communicate (11, 12, 13, 14) the ASPA cancellation to multiple aircraft. These messages are received by the aircraft CNS systems (15) and by the pilots (16). Next, they adapt the mode of the ASAS system (17, 18) and control their aircraft speed along an approach in non-ASPA mode (19), upon which the aircraft flies the updated flight profile (20). It thus follows from this mental simulation that there is considerable increase in the number of needed agents' interactions for the ASAS case in comparison with the conventional case.

In follow-up to the initial response to a weather deterioration, wherein the runway and airspace capacities are reduced and the ASPA operation is cancelled, the controllers have to assure that the aircraft separations get in line with the new capacity requirements. It implies that they typically have to increase the spacing between the aircraft in the sequence. Interactions 21–34 in Table 4 show the agents' interactions for increasing spacing of traffic in the ARR sector; similar interactions exist for the S1 and S2 sectors. These interactions refer to aircraft 3D position and speed estimation by the ATC surveillance system, the hereupon based monitoring of aircraft states by the controller, the specification of heading instructions to increase the spacing, the transfer of the instructions, the interpretation of the instruction by the pilots and their control of the aircraft. Next, the controller keeps monitoring the aircraft position and can provide a vector back to the route if the spacing has been increased sufficiently. These kinds of interactions exist for both the ASAS case and the conventional case. The effects of these interactions strongly depend on the states of the agents. Qualitative reasoning of the dynamic evolution of such agent states is presented next in Section 5.2.

5.2. Analysis of dynamics

In addition to the analysis of interactions presented in above section, mental simulation on the basis of the qualitative agent-based model can provide qualitative insight into the dynamic relations between (aggregated) states of the approach operations in the ASAS and conventional cases. The initial condition for this mental simulation is equal to that of the analysis of interactions, being a stream of aircraft approaching in good weather either in conventional or in ASAS-supported operations. It was argued in the RE workshop that in this nominal condition the number of aircraft per timeframe that can be handled (capacity) in the ASAS case exceeds the capacity in the conventional case. This implies that the mean separation distance in the approach stream is initially smaller in the ASAS case.

The dynamics of the following aggregated states are considered in the mental simulations following this initial condition:

- The capacity (number of aircraft that can be handled in a particular timeframe), shown in Fig. 11;
- The mean separation distance of aircraft in the approach sequence (at the end of the ARR sector), shown in Fig. 11;
- The mean vectoring distance (the mean of the additional distance flown in deviation from the standard approach route as result of vectoring instructions), shown in Fig. 12;
- The mean communication load of the ARR controller (the mean fraction of time that the ARR controller uses for R/T communication with pilots), shown in Fig. 12;
- The mean task load of the ARR controller, shown in Fig. 13;
- The probability of the contextual control mode of the ARR controller (tactical or opportunistic modes), shown in Fig. 13;
- The mean separation distance at the runway threshold, shown in Fig. 14; and
- The frequency of go arounds (per approach), shown in Fig. 14.

The argumentation in support of these plots is provided next.

The capacity reduction and ASPA cancellation (in the ASAS case) due to the weather deterioration at the airport, shown in Fig. 11, is the onset of all other changes in the aggregated states, shown in Figs. 11–14. The capacity is reduced more in the ASAS case than in the conventional case, since the ASAS case supports a larger

Table 4
Nominal agents' interactions in conventional and/or ASAS cases for weather deterioration leading to a reduction in runway capacity and ending of ASPA. For each interaction the trigger and resulting action are listed.

