An Integrated Agent Model Addressing Situation Awareness and Functional State in Decision Making

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Abstract. In this paper, an integrated agent model is introduced addressing mutually interacting Situation Awareness and Functional State dynamics in decision making. This shows how a human's functional state, more specific a human's exhaustion and power, can influence a human's situation awareness, and in turn the decision making. The model is illustrated by a number of simulation scenarios.

Keywords: Situation awareness, functional state, agent model.

1 Introduction

An agent's decision making in realistic situations strongly depends on the situational awareness of the agent; e.g., [2]. When the agent is not aware of certain aspects of the situation that are relevant for the actions to undertake, this may result in actions that are ineffective or even counter-productive. In [5] a computational agent model was introduced to address situational awareness. Having a sufficient extent of situation awareness is a good basis for effective decision making. However, in demanding circumstances this easily may be compromised due to longer periods with high workload and high levels of stress, and due to this, accumulating exhaustion leading to a less optimal functional state; e.g., [1], [3], [4], [10], [12]. Therefore the extent of situation awareness is not constant, but may fluctuate over time. This was not taken into account in the model for situation awareness presented in [5].

The current paper addresses how situation awareness may be affected by increased exhaustion, and how this may lead to less optimal decision making. To this end the situation awareness model from [5] is integrated with a model for functional state in relation to exhaustion introduced in [7], and a decision model presented in [6]. The resulting model shows how depending on fluctuations in load, extra effort may be exerted, but if periods of high load have longer durations, due to the accumulated exhaustion the agent's situation awareness becomes less, and the decision making less optimal. Moreover, the model shows how in subsequent periods of lower load recovery from exhaustion takes place, and this results in higher extents of situation awareness and more optimal decision making.

The paper is structured as follows. In Section 2 a brief introduction of the background literature is presented. Section 3 summarizes the three existing models used in

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the integrated agent model. In Section 4 it is described how the models were integrated to obtain the integrated model. Section 5 shows some of the simulations that have been performed. Finally, Section 6 is a discussion.

2 Theoretical Background

In literature on workload and performance, it is often stated that in order to cope with situations of high task demands, people can make strategic choices [3], in order to protect performance degradation on the primary task. One of these choices is to increase the effort contributed to the task [11]. Unfortunately, as resources are limited, this can only be done for a limited amount of time. Another possibility is to make a shift to simpler strategies within the task, resulting in less use of working memory. An example of this can be found in driving behavior, where car drivers reduce their driving speed when faced with higher task demands [1].

Thus, while it can increase performance on the primary task, a reduced use of working memory can compromise secondary task goals, such as processing speed [3]. In addition, a decrease in the use of working memory can result in less attention available for peripheral cues [10]. Such attentional tunneling, together with less processing capacity available will result in a reduction of situation awareness in high workload conditions [2]. Finally, also decision making is affected by the contribution of effort (e.g., [12]). For example, research showed that in a situation with time-pressure people adjust their decision making strategy to less effortful strategies and will take more risky decisions [9]. The importance of information on human's own performance in the regulation of effort is shown in [11], where people invested higher levels of effort when they were informed of failure. Also, a lack of awareness of a human's own performance (e.g. as a consequence of low effort investment) may result in an impairment of effort regulation [3]. This is confirmed by Matthews and Desmond [8] who found an effort reduction as a consequence of a reduced awareness of performance impairment with the increase of fatigue. In the integration of the three models (as described in Section 3 below) the above described literature will be taken as a source of inspiration for making the connection between the models.

3 The Models Used as a Point of Departure

This section describes the three models that underlie the integrated agent model presented in this paper. First, the situation awareness model is described, followed by the decision making model, and finally, the model expressing the functional state.

Situation Awareness Model. The model for situation awareness used is taken from [5]. Fig. 1 shows the main concepts of the model in the upper left box, whereby the white circles denote the parameters of the model, whereas the dark circles represent processes. For the sake of brevity, the model will merely be described on a high level. For more details of the model, see [5].

