Agent-Based Simulation of Complex Aviation Incidents by Integrating Different Cognitive Agent Models

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Abstract. Aviation incidents often have a complex character in the sense that a number of different aspects of human and technical functioning come together in creating the incident. Usually only model constructs or computational agent models are available for each of these aspects separately. To obtain an overall model, these agent models have to be integrated. In this paper, existing agent models are used to develop a formal, executable agent model of a real-world scenario concerning an aircraft that descends below the minimal descent altitude because of impaired conditions of the flight crew members. Based on the model, a few proof-of-concept simulations are generated that describe how such hazardous scenarios can evolve.

Keywords: aviation, agent-based simulation, agent model, situation awareness, operator functional state, decision making.

1 Introduction

In analysing hazards and incident scenarios in Air Traffic Management (ATM), agent-based modelling has proved to be a fruitful approach [1,3]. As argued in [11], agent-based modelling has considerable advantages over existing approaches such as STAMP [10] and FRAM [8], which have a qualitative nature. Nevertheless, when studying realistic scenarios, it has been found that many of them show a complex interaction of a number of aspects. Often computational models are available for these aspects, but not for their interaction. To obtain such overall models, multiple model constructs need to be integrated. This can be done on an abstract, conceptual level of descriptions of models by their inputs and outputs (model constructs), but to perform simulations, integration at a more detailed level is required. This paper describes how such an integration at a detailed level can be done and illustrates this for a real-world example.

In order to demonstrate how such an integration of models can take place, an existing ATM scenario was used, which is explained in Section 2. Next, in Section 3 it is shown (on a conceptual level) how this asks for integration of a number of models, including the Operator Functional State model (OFS; cf. [2]), the Situation Awareness model (SA; cf. [9]), and a decision model (DM; inspired by [3]). These are the three models on which this section focuses. In Section 4 a formalisation of the integrated models is presented. In Section 5, simulation experiments with the integrated model are described. The simulations illustrate that the integrated model exhibits realistic behaviour as described in the given scenario, and has the ability to produce alternative behaviours. Finally, the results are discussed in Section 6.

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2 Scenario

In a scenario involving a number of adverse factors in addition to a combination of 'get-home-itis' and complacency, this Embraer Phenom 100 Flight Crew was fortunate that Air Traffic Control was able to make a great 'save'. The description of the incident, which was taken from Callback[1], is as follows:

> *While on an RNAV approach at night, the Captain and I became disoriented and started to descend to the MDA prior to the Final Approach Fix (FAF). We thought we had already passed the FAF, but in reality we had only passed the intersection before the FAF. Four miles from the FAF, Tower notified us of a low altitude alert and told us to immediately climb to the published altitude. We acknowledged the instruction and corrected our altitude. The published altitude for that segment of the approach was 2,000 feet and we had descended to 1,400 feet.*
>
> *There were several causal factors for this event: 1.) It was a long duty day. We had already flown roughly eight hours during the course of the day and this was our fourth leg and last leg home. It was dark and we were tired for sure. 2.) During the final leg to our destination, ATC gave us multiple route changes, speed assignments, vectors and a last minute change to the arrival. There was insufficient time to properly configure and brief the approach and corresponding altitudes. 3.) There was some anxiety about getting below the clouds because there are some unique runway conditions currently at this airport. The first 2,000 feet of the runway were unusable due to routine maintenance and we wanted to make sure we identified the runway early so we could visually verify the new touchdown point. 4.) The morning and afternoon thunderstorms in the vicinity challenged us during the course of the day and they left behind pockets of moderate precipitation and turbulence for the arrival. We had to keep clear of the weather cells and keep up with rapidly changing ATC instructions. 5.) Nourishment. We had each eaten a scant breakfast, taken a late lunch, and completely skipped dinner due to flight requirements. I made several comments that I was ready to get down so I could find a place to get something to eat.*
>
> *Looking back on this event, I am most grateful to the safeguards placed within the ATC system. Had we not received the low altitude alert, the history of this particular flight could have been much worse. As the day progressed during long flight legs in rough weather I began to slowly lose my focus and attention to fine detail. Admittedly I was spent. I was safe within legal duty and rest limits, but the anxiety of the trip the night before coupled with the long duty day, dulled my senses and allowed me to slip into a near-lethal combination of "get-home-itis" and complacency.*
>
> *I can see now a few variables I could change to prevent this from happening again in the future. First, advise ATC that we need delay vectors to prepare properly for the approach. I know that is a wildly unpopular choice in a very crowded and busy airspace, however it could have afforded us the opportunity to brief and prepare for the approach. Secondly, make sure that I take a moment to get some nourishment before I embark on a full day of flying. Third, make sure I confirm that the other pilot is fully briefed and ready to commence the approach. Finally, make sure that I get proper rest the night before I embark on a long day of flying.*

