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Spread of Situation Awareness in a Group: Population-Based vs. Agent-Based Modelling

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Abstract—**This paper compares population-based and agent-based simulation of the dynamics of group Situation Awareness. The question how Situation Awareness spreads among a team of agents is important for numerous applications. In this paper, a population-based and an agent-based model of this process are proposed, and applied to a case study in aviation. A number of relevant simulations of the models are performed, to investigate whether the behaviour of the population-based model can approximate the pattern produced by the agent-based model. It was demonstrated that, especially for larger populations, the dynamics of the agent-based simulations can be approximated by population-based simulations, since both models demonstrate a similar pattern.**

Keywords— group situation awareness, aviation, agent-based vs. population-based simulation.

I. Introduction

The concept of *Situation Awareness* (SA) is receiving more and more attention in safety critical domains (such as aviation, air traffic control, warfare, and power plant operation) and emergency services (such as fire fighting, policing or healthcare) [10]. For example, an airline pilot continuously needs to be *aware* of the location of her own aircraft, as well as other aircraft around. The importance of the SA concept is expected to increase even further in the coming decades, due to the increasing role of information technology and automation in all safety critical domains. Moreover, in most safety critical systems, operators do not work as isolated individuals, but as members of groups or teams. Thus, it is necessary to consider the SA of a group instead of only individual SA. However, it is not well understood yet how SA of each individual team member contributes to the formation of group SA and what are the underlying mechanisms of SA spread in groups. In the current paper, these questions are explored from a computational modelling perspective. The approach is inspired by [16], in which a computational agent-based model of beliefs spread in a group is proposed.

Spread of mental states in a group can be modelled both from an agent-based and a population-based perspective. The classical approaches to simulation of processes in which groups of larger numbers of individuals are involved are based on the notion of *population*: in these approaches, a number of groups are distinguished (populations) and each of these populations is represented by a numerical variable indicating their number or density (within a given area) at a certain time point. The simulation model takes the form of a system of difference or differential equations expressing temporal relationships for the dynamics of these variables. Well-known classical examples of such population-based models are systems of difference or differential equations for predator-prey dynamics (e.g., [18], [29]) and the dynamics of epidemics (e.g., [1], [8], [17]). Such models can be studied by simulation and by using analysis techniques from mathematics and dynamical systems theory.

From the more recently developed agent modelling perspective, often it is presumed that simulations based on *individual agents* (in the literature called agent-based or individual-based) are a more natural or faithful way of modelling, and thus will provide better results (e.g., [2], [7], [27]). Although for larger numbers of agents such agent-based modelling approaches are computationally more expensive than population-based modelling approaches, such a presupposition may provide a justification of preferring their use over population-based modelling approaches, in spite of the computational disadvantages. In other words, agent-based approaches with larger numbers of agents are justified because the results are expected to deviate from the results of population-based simulation, and are considered more realistic.

However, in contrast there is another silent assumption sometimes made, namely that for larger numbers of agents (in the limit), the global results produced by agent-based simulations approximate the results of population-based simulations (e.g., [4]). This would indicate that agent-based simulation can be replaced by population-based simulation, which would weaken the justification for agent-based simulation discussed above.

In the current paper we propose a computational agent-based model of SA spread in teams that simulates the formation of SA in a group of agents. As a case study, a scenario in the context of a runway incursion incident is used. The presented agent-based model is contrasted to a population-based model of the same scenario and the simulation results of both models are compared. We investigate in which extent the agent-based model of SA spread in a group of agents can be approximated by a population-based model with the same number of agents. Our hypothesis is that the pattern of SA formation obtained in

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simulation experiments with the agent-based model can be approximated by the results obtained from the experiments with the population-based model.

The current paper is structured as follows. First some background information on Situation Awareness and the modelled case study is given in Section II. In Section III an agent-based model of the case study and its simulation results are described. Section IV provides an overview of a population-based model of the case study; the simulation results of the model in this section are presented and contrasted to the results obtained from the simulation experiments with the agent-based model. Finally, Section V concludes the paper and provides some implications for future research.

II. Background

In this section, first an overview is presented on the literature on Situation Awareness, with an emphasis on SA in teams and on computational models of SA. Next, an example scenario in the domain of Air Traffic Management is described, which is used throughout the paper as a case study to illustrate our approach.