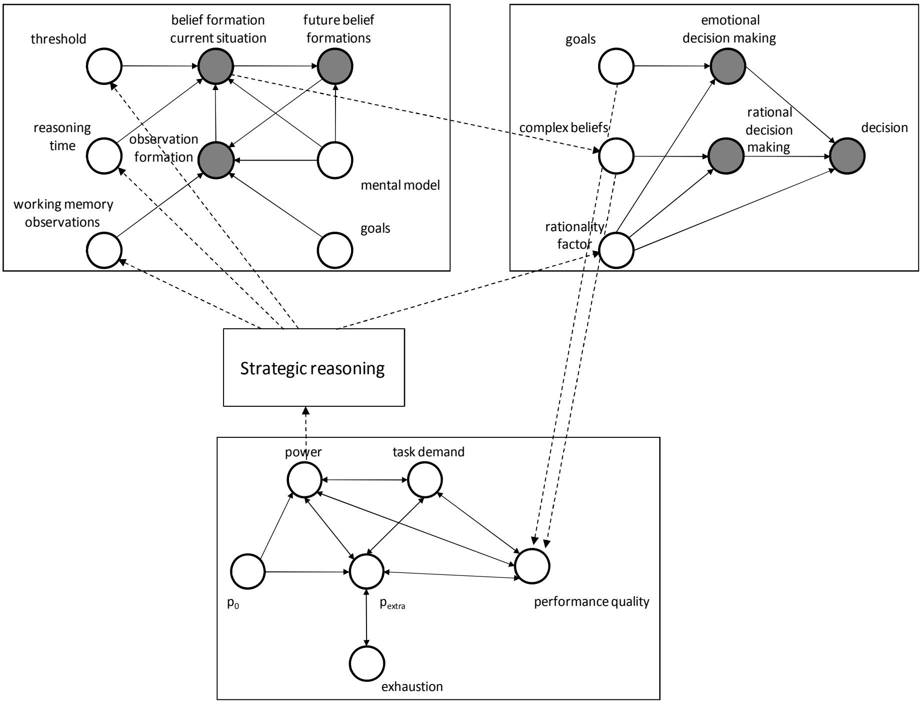

Fig. 1. Individual models and their integration

The essential idea behind the model (which tries to represent human situation awareness as defined in the literature) is that agents form beliefs about the current situation in the world. They do this based upon a mental model they have which expresses connections between these beliefs (e.g. if I have the belief that a holds, then I also believe that b holds). These beliefs are present on two levels: simple beliefs, which express simple facts about the world, and complex belief which encompass more complex statements about the world, and are triggered by combinations of multiple simple beliefs. Each of these beliefs has a certain activation value. The process of forming situation awareness starts when new observations are performed by the agent. This is then an input for the process *belief formation of current situation*. In the process, the observations cause updated activation levels of simple beliefs. Thereafter, the mental model is used to calculate new activation levels based upon the connections between beliefs. How many of such influence calculations are performed depends upon the reasoning time parameter. Furthermore, the threshold parameter expresses how high the activation level of a belief should be before being considered in the updating process. After the reasoning time has been reached, new activation levels for each of the beliefs are present, representing the judgment of the current situation of the agent. The next step is *formation of future belief*, which makes predications of occurrences in the future (in the form of time stamped beliefs with a certain activation level). Given that both the current and prospected situation are updated, a next round of observations can be performed (referred to as *observation formation*), the precise observations to be performed are also derived using the model. This depends upon the future beliefs (what does the agent think will happen), the goals (the agent focuses on important observations with respect to the goals), and the working memory size for observations (i.e. an agent cannot perform an infinite amount of observations). These observations are then performed, resulting in new input for the belief formation process, etcetera.

Decision Making Model. Based upon a certain judgment of the world (e.g. formed by the models for situation awareness described in Section 3.1), the agent can decide on what actions to perform. This is described in the model on decision making, following [6]. In the model (expressed in the upper right box of Fig. 1), emotions and rational utility are both considered as important elements in the decision making process. When looking at the emotional decision making part (the process *emotional decision making*), the options that can be decided upon are weighed based upon the feeling of the options with respect to the goals the agent has (e.g. a fighter pilot might have a negative feeling with the option of returning to base due to an enemy encounter bad for the goal of defeating the enemy). Each goal is hereby attributed with a certain weight, and each option has an emotional score with respect to each goal. A weighed sum is taken for each option. The more rational part (*rational decision making*) evaluated the options based upon the current situation (e.g. the complex beliefs such as part of the situation awareness model) and how well certain options are suited for this situation. Both processes result in a numerical evaluation of the options, and these are combined in the actual *decision making* process. How much each of the evaluations weighs depends on the rationality factor of the agent. For more details on the decision making model, see [6].