Nr	Conv	ASAS	Agent	Trigger	Action
1	×	×	Weather	Random event	Sudden and considerable weather deterioration at airport
2	×	×	TWR Supervisor	Sudden and considerable weather deterioration at airport (1)	Update SA: observe and interpret weather deterioration and decide to reduce runway capacity
3	×	×	TWR Supervisor	Decision to reduce runway capacity (2)	Coordinate with S1/S2/ARR Supervisor
4	×	×	TWR Supervisor	Decision to reduce runway capacity (2)	Inform TWR Controller
5	×	×	S1/S2/ARR Supervisor	Coordination with TWR Supervisor (3)	Update SA: decide on ending of ASPA operation (ASAS case only) and on airspace capacity and separation
6	×	×	S1/S2/ARR Supervisor	Decision on ending of ASPA operation and separation (5)	Inform S1/S2/ARR controllers about ASPA ending (ASAS case only) and separation standard
7	×	×	TWR Controller	Information of TWR Supervisor (4)	Update SA: runway capacity and separation standard
8	×	×	ARR Controller	Information of S1/S2/ARR Supervisor (6)	Update SA: ASPA ending (ASAS case only) and separation standard
9	×	×	S1 Controller	Information of S1/S2/ARR Supervisor (6)	Update SA: ASPA ending (ASAS case only) and separation standard
10	×	×	S2 Controller	Information of S1/S2/ARR Supervisor (6)	Update SA: ASPA ending (ASAS case only) and separation standard
11		×	ARR Controller	Update SA about ASPA and/or separation standard (8)	Communicate end of ASPA operation to multiple aircraft
12		×	S1 Controller	Update SA about ASPA and/or separation standard (9)	Communicate end of ASPA operation to multiple aircraft
13		×	S2 Controller	Update SA about ASPA and/or separation standard (10)	Communicate end of ASPA operation to multiple aircraft
14		×	ATC Comm. System	Communicate end of ASPA operation by ARR/S1/S2 controllers (11, 12, 13)	Transfer communication messages
15		×	CNS System Aircraft-i	End-of-ASPA communication message (14)	Transfer communication messages
16		×	Pilots-i	End-of-ASPA communication message (15)	Update SA: ASPA operation is ended
17		×	Pilots-i	Update SA on end of ASPA (16)	Change mode of ASAS to ASPA off
18		×	ASAS-i	Mode change by pilots (17)	Turn ASPA off
19		×	Pilots-i	Update SA on end of ASPA (16)	Control aircraft along approach in non-ASPA mode
20	×	×	Aircraft-i	Control aircraft in non-ASPA mode (19)	Fly along controlled trajectory
21	×	×	ATC Surveillance System	Internal repeating trigger	Update aircraft position and speed data
22	×	×	ARR Controller	Internal repeating trigger	Update SA on aircraft in sector using ATC surveillance data
23	×	×	ARR Controller	Update SA on aircraft in sector (22)	Decide and communicate heading to aircraft in case of separation problem
24	×	×	ATC Comm. System	Communicate heading to aircraft (23)	Transfer communication message
25	×	×	CNS System Aircraft-k	Heading message (24)	Transfer communication message
26	×	×	Pilots-i	Heading message (25)	Update SA on heading requested by controller
27	×	×	Pilots-i	Update SA on heading (26)	Implement heading change
28	×	×	Aircraft-i	Implement heading change (27)	Fly heading
29	×	×	ARR Controller	Update SA on aircraft in sector, following heading change (21, 23)	Provide heading back to route if separation problem is resolved
30	×	×	ATC Comm. System	Communicate heading to aircraft (29)	Transfer communication message
31	×	×	CNS System Aircraft-i	Heading message (30)	Transfer communication message
32	×	×	Pilots-i	Heading message (31)	Update SA on heading requested by controller
33	×	×	Pilots-i	Update SA on heading (32)	Implement heading back to route
34	×	×	Aircraft-i	Implement heading change (33)	Fly heading back to route

capacity in undisturbed circumstances. As a result of the controller strategies, the mean separation between the aircraft is expected to gradually increase following the reduction of the capacity (Fig. 11). The largest increase in the mean separation distance is achieved in the ASAS case, following the largest decrease in capacity.