3 High-Level Overview of the Integrated (SA-OFS-DM) Model

This section describes at a high level how the scenario asks for formal integration of the model constructs for Situation Awareness, Operator Functional State, and Decision Making. Parts of the description are taken from [4].

3.1 Separate Model Constructs

The *situation awareness* model [9] is a computational refinement of the conceptual model of Endsley [5], which includes the perception of cues, the comprehension and integration of information, and the projection of information for future events. It consists of 4 main components (see the bottom part of Fig. 1): (1) performance of observations; (2) and (3) belief formation on the current situation (simple and complex beliefs); (4) belief formation on the future situation and (5) mental model. For a detailed description of the model see [9].

[1] Callback newsletter. `http://asrs.arc.nasa.gov/publications/callback.html`. July 10th 2012.

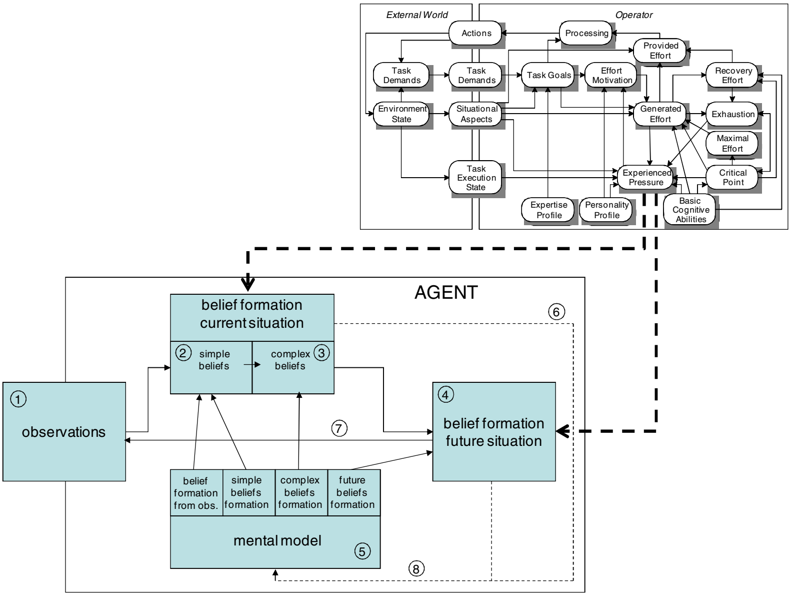

Fig. 1. Integration of Models for OFS and SA

The operator functional state model construct (see top part of Fig. 1) determines a person's *functional state* as a dynamical state, which is a function of task properties and personal characteristics over time. The model is based on two different theories: (1) the *cognitive energetic framework* [7], which states that effort regulation is based on human resources and determines human performance in dynamic conditions, and (2) the idea that when performing physical exercise, a person's generated power can be maintained at some maximal *(critical power)* level without leading to more exhaustiveness [6]. In the upper part of Fig. 1, the concepts on the left hand side denote external factors (such as task demands and environmental conditions), whereas the concepts on the right hand side denote internal states of the operator (such as experienced pressure, exhaustion, and motivation), The concepts in between denote interaction states (i.e., related to the operator's observations and actions). For a detailed description see [2].