A. Situation Awareness

Situation Awareness is commonly agreed to be a central concept in the study of safety critical systems, such as Incident Management or Air Traffic Control. A large body of literature exists in which the notion of SA is used to understand, explain or predict the dynamics of scenarios in which human behaviour (and often human error) plays a role. One of the founders of the concept is Mica Endsley, who defined SA in the 1990s as “the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future” [10]. Endsley also proposed a theoretical model of SA formation via three steps (perception, comprehension, and projection), on which various other authors have based their work.

At that time, situation awareness was to a large extent considered to be an individual construct [23]. However, in reality SA also plays an important in the context of *teams* of collaborating agents. Different team members may view and interpret the environment in which they are functioning differently, and for this reason the SA they have about the environment may also be (partially) different [3], [11], [22], [23]. To study SA from that perspective, the notion of *shared SA* has been put forward. According to Endsley and Jones, shared SA is “the degree to which team members possess the same SA” [11]. It is related to, but not to be confused with team SA, a concept that refers to the degree to which each team member possesses the SA required for his or her responsibilities [23]. Shared SA has most notably received attention in the military [12] and command and control [21] domain. In [5], an extensive literature study on shared SA is presented. According to this study, shared SA is a complex process that is influenced by many different factors, including mental states of agents (like beliefs and goals) and inter-agent concepts (like communication, trust and hierarchical relations).

Computational modelling of (shared) SA has not received widespread attention in the literature yet. Regarding SA from an individual perspective, some authors have developed formal models based on Endsley’s theory (e.g., [15], [26]). Regarding shared SA, most notable results can be found in the distributed team work and military domain [3], [12] and command and control domain [30], as well as some results in the areas of air traffic control [19], [28] and teamwork [5], [14], [24].

A number of these computational models commit to the assumption that shared SA can be modelled in terms of *beliefs* of the different agents involved in a scenario (e.g., [5], [15], [19], [28]). To this end, often domain-specific constructs (such as logical propositions or state variables) are introduced for the elements that play a role in the domain at hand (e.g., the weather, or the presence of aircraft). The idea is that, by enabling different agents to assign different values to their individual beliefs about these elements (either using Boolean values, or using numerical values to express some ‘degree’ of beliefs), the modeller has a means to quantify the extent to which beliefs are shared among a team of agents. In the current paper, a similar approach is used, i.e., shared SA is represented in terms of differences between values of beliefs. We focus on the question to what extent the dynamics of shared SA can also be modelled using a population-based approach (as opposed to an agent-based approach). To make this comparison feasible, beliefs are modelled using a 3-valued representation (i.e., with values *unknown*, *correct*, and *incorrect*).

B. Scenario

In the following sections, the spread of situation awareness between agents in a team will be modelled from two perspectives, namely an individual agent-based perspective and a population-based perspective. Although the model is independent from a particular domain or scenario, to enhance understanding, a specific case study in the domain of Air Traffic Management is used throughout the paper as an illustration of the approach. The case study consists of (a simplification of) an existing scenario in the context of a runway incursion incident that occurred in 1995 [6]. This scenario was obtained by performing a semi-structured interview with an available expert, a 2 years retired pilot of a European civil aviation company.

The runway incursion incident took place during the departure of an Airbus A310 of a civil aviation company from one large airport in Europe. Although the details of the interview and the case study are not shown here (see [6] for this purpose), a summary of the scenario is provided below.

The Airbus was preparing for the departure: the pilot-in-command was sitting on the left and the co-pilot on the right seat in the cockpit and they were ready to start taxiing. They were supposed to taxi to runway 03 in the north-east direction. The Airbus received permission to taxi and started taxiing to its runway. Approximately at *the same time, a military Hercules aircraft that was ready for the departure as well received permission to taxi in the north-west direction from its parking gate. The Hercules was supposed to take off from runway 36 that crossed with runway 03 that was designated for the Airbus. Both aircraft were taxiing to their runways. During the taxiing, the Airbus received its flight route from the air traffic controllers. Some time later, when the Airbus was near the runway designated for taking off, it switched from the taxiing radio frequency to the frequency of the Tower and received permission to line up on the assigned runway. The Hercules was still at the taxiing radio frequency and also received permission to line up, while at the same time the Airbus received permission to take off at the radio frequency of the Tower. However, due to unknown reasons[1], the Hercules pilot interpreted his permission for lining up as permission for taking off and started taking off on runway 36. As a result of this mistake of the pilot of the Hercules, two aircraft were taking off simultaneously on crossing runways, and none of the crews were aware of that. The air traffic controllers in the Tower observed the conflicting situation and communicated a 'STOP' signal to the pilot-in-command of the Airbus, while the Airbus was still on the ground (but at high speed). The pilot had to make a quick decision about the termination of the take-off as there is a point in this process that one cannot safely do this anymore. After having analysed the situation, the pilot-in-command of the Airbus gave a command to the co-pilot (who controlled the aircraft) to abort the take-off and start braking on the runway. During braking, the crew of the Airbus saw the Hercules flying close in the air above their own aircraft at a distance of about 5 meters. A serious collision was prevented.*