Before the capacity reduction, the mean communication load of the ARR controller is expected to be less in the ASAS case than in the conventional case, since then the separation control is regulated by the ASPA system. Following the capacity reduction, a strong increase in the mean communication load (Fig. 12) is expected in the ASAS case, since firstly the end of the ASPA operation needs to be communicated to the aircraft and secondly there needs to be a considerable number of vectoring operations to increase the separation distances. In the conventional case, the increase in communication is expected to be more modest, since no ASPA operation needs to be ended and the mean separation needs to be increased to a smaller extent. When the separations in the sequence have been stabilized in correspondence with new runway capacity, the communication load is decreased to a new value that is commensurate with the vectoring operations. The mean vectoring distance in Fig. 12 shows a considerable increase in the ASAS case, since a large change in separation distance needs to be achieved, whereas a more modest bump is expected in the conventional case.

Fig. 13 shows the mental simulation results for the task load and the control mode of the ARR controller. In line with the large increase in R/T communication as explained for Fig. 12, the task load of the ARR controller is expected to increase considerably in the ASAS case, and to a larger extent than in the conventional case. In relation with this change in task load, the contextual control mode of the ARR controller is expected to mostly switch from tactical to opportunistic as a result of the capacity reduction, and this switch to the opportunistic control mode is more dominant in the ASAS case. Working in the opportunistic control mode implies in the model, that the ARR controller is performing tasks (monitoring, decision making, communication) more quickly. Although thus more tasks are performed in the opportunistic mode, the stochastic variability in the task performance has been modelled to increase in the opportunistic mode, leading to a larger likelihood of tasks not being performed as they should or as intended.

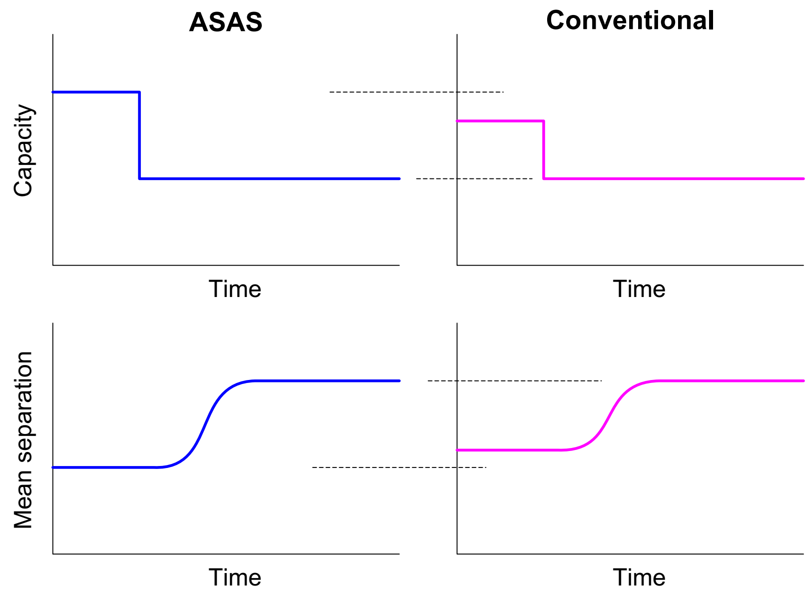

Fig. 11. Mental simulation results for the ASAS and conventional cases, for a situation of weather deterioration at the airport. Top row shows the decrease in capacity. Bottom row shows the mean separation distance of aircraft in the approach sequence.