The (experienced-based) *decision making* model construct is taken from [3,4]. An extensive description of this model construct is beyond the scope of this paper, but the main idea is that in decision making processes a number of action options are distinguished, and that a model for decision making results from a valuation (e.g., expressed in terms of a real number) for each of the options, in such a way that the action option with the highest associated value is selected to be performed.

3.2 Modelling Interaction between Functional State and Situational Awareness

In many situations in which an operator has a less effective functional state, characterized by high levels of experienced pressure and exhaustion, this affects in a dynamical manner his or her situation awareness, and in turn this impaired situation awareness leads to inadequate decisions. This section focuses on this dynamical interaction pattern. To illustrate this, consider the following: stress or exhaustion may cause a person to make errors in observation (like missing an item on a radar screen), but even when the items have been observed correctly, stress or exhaustion may also induce errors in the way the person processes and interprets the observed items (e.g., even when a pilot observes a low altitude alert, (s)he may interpret this as coherent with approaching an airport and fail to conclude from this that it is necessary to climb to a higher altitude). In terms of the classical sense-reason-act cycle, an operator functional state may influence both the sensing process and the reasoning process, and it may even influence the acting process, which will be explained later.

The scenario described in Section 2 above is a clear example of a situation where functional state affects situation awareness: a pilot misinterprets an important ATC instruction, among others because of fatigue. This is illustrated by the following statement: '*We thought we had already passed the FAF, but in reality we had only passed the intersection before the FAF*'. Hence, although the pilots observed that they had just passed the intersection before the FAF, they interpreted this as having passed the FAF itself. This example illustrates that stress and exhaustion may lead to errors in *interpretation*: they cause human beings to make certain errors in inferences, which they would not have made when they were in their usual functional state. Below, this process of erroneous inference is represented as an incorrect type of belief formation, which is one of the steps modelled in the situation awareness model.

The integration of the models for OFS and SA is visualised in Fig. 1. Note that this picture addresses the case that from the functional state the state of experienced pressure (or stress) influences situation awareness; there are also ways in which exhaustion may affect situation awareness. As shown in Fig. 1, the concept of experienced pressure may interact with concepts in the situation awareness model in two ways: it may impact both the formation of current beliefs and of future beliefs.

In the OFS model the concept of experienced pressure is represented in terms of a variable with a real value in the domain [*0*,*1*]. For the integration a mechanism was added that models how this variable affects the process of belief formation in the SA model. This mechanism also accounts for having an agent make *incorrect* inferences. To obtain this, an extension of the situation awareness model is needed. This is done by including in the mental model of it a number of incorrect connections between beliefs (e.g., some 'default rules'), which trigger with low strength normally, and to ensure that these connections have a higher probability to be triggered in case the value for experienced pressure is high. This mechanism allows the model to produce errors or perform biased reasoning when somebody is under high pressure.

3.3 Integration with Decision Making

The next step is to integrate the OFS and SA models addressed above with the model DM for decision making, taken from [3]. An overview of the different connections for this integration is shown in Fig. 2. The obtained patterns are as follows:

OFS model $\rightarrow$ experienced pressure $\rightarrow$ SA model $\rightarrow$ adequacy of beliefs

adequacy of beliefs $\rightarrow$ DM model $\rightarrow$ adequacy of initiated actions

So, the OFS model affects via experienced pressure the adequacy of beliefs generated by the SA model, and the adequacy of beliefs resulting from the SA model is a basis for adequacy of initiated actions. In short, by high levels of experienced pressure, decisions become less adequate. Furthermore, there is an effect of exhaustion on the readiness or willingness for a human operator to spend effort to get additional observation information at specific issues where needed, for example, to acquire lacking information or get confusing information clarified:

OFS model $\rightarrow$ exhaustion $\rightarrow$ SA model $\rightarrow$ readiness for observation

So, high levels of exhaustion reduce such readiness within Situation Awareness. Moreover, exhaustion also has a similar direct effect on readiness for decision making about and iniatiation of actions in general:

OFS model $\rightarrow$ exhaustion $\rightarrow$ DM model $\rightarrow$ timely initiation of actions

This indicates an effect of exhaustion on readiness for actions to be actually performed when circumstances ask for it. High levels of exhaustion may reduce readiness to undertake any action, as action requires effort, and therefore affects the timeliness of acting; this may imply that in circumstances that require action, such action is not undertaken (or too late). For observation actions in particular the effect on readiness comes from two sides. They have an effect of exhaustion like any other action. But via the SA side they already have another effect from exhaustion. Due to this double effect, high exhaustion levels may even lead to more reduced timeliness of observation actions than of other actions. An overall result may be that in situations of high exhaustion levels, persons tend not to act or act too late, and especially tend not to actively acquire or try to clarify lacking or confusing information. Not initiating observation actions has a negative effect on adequacy of beliefs:

DM model $\rightarrow$ initiating observation actions $\rightarrow$ SA model $\rightarrow$ adequacy of beliefs

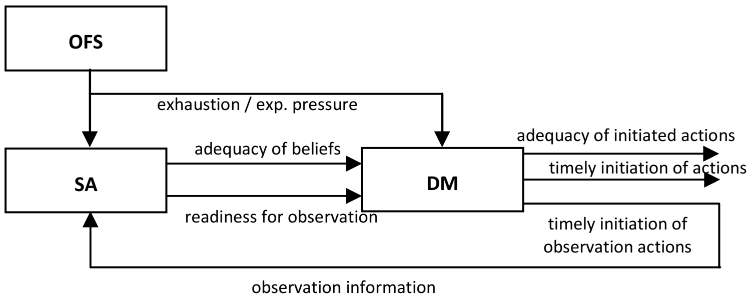

Fig. 2. Integration of Models for Functional State, Situation Awareness, and Decision Making

4 Formalisation of the Integrated Model

This section describes the formalisation of the integrated model. It has an emphasis on the impact of experienced pressure on situation awareness (via interpretation errors, as described above) and decision making. The mechanisms that describe the dynamics of experienced pressure itself (as a result of, among others, high task level) are not shown; for details about this, see [2].

The proposed model consists of five main components: *observations*, *simple beliefs*, *derived simple beliefs*, *complex beliefs* and *actions* (see also Fig. 1). In this model observations from the world are performed by the agent, and these observations are transformed into simple beliefs about the current situation. Simple beliefs concern simple statements that have one-to-one mapping to observations (e.g., an observation of a particular element in a display, an FAF point or an intersection point). Furthermore, simple beliefs provide an input for generation of derived simple beliefs. Derived simple beliefs represent more abstract simple statements about the world that may refer to past situation (e.g., in this scenario the belief that an FAF point has been passed by an aircraft). Derivable simple beliefs are used to generate complex beliefs and based on them also decision-making takes place. The most important formal relations between the variables in the components are as follows.

R1 - Observations

$$V_{observation\_result\_x} = \omega_{observation\_x} V_x \qquad (1)$$

This formula determines the activation level of observation of world fact x. These levels have a value within the range of [0, 1], depending on the degree of certainty of an observation. Here, $\omega_{observation\_x}$ is a parameter within the range of [0, 1] that defines the quality of the observation process. In the simulations $\omega_{observation\_x} = 1$ has been taken (assumption of faithful representation of the world by the observation).