For the current paper, the crucial part of the scenario concerns the fact that different parties (Airbus crew, Hercules crew, Tower controllers) have different beliefs about the question whether or not the Hercules received a permission to take off. In reality, this permission has *not* been given. However, at a certain point in time, the different parties involved have different types of belief about this. In particular, the Tower controllers in charge of issuing take off clearance have *correct* beliefs (i.e., they are aware that no clearance had been given). In contrast, the Hercules pilot has an *incorrect* belief (i.e., he incorrectly believes that he has received take off clearance). Finally, various crew member of the Airbus (such as the captain, the co-pilot, and other crew) have an *unknown* belief (they simply do not know whether a take-off clearance has been given to the Hercules). In the following sections, several alternative variations of this situation will be modelled.

In addition, we will model how the scenario might develop when the agents exchange information. For example, once the Airbus captain starts communicating with the Tower, he will receive information about who received take off clearance, hence allowing him to update his beliefs (in this case: from value *incorrect* to *correct*). However, in certain situations also other transitions between belief states are possible (for instance, in case the pilot is not convinced by this information, his belief might change from *incorrect* to *unknown*). In the following section, a mechanism is put forward to represent the dynamics of such processes.

III. Agent-Based Model of SA Dynamics

This section presents a simple agent-based model to describe the spread of situation awareness within a team, as sketched in the previous section. The agent-based model is described formally in Section III.A, and number of illustrative simulation runs (inspired by the runway incursion case study) are discussed in Section III.B.

A. Model Description

The agent-based model assumes the existence of a population of N distinct agents that are involved in a certain scenario (e.g., pilots, crew members, air traffic controllers, etc.). Initially, each agent has a belief about a particular information element *IE*, which is assigned one of three values: *correct*, *incorrect* or *unknown*. For simplicity, the current paper assumes that a scenario contains only 1 information element of interest (i.e., whether or not the Hercules aircraft has received take off clearance). The value that is assigned to the belief of agent A about this information element at time point t is represented by $BeliefState(A, t)$.

As explained in the previous section, agents have the capability of adapting their beliefs based on the information they receive from other agents. The problem of changing beliefs based on new information has received widespread attention in the literature, and is known under the name *belief revision* [13]. Most approaches to belief revision are based on logic, and assume that the beliefs held by agents are represented as sets of propositional variables. Then, the question of how to update one's beliefs has to deal with several issues, e.g., when to trust new information over one's current beliefs, and how to bring a prioritisation into a set of beliefs? Since the current paper assumes that there is only 1 relevant information element, we can abstract from many of these issues. In addition, we assume that the source of the new information always is another agent[2] (i.e., the belief is updated based on *belief contagion* [16]). As a result, the belief revision problem is reduced to the following question: if an agent A with belief state X receives information from an agent B with a (different) belief state Y, does agent A update its belief state to Y or not? In this paper, this question is addressed by introducing probabilities; more specifically, we introduce a separate probability for each possible transition[3]. For example, the probability of switching from an *unknown* state to a *correct* state is represented by $p(u,c)$, the probability of switching from an *correct* state to a *unknown* state is represented by $p(c,u)$, and so on. An overview of all possible belief transitions of one agent is depicted in Figure 1 (where the nodes denote the agent's belief states, and the edges

[1] This misinterpretation might be explained by the fact that the pilot of the Hercules got used to the routine procedure of taxiing from the same military parking place at this airport and perhaps also of taking off from the same runway. And in many past cases, the line up procedure was often immediately followed by taking off, as permissions for lining up and taking off were sometimes given simultaneously.

[2] Although this paper focuses on incoming communication only, there are of course other potential sources (see [5] for an overview).