Functional State Model. The last model is a model representing the functional state of a human. A human's functional state can be defined as the combination of cognitive factors such as performance, effort and exhaustion (e.g., [4]). The model is shown graphically in the bottom part of Fig. 1 and presented in more detail in [7]. The model describes how an agent selects the amount of power to provided (i.e. how much effort does the agent want to put into a certain process). It is assumed that the agent strives for a certain *performance quality*. In order to achieve this quality, the agent must meet certain *task demands*. To meet these demands, the agent can input a certain *power* in the particular task at hand. This power is a combination of the basic power (p_o) and the extra power (p_{extra}). The basic power is inspired by a critical point, which is often seen in literature on exercises and sports. Once an agent needs to provide power above this point (i.e., the agent needs to provide extra power p_{extra}) the agent eventually will become exhausted. Once the exhaustion level reaches a certain level, the agent can no longer provide this additional power, and fall back to the basic power level.

4 Integrating the Three Models

In this Section, the three models that have been explained independently in Section 3 are combined into one model. This then results in a full agent to determine how much effort to spend, derive the situation using the selected appropriate effort within the situation awareness model, and derive an appropriate action given the perceived situation. How these models are connected will be explained in Section 4.1.

Thereafter, the strategic reasoning which takes place in various parts of the combined model is explained in more detail.

4.1 Interactions between the Models

Fig. 1 also shows the connections between the three models. The dashed arrows are the links between the concepts in the different models. Starting with the model for the *functional state* of the agent determines how much power to provide, this amount of power is an input for a *strategic component* that determines how to divide this power across the *situation awareness model* and the *decision making model*. To be more precise, it determines what value to select for:

1. The threshold in the situation awareness model (when are states considered).
2. The reasoning time in the situation awareness model (how much time is available to make calculations using the mental model).
3. The amount of working memory to be spent on observations to feed the situation awareness model.
4. The rationality factor in the decision making process (are more shortcuts used or is there more time to make a rational choice).

How these choices are precisely made and how these are quantified is explained in Section 4.2. Note that these choices are based upon the description of the relevant work as presented in Section 2 and are not trivial to define, especially due to the fact that the literature often does not describe these relationships in a very precise manner.
The second element is to connect the *situation awareness model* with the *decision making model*. This combination is established by means of the complex beliefs about the current situation (i.e., the activation levels thereof). This judgment of the situation can be used to derive what options are appropriate.

The last link between the models is the derivation of the performance quality. The idea is that the performance quality can be determined by means of the goals that have been set by the agent (which are part of both the *decision making model* and the *situation awareness model*) and the current judgment of the situation (i.e. the complex beliefs), i.e. the performance quality expresses in how far the current situation (at least he situation perceived by the agent) contributes to the current goals. Note that this is not an objective measure, but the judgment of the agent itself, which is used as a steering instrument by the agent. It is assumed that each goal has a certain activation level (as already explained in the individual models):

goal_activation_level(goal, t)

Furthermore, the complex beliefs have a certain activation value as well:

complex_belief_activation_level(complex_belief, t)

In order to derive the performance quality, knowledge is present in the agent which expresses how much a certain complex belief contributes to a certain goal:

contributes_to_goal(complex_belief, goal, t)

The performance quality is determined by calculating per goal in how far the current situation fulfills this particular goal:

goal_contribution(complex_belief, goal, t) = complex_belief_activation_level(complex_belief, t) ·
contributes_to_goal(complex_belief, goal, t)

Then, the maximum is taken across all complex beliefs as these already provide an integrated view of the whole situation.