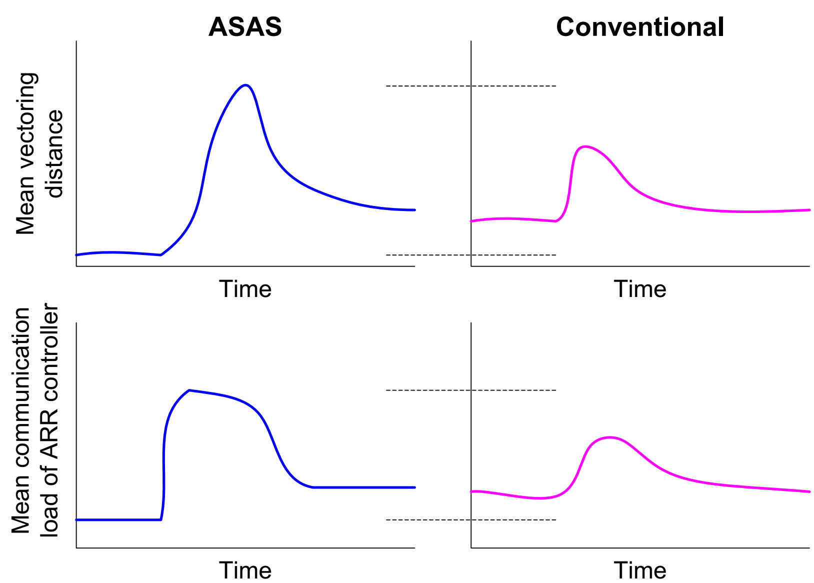

Fig. 12. Mental simulation results for the ASAS (left) and conventional (right) cases, for a situation of weather deterioration at the airport. Top row shows the mean vectoring distance. Bottom row shows the mean communication load of the ARR controller.

Fig. 14 shows the mental simulation results for the mean separation at the runway threshold and the frequency of go arounds instructed by the TWR controller. It is expected that the frequency of go arounds increases, since the required increase in separation is not always achieved. Moreover, the frequency of go arounds is expected to be higher in the ASAS case, since in this case the capacity reduction is larger and the S1, S2 and ARR controllers have a dual job of both ending the ASPA operation and increasing the separation.

5.3. Use of mental simulation results in the RE cycle

The mental simulation results for the interactions and dynamic relations presented in above sections were derived on the basis of the qualitative agent-based model and supported by knowledge of the strategies used for the deteriorated weather condition achieved in a workshop with controllers and pilots. The types of interactions in the agent-based model, and the mental simulation results for the increase in vectoring, task load and go arounds following the runway capacity decline are in line with the strategies and expectations expressed during the workshop. However, the interactions and details of the dynamic relations were not discussed with pilots and controllers during a follow-up workshop, nor were other types of validation exercises done for these results.

Given the uncertainty in the current results of the mental simulations, they can best be formulated as hypotheses, as a basis for further research. The following hypotheses regarding the adaptive capacity of the sociotechnical system of the approach operations in dealing with the sudden weather deterioration have been identified.

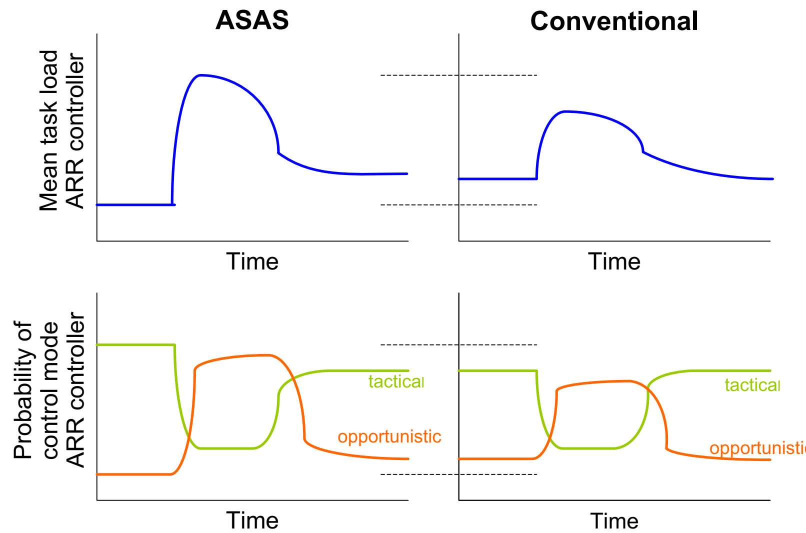

Fig. 13. Mental simulation results for the ASAS (left) and conventional (right) cases for the situation of strong weather deterioration at the airport. Top row shows the mean task load of the ARR controller. Bottom row shows probability of attaining tactical/opportunistic control modes by the ARR controller.