[3] This part of the model has deliberately been kept simple, to allow a comparison with a model at a population-based level. Nevertheless, it is not difficult to extend the approach based on more sophisticated belief revision techniques (e.g., taking the reliability of the sending agent into account [5]).

probabilities to switch between states upon receiving new information)[4]. Note that, although for completeness they are part of the figure, the probabilities of moving from any state to the same state are always 1 (e.g., if an agent with a *correct* belief receives another *correct* belief, it will obviously stay in state *correct*).

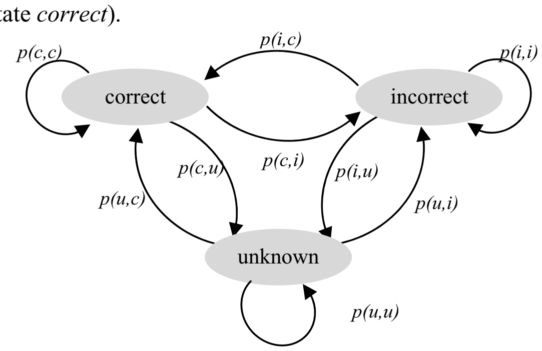


Fig. 1. Dynamic relationships in the agent model

Based on this mechanism, the dynamics of the belief contagion are represented as follows. At every time point, each agent *B* randomly picks another agent *A* to whom it communicates new information. The following formulae determine whether or not agent *A* updates its *correct* belief based on the belief value of agent *B* (where *r* is a randomly drawn number between *0* and *1*). Similar formulae are used for the case agent A has belief value *incorrect* or *unknown*.

```
/* Agent A with correct belief receives info from B with correct belief */
   if      BeliefState(A, t) = correct
   and     BeliefState(B, t) = correct
   then    BeliefState(A, t+1) = correct
/* Agent A with correct belief receives info from B with incorrect belief */
   if      BeliefState(A, t) = correct
   and     BeliefState(B, t) = incorrect
   and     r ≤ p(c,i)
   then    BeliefState(A, t+1) = incorrect     /* A is convinced by B */
   if      BeliefState(A, t) = correct
   and     BeliefState(B, t) = incorrect
   and     r > p(c,i)
   then    BeliefState(A, t+1) = correct       /* A is not convinced by B */
/* Agent A with correct belief receives info from B with unknown belief */
   if      BeliefState(A, t) = correct
   and     BeliefState(B, t) = unknown
   and     r ≤ p(c,u)
   then    BeliefState(A, t+1) = unknown       /* A is convinced by B */
   if      BeliefState(A, t) = correct
   and     BeliefState(B, t) = unknown
   and     r > p(c,u)
   then    BeliefState(A, t+1) = correct       /* A is not convinced by B */
```

B. *Agent-Based Simulations*

A number of agent-based simulation experiments have been performed using standard simulation software. First, simulations were performed in order to observe the behaviour of the individual agents and patterns that are exhibited by the model during individual simulation runs. Inspired by the case study of Section II.B, two scenarios were simulated based on the agent-based model: a nominal scenario where the mental states and expectations of agents are not biased; and a scenario that represents the 'group think', or 'wishful thinking' phenomenon [25]. 'Group think' occurs when agents have a tendency to adopt incorrect beliefs because these beliefs are more wishful and more desired. Both scenarios include 8 agents (e.g., 4 crew members on board of the Airbus, 2 crew members of the Hercules, and 2 Tower controllers). For each scenario, plausible parameters and initial settings have been set by hand; they are listed in Table 1.

TABLE I. PARAMETERS AND INITIAL SETTINGS OF THE AGENT-BASED MODEL IN TWO SIMULATED SCENARIOS

	Parameters						Initial settings		
	p(u,c)	p(u,i)	p(c,u)	p(c,i)	p(i,u)	p(i,c)	#u	#c	#i
scenario 1	0.2	0.15	0.1	0.02	0.05	0.04	4	2	2
scenario 2	0.15	0.1	0.1	0.02	0.05	0.01	4	3	1

Examples of two simulation runs for Scenario 1 are shown in Figure 2. The (100) time steps are represented on the horizontal axis[5] and the number of agents in a particular state per time step is represented on the vertical axis.