R2 - Simple beliefs

$$V_{belief\_simnew} = (1-\beta) * \gamma * V_{belief\_simold} + \beta * th(\tau, \sigma, V_{observation\_new} * \omega_{obs\_simbelief} * (1 + \alpha * EP)) \qquad (2)$$

This formula defines how activation of simple beliefs is determined on the basis of observations. Here, β is a recency parameter that defines the contribution of a new observation to the value of a belief, γ is a decay factor for the belief, ω_{obs_belief} is a parameter that defines a connection between observations and simple beliefs.

Furthermore, α is a randomness parameter within a range of [-1, 1] that expresses the random variability of observation interpretation and may contribute to a wrong interpretation of a belief. This models how the extent of error in interpretation depends on experienced pressure with level EP; this experienced pressure (or stress), is what a human agent experiences during demanding task execution. A threshold function is used in this formula in order to translate the level of an observation to a value contributing to the activation value of a simple belief. The threshold function has two parameters: τ and σ that define the threshold value of the function and its steepness respectively.

R3 - Simple derived beliefs

$$V_{belief\_der} = \max(V_{belief\_der1}, V_{belief\_der2} \ldots V_{belief\_dern}) * \omega_{simbelief\_derbelief} \qquad (3)$$

This formula defines that only one simple belief with the highest value is propagated further and activates the relevant simple derived belief.

R4 - Complex beliefs

$$V_{belief\_com} = V_{belief\_der} * \omega_{derbelief\_combelief} \qquad (4)$$

This formula defines how activation of complex beliefs is determined on the basis of derived beliefs.

R5 - Actions

$$\begin{array}{ll} \text{If } V_{belief\_com} > \textit{activation\_threshold} & V_{action} = 1 \\ \text{else} & V_{action} = 0 \end{array} \qquad (5)$$

This formula expresses that if an activation value of a complex belief is higher than a threshold, then a relevant action is performed.

To apply this model to the scenario, it was instantiated as described by Fig. 3.

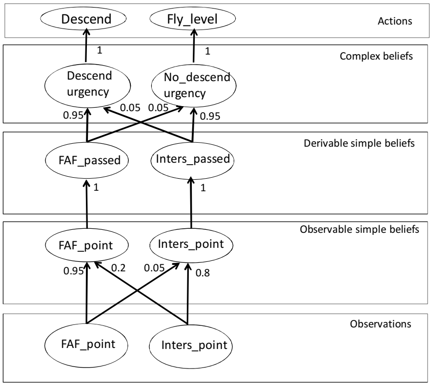

Fig. 3. Instantiation of the Integrated Model to the Scenario

Table 1. Parameter Settings

Parameter	Description	Value
activation_threshold	Beliefs with values above this threshold are activated	0.5
τ_{obs}	Threshold parameter of a threshold function that expresses the value at which an observation to belief contribution of 0.5 is established	0.2
σ_{obs}	Parameter of a threshold function defining the steepness of the curve	0.4
α	Randomness factor that defines the degree of influence of experienced pressure on the formation of simple beliefs from observations	Random value from [-1 , 1]
β	Decay factor of simple beliefs	0.8
γ	Recency factor that defines how much a new observation contributes to the formation of a simple belief	0.7
FAF2FAF	Connection value from the observation of an FAF point to a correct simple belief about FAF point	0.95
FAF2intersection	Connection value from the observation of an FAF point to a wrong simple belief about an intersection point	0.05
intersection2intersection	Connection value from an observation of an intersection point to a correct simple belief about an intersection point	0.8
intersection2FAF	Connection value from an observation of an intersection point to a wrong simple belief about a FAF point	0.2[2]
FAF2FAF_passed	Connection value from simple belief about a FAF point to a simple derived belief about passing FAF	1
intersection2inters_passed	Connection value from simple belief about an intersection point to a simple derived belief about passing FAF	1
FAF_passed2desc_urgency	Connection value from simple derived belief about passing FAF to a complex belief about descend urgency	0.95
FAF_passed2nodesc_urgency	Connection value from simple derived belief about passing FAF to a complex belief about no descend urgency	0.05
inters_passed2nodesc_urgency	Connection value from simple derived belief about passing an intersection to a complex belief about no descend urgency	0.95
inters_passed2desc_urgency	Connection value from simple derived belief about passing an intersection to a complex belief about descend urgency	0.05
descend_urgency2action_ descend	Connection value from complex belief about descend urgency to a descend action	1
no_descend_urgency2fly_level	Connection value from complex belief about no descend urgency to a fly level action	1