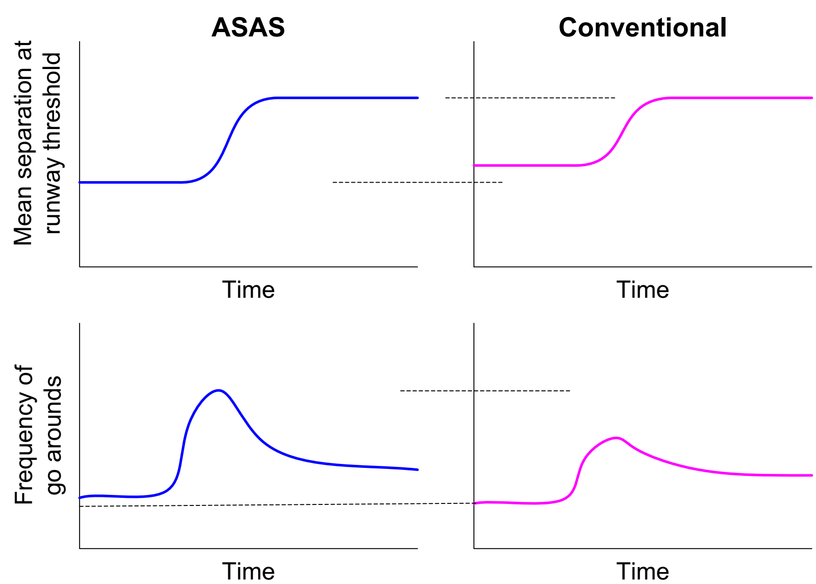

Fig. 14. Mental simulation results for the ASAS (left) and conventional (right) cases for the situation of strong weather deterioration at the airport. Top row shows the mean separation distance at the runway threshold. Bottom row shows the frequency of go arounds as instructed by the TWR controller.

- The varying condition is expected to imply a considerable increase in the task load of the ARR, S1 and S2 controllers in the ASAS case, since they need to communicate the end of the ASPA operation to the aircraft in their sectors, as well as to decide on and communicate vectors to their aircraft so as to assure the increased separation standard.
- Such increased task load has impact on the way of working of the ARR, S1 and S2 controller. In reference to the contextual control mode model of Hollnagel (1993) this may lead to a larger probability of working in an opportunistic control mode and to more deviations in task performance. Such deviations have to be recognized and dealt with somehow by the sociotechnical system, thus stretching the adaptive capacity.
- It is expected that the varying condition leads to an increase in the frequency of go arounds, especially in the ASAS case. The aircraft being sent around have to be added to the approach sequence once again, thus putting further demand on the adaptive capacity.

As part of the RE cycle of Fig. 1, above hypotheses may be studied by using the approaches introduced in Section 2.3.3. A key approach for a more profound analysis is the further development, parameter quantification, and computer simulation of a quantitative agent-based model. This will allow a deeper understanding of the relations and the timing implications on the performance of the sociotechnical system. It will allow getting quantitative results for the graphs such as in Figs. 11–14, and more. Such quantitative agent-based modelling and simulation may also be used to determine an appropriate maximum capacity of ASPA operations, such that the sociotechnical system can effectively attain lower capacities in the case of sudden weather changes. The attained capacity value may be validated by human-in-the-loop simulations for the varying condition considered.

If the identified hypotheses would be verified in additional research, they could be used to identify recommendations to improve the design of the ASAS operation for dealing resiliently with the bad weather situation. If so, such design recommendations could include:

- Find ways to reduce the task load of ARR, S1 and S2 controllers in the situation that the ASPA operation needs to be cancelled and the capacity needs to be reduced. For instance, by adding a temporary assistant, or by developing a tool for quickly communicating end of ASPA operation to aircraft.
- Use a maximum capacity in ASPA operations which can be effectively downsized in the case of sudden runway capacity reduction.
- Assure that aircraft going around can be effectively integrated in the approach stream.

6. Discussion

Following a discussion of some recent reviews we identified the need in RE for more structured modelling approaches for analysis of resilience in sociotechnical systems that can support both qualitative and quantitative studies. In this paper we presented ABMS as an approach towards this need. Although in general ABMS is considered to be a quantitative approach, in this paper we showed that development of an agent-based model starts with a qualitative development step and that mental simulation can be used to obtain qualitative results. Such qualitative analysis was illustrated in detail for aircraft approach operations using conventional systems and ASAS.