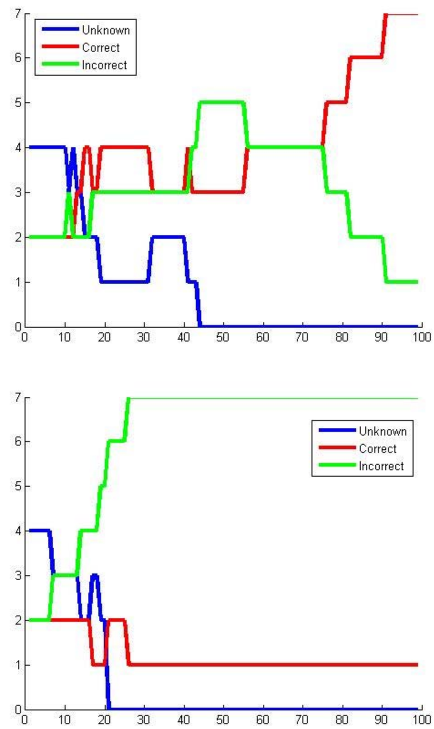


Fig. 2. Two example simulation runs of the agent-based model

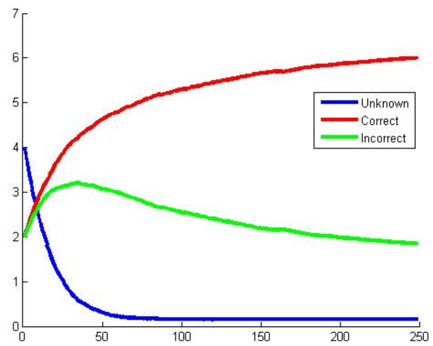
As can be seen in the figures, the belief states of the different agents may fluctuate rapidly. In the simulation in the upper graph, after 100 time steps 7 agents have a correct belief about the situation, whereas 1 agent has an incorrect belief. In

[4] Although they are depicted in Figure 1 for completeness, no explicit parameters are needed to specify the transition of any belief state to itself.

[5] Note that these scenarios are longer than the one described in Section II.B.

the simulation in the lower graph, the opposite situation is the case (7 agents with an incorrect belief, and 1 with a correct belief). In both examples, the number of agents with the unknown belief state has reached 0 at the end of the simulation. Note that neither of these simulations has reached an 'equilibrium' state in which no further changes occur, since in theory it is possible that the single agent with the deviating belief convinces some of the other agents to also have that belief. However, when running these simulations with 8 agents a bit longer, in the end always an equilibrium state is reached in which all agents have the same belief (usually after about 200 time steps): in most of these cases all agents have a correct belief, but in rare cases all agents end up in the state 'incorrect' or 'unknown'.

Since this agent-based model contains a random element, the model's behaviour patterns vary per simulation run (as illustrated above). In order to get an idea of a general pattern of the agents' behaviour, the results over 1000 simulation runs per scenario were averaged; see Figure 3. Here, also the simulation time has been extended to 250 time steps. In the upper figure, the 'average' pattern of belief spread is depicted for the nominal scenario where the agents do not have any expectation biases.



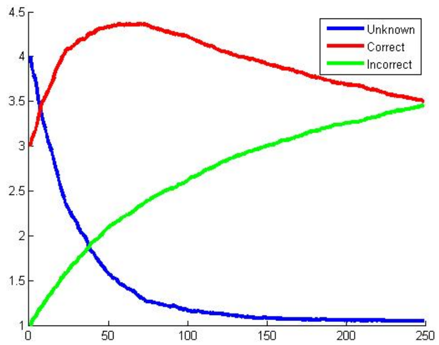


Fig. 3. Average over 1000 agent-based simulations
(Top - Scenario 1 'Nominal'; Bottom - Scenario 2 'Wishful Thinking')

In this case the system's state has a tendency towards the situation where correct beliefs dominate. In the end, it approaches an equilibrium with about 6 agents in the correct state and 2 in the incorrect state (and almost 0 in the unknown state). Interestingly, this is a different situation compared to the individual simulation runs depicted in Figure 2, which would usually end up in 'all-or-nothing' situations where all agents eventually had the same belief. Concerning the 'wishful thinking' scenario (where agents are biased towards incorrect beliefs, see right part of Fig. 3), eventually an equilibrium is approached with about 3.5 agents in the states correct and incorrect, and 1 agent in state unknown.

IV. Population-Based Model of SA Dynamics

As opposed to an agent-based approach, in the current section we explore to what extent it is possible to simulate the spread of SA within a team using a population-based approach, which abstracts from details of individual agents. This population-based model is described formally in Section IV.A, and a number of illustrative simulation runs (with comparable settings as in Section III.B) are discussed (and compared with the agent-based simulations) in Section IV.B.