[2] Note that this value has been chosen relatively high to represent a 'wishful thinking' process: pilots expect to observe the FAF due to a (possibly unconscious) desire to reach the point of arrival.

An overview of the parameter settings used is given in Table 1. The setting of these values determines how the dynamic Experienced Pressure (EP) variable from the OFS model affects the values of simple beliefs that are formed from observations of an intersection point and a FAF point. In particular, due to the influence of EP and randomness parameter α in formula R2, the value of an erroneous simple belief about passing the FAF point may become higher and thus propagated further to derived simple belief module as only the highest simple belief is taken for further processing.

5 Simulation Results

In order to illustrate how differences in task load influence the dynamics of functional state and situation awareness, in total 10000 simulations were performed (using the Matlab environment): 5000 with a scenario where values of the Task Level (TL) were taken according to the Callback case study and 5000 with a hypothetical scenario where the value of TL is lower. In addition, the relation between Task Level and the probability of incorrect actions was analysed in more detail.

5.1 Simulation of a Scenario with High Task Level

For this scenario, 5000 simulations were performed. In this scenario the Task Level (TL) value in the OFS part of the integrated model varies over time, according to the case study. According to the OFS model [2], TL is a variable that represents the (objective) amount of tasks that are to be done by an operator at a given time point. In principle, the variable ranges over the domain [0, ∞), but in practice values are taken in the domain [100, 500], where 100 represents a situation of relative underload (e.g., for a pilot, flying in mid air without any special demands), and 500 represents a situation of extreme overload (e.g., performing final approach in extreme weather circumstances). To simulate the Callback scenario, TL was set to 200 for the first part of the simulation (representing the beginning of the shift), then to 400 for a while (representing the multiple route changes), and finally to 500 (representing the phase while approaching the destination point).

Of 5000 simulations, there were 32 occurrences of an erroneous belief and hence a wrong descend action. The differences between these simulations are the result of the randomness parameter α in rule R2. Fig. 4 is an example of a simulation in which an erroneous belief occurs. Here, the two graphs at the top indicate states from the Operator Functional State model construct, and the two graphs at the bottom indicate states from the Situation Awareness model construct and the Decision Making model (in particular the state 'Descending action'). As can be seen in Fig. 4, at time point 50 the descend action is performed while there is no observation of the FAF point; instead the intersection point is observed, but erroneously interpreted as FAF (the activation value for the incorrect simple belief about FAF is higher than for the correct belief about intersection point). In the top left part of Fig. 4 it can be seen that the experienced pressure of the agent is increasing with the increase of Task Level and the performance quality is decreasing (top part of the figure).

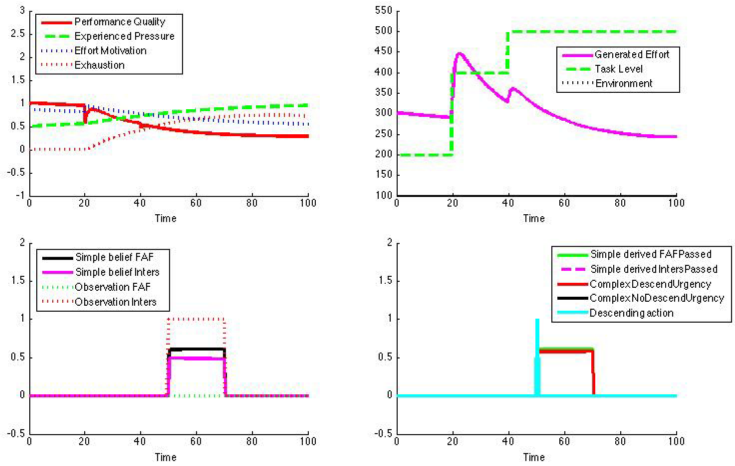

Fig. 4. Wrong descend action is performed as a result of incorrect Situation Awareness