An agent-based model of a sociotechnical system represents a collection of human agents and technical system agents which interact among each other and with the environment in which they reside. The agents have time-dependent states, inputs and outputs, and the evolution of these states, the impact of the input signals on the states, and the implications of the states for the output signals are represented by sets of model constructs. In the application case, eleven model constructs were used, which were chosen from a library of model constructs that was developed for ATM sociotechnical systems. For the human agents these model constructs included multi-agent situation awareness, as a key construct for the agent's situation awareness in a multi-agent environment, several task-related (identification, scheduling, execution, decision making) model constructs, task load and contextual control mode as workload-related model constructs, and variability-related model constructs representing dynamics, stochasticity and errors in human performance. For the technical system agents smaller sets of model constructs were used, including multi-agent situation awareness, decision making, system mode, and dynamic and stochastic variability. Overall, the detailed qualitative description along these agent-based model constructs provides a well-defined and structured overview of the information flows, task work done, workload, and dynamic and stochastic performance variability of the humans, as well as of the information flows and performance of the technical systems in the operation studied. As such, the achieved agent-based model is an analysis result in itself, which structures the understanding of the task performance, interactions, and the inherent variability of the operations.

The developed agent-based model was used for structured qualitative reasoning about the dynamic interactions between the agents and their effects on agents' variables. This kind of reasoning is termed 'mental simulation' as it is completely based on specialist model-based reasoning, without using computer implementation and simulation of the agent-based model. Using such mental simulation for the modelled conventional and ASAS operations, we identified several differences between the operations for dealing with varying conditions. These differences refer to the number and kinds of interactions between the human and technical system agents, and to the dynamic evolution of performance variables, such as the mean separation, the vectoring distance, the task load, the contextual control mode, and the number of go arounds during final approach. As thus illustrated, mental simulation can provide insight into the sociotechnical system performance and provide feedback for design and additional analysis.

The development of a qualitative agent-based model and the mental simulation using this model are part of an RE approach for analysis and improvement of the resilience of a sociotechnical system. Main methods in this RE cycle are workshops with human operators who are proficient in the operations studied. Workshops are common in RE approaches and they can effectively provide a broad range of strategies used by operators in all kinds of contextual conditions. The analysis towards a proper understanding of how the combined strategies and behaviours of interacting human operators and technical systems have impact on the adaptive capacity of a sociotechnical system for dealing with ranges of varying conditions is however far more difficult. As such, for more complex operations, analysis results tend to be high level only, or very uncertain with respect to performance indicators, or results cannot be obtained at all by workshop centred RE approaches. The qualitative ABMS approach is a first step towards a more structured analysis, which is supported both by the development of a qualitative agent-based model and by mental simulation. It was illustrated in detail in this paper how insights can thus be obtained for air traffic operations in varying conditions.

In the application case we focused on a particular sudden bad weather condition that influences aircraft approach operations, we used qualitative agent-based modelling to arrive at the hypothesis that operations in the ASAS case for this condition are less resilient than in the conventional case, and next we presented some options to improve the resilience of the operation in the ASAS case for the sudden bad weather condition. These steps were all part of an RE cycle that provides feedback to design in order to improve resilience. Although we argued that the resilience for dealing with the sudden bad weather condition is less in the ASAS case, this does not imply that overall the resilience of the ASAS operations would necessarily be less. We did not study the overall level of resilience and we recognize that considerably more research would be needed to arrive at conclusions on this. Questions within such research would include the following: What is the overall set of varying conditions for studying the resilience of the operation? How often do these varying conditions occur? What is the impact of the strategies for dealing with these varying conditions on performance indicators of interest? How can these various impacts on performance indicators be combined for all varying conditions to come at statements on the overall resilience of the sociotechnical system?