A. Model Description

The literature contains a number of successful attempts to model the dynamics of processes involving many agents from a population-based perspective. One of the classical application domains is the spread of epidemics over a population. The analysis of epidemics via this type of model has a long history, going back, for example, to [17]. The main principle boils down to splitting up a population into a number of distinct sub-populations. In the case of the classical epidemics model, these sub-populations refer to groups of Susceptible, Infected, and Recovered agents (hence the model is sometimes called the SIR-model). The size (or density, if spatial aspects are included) of each sub-population is then represented in terms of a real-valued variable, and its dynamics in terms of differential equations that depend on the values of the variables representing the other sub-populations. In addition, several parameters are used that influence the speed of the processes, such as contact frequencies and recovery rates (see also [4]).

In the current section, we present a population-based model for belief spread that was inspired by this principle. In this model, sub-populations are introduced for each of the three belief values mentioned in Section III. Thus, we assume distinct sub-populations for individuals with *correct*, *incorrect*, and *unknown* beliefs. The dynamics of each of these sub-populations depends on 1) its own size, 2) the size of the other sub-populations, and 3) some transition rates that determine the speed by which individuals adapt their beliefs from one type to another. In summary, the following concepts are used in the model[6]:

- sub-population of individuals with correct belief
- sub-population of individuals with incorrect belief
- sub-population of individuals with unknown belief
- transition rates between different groups

[6] For simplicity, this model does not include parameters for notions like contact frequency, as is often done in population-based models. However, such parameters can be added following the approach described in [4].

To formalise these concepts, the following variables and parameters are used:

C	size of the population of individuals with correct belief
I	size of the population of individuals with incorrect belief
U	size of the population of individuals with unknown belief
γ_{UC}	transition rate from U to C
γ_{UI}	transition rate from U to I
γ_{IC}	transition rate from I to C

Next, the dynamic relationships between these concepts can be determined. To ensure that the model represents the same process as the agent-based model introduced in Section III (hence enabling a fair comparison), the transitions shown in Figure 1 are again taken as a basis. However, since we deal with populations instead of individual agents, all transitions from any belief state *X* to any belief state *Y* are now combined (in one formula) with all transitions from *Y* to *X*. As a result, only three transition rate parameters are needed, namely (γ_{UC}, γ_{UI} and γ_{IC}), which can have positive as well as negative values. For example, in case γ_{UC} is set to 0,01, this means that, per time unit, slightly more agents move from state *unknown* to *correct* than vice versa. Instead, if γ_{UC} is set to -0,01, slightly more agents move from *correct* to *unknown*. Using these parameters, the following temporal relationships are used to specify all transitions:

$$C(t+\Delta t) = C(t) + (U(t)*C(t)*\gamma_{UC} + I(t)*C(t)*\gamma_{IC}) * \Delta t$$
$$I(t+\Delta t) = I(t) + (U(t)*I(t)*\gamma_{UI} + C(t)*I(t)*\text{-}1*\gamma_{IC}) * \Delta t$$
$$U(t+\Delta t) = U(t) + (C(t)*U(t)*\text{-}1*\gamma_{UC} + I(t)*U(t)*\text{-}1*\gamma_{UI}) * \Delta t$$

As an illustration of these relationships, consider the first equation, specifying the change of the sub-population with *correct* beliefs per time unit. This formula states that the size of this sub-population at a next time point equals the size at the previous time point plus (or minus) the agents that have just 'changed their mind' based on interaction with other agents. These agents that changed their mind are represented by the agents that changed from *unknown* to *correct* (i.e., $U(t)*C(t)*\gamma_{UC}$) and those that changed from incorrect to correct ($I(t)*C(t)*\gamma_{IC}$). This mechanism reflects the property that more agents are likely to move between sub-population *X* and *Y* if these groups are larger in size. Also note that, by these relationships, the sum of the three populations always remains the same: what adds to one population subtracts from another. In differential equation form these formulae are represented as follows:

$$\frac{dC(t)}{dt} = U(t)*C(t)*\gamma_{UC} + I(t)*C(t)*\gamma_{IC}$$
$$\frac{dI(t)}{dt} = U(t)*I(t)*\gamma_{UI} + C(t)*I(t)*\text{-}1*\gamma_{IC}$$
$$\frac{dU(t)}{dt} = C(t)*U(t)*\text{-}1*\gamma_{UC} + I(t)*U(t)*\text{-}1*\gamma_{UI}$$