Fig. 5 is an example of a simulation with the same initial settings where no erroneous belief is formed and wrong action is performed, in spite of high experienced pressure. The activation value of the correct simple belief about intersection is higher and propagates further to form a derived simple belief about passing an intersection point.

5.2 Simulation of a Scenario with Medium Task Level

Also 5000 simulations of a hypothetical scenario were performed. Here the Task Level (TL) value in the OFS part of the integrated model stays low (TL=150) during the whole simulation. Of 5000 simulations, there were no occurrences of a wrong

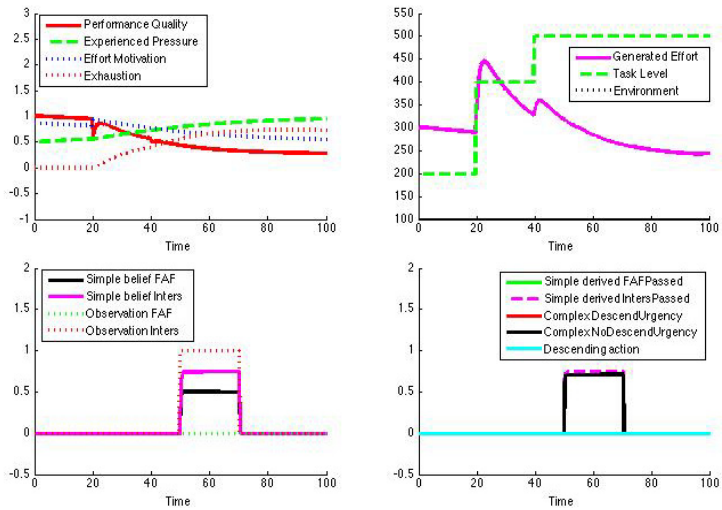

Fig. 5. No descend action is performed thanks to correct Situation Awareness

descend action. Fig. 6 is an example simulation. As can be seen in Fig. 6, no descend action is performed and beliefs about the intersection point are correct. At the top bottom part of Fig. 6 it is shown that the dynamics of Experienced Pressure (EP) of the agent differ from the Callback scenario: it is decreasing instead of increasing. Effort motivation decreases as well, as a result of probably too low task level.