The understanding that the overall performance of a complex sociotechnical system can be highly variable is one of the foundations of the RE field. This overall performance variability is due to the intrinsic stochastic dynamics of the elements of a sociotechnical system and its environment, and due to all their interactions. The overall performance can be regarded as emergent, as it cannot be understood by its single elements, but only by considering the totality of all elements and interactions. The description of its elements and interactions in the qualitative agent-based model supports analysts to reason in a structured way about the overall performance of the sociotechnical system. It is clear, nevertheless, that such mental simulation is only a first step towards understanding the overall performance. A principal limitation of mental simulation is that it is less feasible for models with more complex interactions to keep track of all possible implications of stochastic variations, dynamics and interactions of the agents that may follow a particular initial condition. Mental simulation results are therefore bound to mainly describe selected aggregated variables at a high level for more usual modes of working and interactions, and to neglect details in variations and less usual performance aspects. If it can be argued in cooperation with stakeholders, that the level of the uncertainty in the mental simulation results is commensurate with the objectives of the RE cycle and no quantitative results are needed, then the mental simulation results can be accepted as a final result of Step 3 of the RE cycle and used as a basis to identify improvements in resilience. If such uncertainty is not acceptable or quantitative results are needed, then the next step towards development, implementation and computer simulation of a quantitative agent-based model should be pursued. Computer simulations can overcome the limitations of mental simulation by evaluating in detail all stochastic variations, dynamics and interactions in the agent-based model. Another advantage of computer simulations is that they can be completely tractable, in contrast with the reasoning of an analyst during mental simulations or the reasoning of operational experts during a workshop.

Quantitative ABMS steps have not been addressed in detail in this paper, as our objectives are to present the principles of ABMS as a way to support RE and to show how ABMS can provide qualitative results. The follow-up steps for quantitative ABMS can in general be pursued using various methods and tools, such as presented in overviews of Macal and North (2010) and Van Dam et al. (2013). A specific way how quantitative ABMS for RE may be achieved is by using methods from agent-based dynamic risk modelling (DRM) (Blom et al., 2006; Everdij et al., 2014). Agent-based DRM has used model constructs similar to those shown in this paper, model formalization by dynamically coloured Petri nets, and Monte Carlo simulations for estimating accident probabilities of air traffic scenarios. A key difference is that agent-based DRM requires rare event estimation techniques to assess the very low accident probabilities of air traffic scenarios, whereas ABMS for RE focuses on understanding effects of strategies and adaptive capacity for the performance of the sociotechnical system in the context of varying conditions. To arrive at the low accident probabilities in agent-based DRM, specialist knowledge on rare event estimation and typically long computation times are needed. ABMS for RE does not need the many replications in Monte Carlo simulations, since it is not focused on estimation of very rare events. As such, the scenarios and aspects of the sociotechnical system considered in ABMS for RE may be more extensive and represented in more detail. In the light of the emphasis on everyday actions and outcomes in Safety-II (Hollnagel, 2014), this means that these may be modelled and understood in more detail using ABMS for RE. Thus achieved insight into the most important aspects of the sociotechnical may next be used in more dedicated models as part of agent-based DRM for assessment of accident probabilities. Such connection between ABMS for RE and agent-based DRM needs to be studied in follow-up research.

A key question for using results of ABMS in the RE cycle is: what is their validity? In other words, how well do the models and simulation results represent reality, within the specific context for which the model was developed? We like to discuss validity using the concept of uncertainty, i.e. the extent by which something is not certain. We already discussed one source of uncertainty, which is especially relevant for the qualitative ABMS phase, being the uncertainty due to limitations of the mental simulation process. Another main source of uncertainty is lack of complete knowledge of elements and their interactions in the sociotechnical system and/or limitation of the ways that they are represented in the agent-based model. In the qualitative ABMS phase this concerns the high-level specification via model constructs and their interconnections. In the quantitative ABMS phase this would concern the structure of the formal models and the quantification of their parameters. It is clear that the level of uncertainty in models of sociotechnical systems can be large, as many of their aspects are often not known precisely. In the RE domain, conceptual models are frequently used, which by their nature are generic and therefore uncertain for a particular sociotechnical system. A qualitative agent-based model, such as illustrated in this paper, provides more detail for the interacting agents and their constituent models and thereby may describe the performance of the sociotechnical system with more certainty. Nevertheless, it is clear that a qualitative model primarily describes types of mechanisms and interactions, and that the level of uncertainty in the achieved mental simulation results may well be significant. The most accurate results may be achieved by a quantitative agent-based model in combination with computer simulation. Whether results with low uncertainty can actually be realized in the quantitative ABMS phase depends on the validity of the individual agents' models, the validity of the integrated set of all models for the operational context, and the appropriateness of the parameter values. There are various ways to evaluate the level of uncertainty in these components and in the overall results, including comparison with results in the literature, comparison with available measurement data of related experiments or real operations, and discussion with operational experts in the RE cycle. Quantitative ABMS can also effectively support analysis of the sensitivity of performance indicators for parameter variations, as a way to gain an understanding of the relative importance of model parts for performance indicators of interest. The ways that quantitative ABMS can most effectively be applied in RE needs to be studied in detail in follow-up research.