In the next subsection, the behaviour of this population-based model will be compared with the agent-based model introduced in Section III. To make the simulations comparable, we need to make the following assumption on the relation between parameters is both models:

$$\gamma_{UC} = p(u,c) - p(c,u)$$
$$\gamma_{UI} = p(u,i) - p(i,u)$$
$$\gamma_{IC} = p(i,c) - p(c,i)$$

B. Population-Based Simulations

Similar simulation experiments as the ones described in the previous subsection have been performed by applying the population-based model to the same two scenarios. An overview of the parameters of the model and initial settings per scenario is given in Table 2. Simulation results are depicted in Figure 4.

TABLE II. PARAMETERS AND INITIAL SETTINGS OF THE POPULATION-BASED MODEL IN TWO SIMULATED SCENARIOS

	Parameters			Initial settings		
	γ_{UC}	γ_{UI}	γ_{IC}	#unknown	#correct	#incorrect
Scenario 1	0.1	0.1	0.02	4	2	2
Scenario 2	0.05	0.05	-0.01	4	3	1

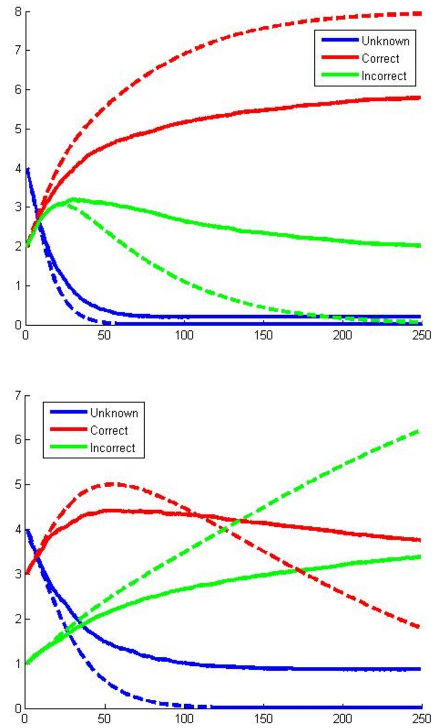


Fig. 4. Comparison between agent-based (solid lines) and population-based (dotted lines) simulation with 8 agents
(Top - Scenario 1 'Nominal'; Bottom - Scenario 2 'Wishful Thinking')

Again, the upper figure shows the nominal scenario and the lower figure the wishful thinking scenario. The results of the population-based simulations are depicted using the dotted lines. For the purpose of comparison, also the average results of 1000 agent-based simulations (as in Figure 3) have been included; these are depicted using the solid lines.

As can be seen from the figures, for both scenarios there are substantial differences between the pattern of the population-based simulation and the average pattern of the agent-based simulations. In principle, this is in conflict with our initial hypothesis, namely that the pattern of belief spread in population-based simulations would approximate the pattern demonstrated by agent-based simulations. However, it is important to realise that the comparison was made for a very small population size of only 8 agents. As a result of this small number (combined with the randomness), in many instances of the agent-based simulation runs the *all-or-nothing* effect mentioned in the Section III occurs. To be more precise, for small population sizes it may happen that all agents 'accidentally' end up in an unusual state (e.g., in most cases all agents become *correct*, but in some exceptional cases all of them become *incorrect* or *unknown*) and the population will not be able to recover from this (after all, if all agents have become *incorrect*, no agent will ever become *correct* again). Instead, for the population-based model this will not occur, because the model is a) deterministic (hence there is no issue of exceptional cases) and b) continuous (hence the size of a sub-population can only approximate 0, but can never make a sudden jump to 0).

As explained above, for a small population size of only 8 agents it is possible that individual runs of the agent-based model sometimes end up in an unusual equilibrium state. Instead, for much larger population sizes this is very unlikely to happen. For this reason, it is expected that for larger population sizes the agent-based simulations will resemble the population-based simulations much more. To test this hypothesis, additional simulation runs with larger population sizes were performed, both with the agent-based and the population-based model. In Figure 5, results are shown of simulations with the same settings as 'scenario 1' above, but instead of the initial distribution of agents 4-2-2 (for *unknown-correct-incorrect*), the distribution 50-25-25 was used. As shown in the figure, in this case the simulations are clearly very similar, which confirms our hypothesis that the size of the population plays an important role. Additional simulations, with a large variety of settings for all parameters (using population sizes up to 100.000 agents) have also confirmed this.