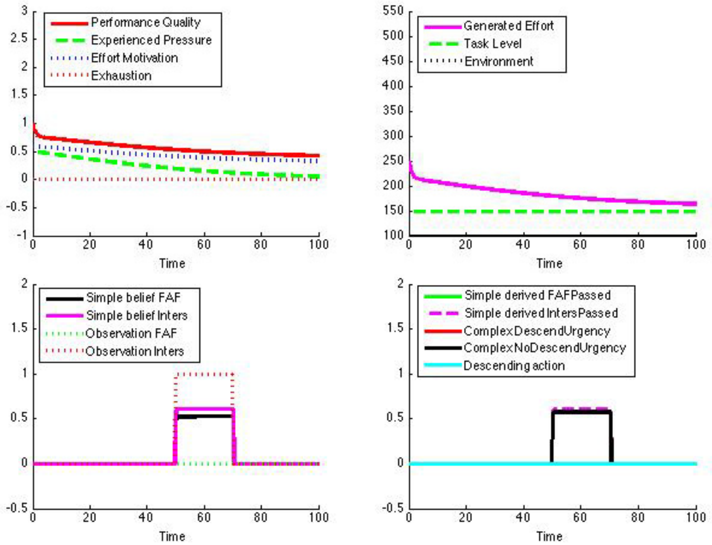

Fig. 6. Hypothetical scenario with low Task Level

5.3 Relation between Task Level and Wrong Actions

To analyse the relation between Task Level (TL) and the probability of incorrect actions in more detail, a number of additional simulations have been run. In these simulations, the value of TL has been varied in a systematic manner with an incrementing interval of 25. It has been done as follows: first, 5000 simulations have been run with the setting TL=100 (during the entire simulation, i.e., TL was not dynamic in these simulations). Next, 5000 simulation have been run with TL=125, then with TL=150, and so on, until TL=500. Totally there were 17 variations of TL. For each of the settings for TL, we counted for how many of the simulations the descend action was performed. The results are shown in Fig. 7, where the x-axis represents TL, and the y-axis the number of incorrect actions recorded.

As can be seen in Fig. 7, the relation between Task Level and the number of wrong descend actions is not linear. In the beginning when TL increases from 100 to 275, there are no wrong actions performed. Further the number of wrong actions systematically increases up to TL=425. With the TL value higher than 425 the number of times when wrong descend actions occur starts fluctuating randomly.

This pattern can be better understood after examining the relations between Task Level and Experienced Pressure (see Fig. 8). This simulation was performed in order to observe the dynamics of EP as a function of TL. Here again 5000 simulations were performed for each level of TL which was kept constant during one simulation. The value of EP was recorded from the last simulation of each TL level and only at one time point that corresponds to the observation of an intersection point by the pilots. As you can see in Fig. 8, the EP curve represents a logistic function that grows rapidly within the range of TL= [150, 300] and stabilizes afterwards when TL=450. It means that after TL higher than 450 EP increases very slowly and making the task more difficult does not influence EP much. This pattern of EP explains the fluctuations of the number of wrong actions in Fig. 7 when TL > 450.

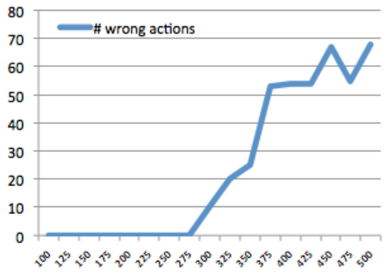

Fig. 7. Relation between *Task Level* (x-axis) and the number of *wrong actions* (y-axis)

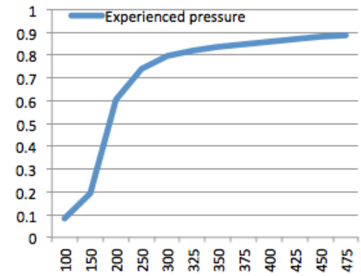

Fig. 8. Relation between *Task Level* (x-axis) and *Experinced Pressure* (y-axis)

6 Discussion

The main goal of this paper was to discuss how complex aviation incidents can be modelled by integrating existing computational agent models for different aspects of human functioning. This has been illustrated by a real-world scenario, thereby integrating models for Operator Functional State, Situation Awareness and Decision Making. As also confirmed by a series of interviews with domain experts in ATM (air traffic controllers and pilots), the integrated agent model exhibits realistic behaviour. It shows how accumulation of high workload leads to higher exhaustion and experienced pressure, which in turn affect the situation awareness in such a way that the probability to form erroneous beliefs results increases. As decisions are based on such beliefs, the model shows that therefore wrong descend decisions can be made. Hence, it can provide useful insights in the dynamics of cognitive and physiological processes that affect performance in a non-linear fashion. It can be used by safety experts to make incident and accident predictions given particular circumstances.

For future work, more simulations could be performed, by varying other parameters of the OFS model, such as personality and experience. Also prospective scenarios to make predictions can be investigated. In addition, sensitivity analysis can be performed regarding the adopted parameter values. Finally, on the long term, the model can be embedded into an intelligent support system that is capable of making a detailed estimation of human performance in demanding circumstances.

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