How do ABMS and mental simulation compare with FRAM (Hollnagel, 2012)? Some high-level observations are provided next, but we recognize that a more detailed comparison would be needed to arrive at more definitive conclusions. The functional analysis-based approach of FRAM is structured by a single model construct, which describes input, output, time, control, preconditions and resources for each function or activity in a sociotechnical system. An advantage of this single model construct is that it can be easily explained to a wide audience, but main limitations are (1) it is very abstract, such that it may be difficult to represent nuances of a sociotechnical system, and (2) the function-based focus does not explicitly account for the boundaries between entities (humans, technical systems) in the sociotechnical systems, nor for their dynamic states. This can be contrasted with the library of model constructs in ABMS, which enables more nuanced and detailed modelling, and its agent perspective, which explicitly accounts for the boundaries between entities and which is state-based. FRAM employs mental simulation as its principal evaluation means. This model-based reasoning is primarily focused on arguing about interactions between functions rather than on the dynamics of sociotechnical systems.

A fundamental question is to what extent detailed and possibly quantitative models can be used to study and improve resilience. Woods (2015) stresses that key for resilience is the ability of a system to deal with surprise events. Woods uses concepts as graceful extensibility and sustained adaptability to discuss the capacity of a sociotechnical system to deal effectively with surprises. Two types of surprise events can be distinguished: (1) surprises for the agents but known to the modeller, and (2) surprises unknown to the modeller. Type 1 surprises can be included in an agent-based model, where agents possess particular sets of strategies for a range of varying conditions that are known by the agent, but which exclude the type 1 surprises. Next it can be analysed what the effect is of the agent-based model for the surprise event, such as the rebound of robustness with respect to the event. In this way insight is gained into the capacity of the modelled sociotechnical system to deal with a particular type 1 surprise and this knowledge can be used to improve the resilience of the actual system. Type 2 surprises pose a difficulty for modelling, as these are not a priori known and thus cannot be modelled. What can be done for type 2 surprises, however, is to evaluate the capability of the agent-based model for dealing with large sets of different type 1 surprises in combination with other varying conditions, and to use this knowledge to improve the sociotechnical system. As long as there is some similarity of type 2 surprises with the studied set, this may help to attain a more resilient system also for these surprises. It can be recognized that in these analyses for type 1 and type 2 surprises, system responses such as considered in the rebound and robustness concepts are used as bridges towards attaining resilience in the graceful extensibility and sustained adaptability concepts of Woods (2015).

In conclusion, ABMS is a detailed analysis approach for studying resilience of sociotechnical systems that offers a flexible range of model constructs enabling representation of the work-as-done in the system. The agent-based perspective fits well with usual views on elements of a sociotechnical system and it naturally couples states and behaviour of the agents. Simulation in ABMS can be done mentally, leading to qualitative results as shown in this paper, or it can be pursued by computer simulation. The capability to evaluate many interacting varying conditions by computer simulations sets open the door to truly studying performance variability in normal situations, as envisioned in Safety-II, rather than focusing on some restricted non-nominal cases, as typically addressed in Safety-I. This will be further pursued in follow-up research.

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