To conclude, our comparative study has pointed out that for large population sizes, the presented population-based model approximates the results of the agent-based model. In addition, it is important to state that the population-based model is computationally less complex. As an illustration, the simulation time of the population-based model is less than 1 second, independent of the population size. Instead, the simulation time of the agent-based model increases linearly with the amount of agents (1.17s for 1000 agents, 2.34s for 2000 agents, 3.51s for 3000 agents, etc.) and with the number of simulation runs. And even though for large population sizes it becomes less necessary to generate many simulation runs of the agent-based model, this still is an argument to use the population based model in case one is interested in studying the dynamics of situation awareness in a large population. In contrast, in case one is interested in the SA patterns within smaller groups (such as the aviation example shown in Section II.B), a population-based model does not seem to be a reliable approach.

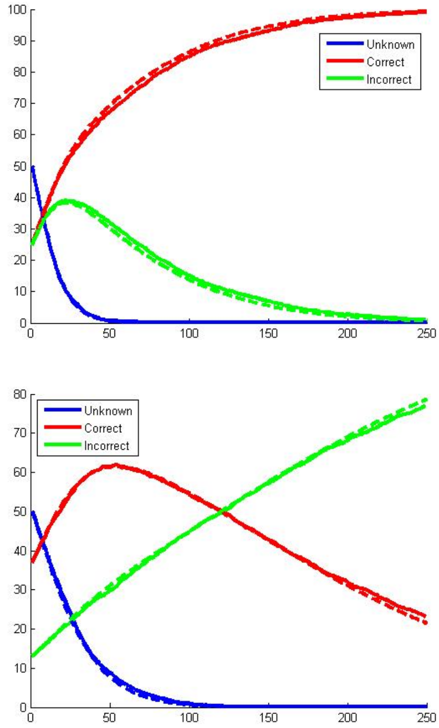


Fig. 5. Comparison between agent-based (solid lines) and population-based (dotted lines) simulation with 100 agents
(Top - Scenario 1 'Nominal'; Bottom - Scenario 2 'Wishful Thinking')

V. DISCUSSION AND FUTURE WORK

This paper presented a comparison of two approaches towards computational modelling of spread of Situation Awareness in teams: an agent-based approach and a population-based approach. These two models were applied to a case study in aviation and relevant simulations of the models were performed to investigate whether the behaviour of the population-based model can approximate the pattern produced by the agent-based model. It was demonstrated that, for large population sizes, the agent-based approach might indeed be substituted by a (computationally less expensive) population-based approach, since similar patterns are produced. Instead, when studying the dynamics of smaller groups, a population-based approach becomes less reliable. These findings are similar to conclusions reported in the domain of Biology [8].

Of course, there are also other reasons why an agent-based approach may be favourable over a population-based approach, such as the possibility to model local strategies and topological-based behaviours, which are difficult to represent at a population-based level. Such aspects were however left outside the scope of the current paper, where we deliberately focused on those aspects of agent-based models that can also be captured as a population based level.

For a more extensive discussion of similarities and differences between agent-based and population-based approaches, the reader is referred to [20]. That paper also provides more arguments in favour of using agent-based modelling in certain cases, such as the possibility to model heterogeneous agents and the increasing availability of dedicated tools. In addition, they claim that researchers '… should consider explicit case comparisons of their agent-based models with existing or potential equation-based models where relevant'. The current paper can be seen as a next step in that direction, providing more insight into the conditions in which both approaches may or may not lead to similar results.

In addition to computer scientists, the current work could be interesting for various other stakeholders, including social scientists, human factors experts, and managers in organisations, since the simulations provide more insight into the dynamics of SA in a group and its non-linear dependence on factors as 'wishful thinking' and communication.

For future work it would be interesting to study more and different simulation scenarios, and to perform a sensitivity analysis on both models in order to identify optimal parameters. In addition, a more realistic centralised agent-based model of a group can be developed which considers the organisational hierarchy in a team, such as modelling of a team leader whose opinion weighs higher in comparison to other team members. Also, more sophisticated mechanisms for belief revision could be included, and related to a similar mechanism on the population-based level. Finally, the agent-based model could be extended with personality characteristics, such as modelling of team players that adopt others' beliefs easily and individualistic personalities who do not accept the opinions of others and persist in their own beliefs and interpretations of a situation.

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