$$\text{overall\_goal\_contribution(goal, t)} = \max(\text{goal\_contribution(complex\_belief}_1\text{, goal, t), ..., goal\_contribution(complex\_belief}_n\text{, goal, t)}$$

Finally, the weighed sum is taken over all the goals to derive the performance quality:

$$\text{current\_performance\_quality(t)} = \Sigma_{G:GOALS}\, \text{goal\_activation\_leve(G, t)} \cdot \text{overall\_goal\_contribution(G, t)}$$

4.2 Strategic Reasoning

Strategic reasoning takes place in two parts of the model. First of all, in the model of the functional state of the agent as the agent needs to determine how much power is to be provided. The second strategic choice takes place in the strategic division of resources among the various elements that require power in the other models. Again, these choices made in this component are grounded within Psychology and are formalizations of high-level theories found in the literature.

4.2.1 Determining the Extra Power to be Provided

The first step that the agent needs to take is to determine how much power it wants to provide in order to achieve the task at hand. How much power the agent will deliver mainly depends on the performance quality the agent wants to deliver (*desired performance quality*), and the *current performance quality*. For the agent, the precise relationship between the power being provided and the performance quality is not crisp and clear: the agent needs to undergo a process of trying to put more power in, and seeing whether that results in a suitable performance quality (i.e. the *current performance quality* is approximately equal to the *desired performance quality*). In case the agent is underperforming, it will provide more power; in case it is performing above the desired quality, it will tend to reduce the provided power. Essentially, the agent only varies the power provided in addition to the basic power level (i.e. p_{extra}). How much the agent will change its power setting can be determined by means of a number of alternative algorithms. The simplest algorithm involves a standard increase/decrease of the power with a value γ.

$$p_{extra}(t+\Delta t) = \text{Pos}(p_{extra}(t) - \gamma \cdot \text{th}(\sigma, \text{desired\_performance\_quality(t), current\_performance\_quality(t)}) \cdot \Delta t)$$

In this formula, the function $th(\sigma,\tau,V)$ is a threshold function that maps the value V to the interval [-1,1] whereby values of $V > \tau$ result in a value greater than 0 (and vice versa), and a value equal to the threshold results in an evaluation to 0. An example of such a function is for instance:

$$\text{th}(\sigma, \tau, V) = (2 \cdot (1/(1+e^{-4\sigma(V-\tau)}))-1)$$

The function $Pos(X)$ evaluates to X in case $X \geq 0$ and 0 otherwise.

A second option to determine the power setting is to use a more advanced sensitivity-based approach whereby the agent takes the previously experiences influence of the provided power upon the performance quality into account. This can be formulated by means of a mathematical equation as follows:

$$p_{extra}(t+\Delta t) = \text{Pos}(\, p_{extra}(t) + \beta \cdot (\text{p\_pq\_sens(t)} \cdot (\text{desired\_performance\_quality(t)} - \text{current\_performance\_quality(t)}) \cdot \Delta t)$$

where

$$p\_pq\_sens(t) = (p_{extra}(t) - p_{extra}(t-\Delta t)) / (current\_performance\_quality(t) - current\_performance\_quality(t-\Delta t))$$

The idea of the above equation is that the effect of a difference in additional power with respect to the performance quality is calculated, and this sensitivity is used to adapt the extra power to be provided.

The approach mentioned above can work well, but the disadvantage is that the agent does not know in advance whether the power provided results in a reasonable performance quality. It is more a matter of trial and error. A more realistic agent would try a certain power in his mind, and project whether this effort would indeed be sufficient. This is therefore the way in which it is assumed to take place in this paper as well. The agent performs one fictive run of the model (thereby using an own world model) to see whether the intended power results in a sufficient quality. Based upon this the agent can still make adjustments based upon the strategies described above.

4.2.2 Strategic Distribution of Resources

The second strategic part about which the agent needs to reason lies within the strategic division of the resources which are spent by the agent over the various parts of the reasoning. More in specific, the component determines how to spread resources over: (1) the threshold used to update the beliefs for situation awareness, (2) the reasoning time within the situation awareness model, (3) the working memory available to perform observations, and (4) the rationality factor used in the decision making process. In order to facilitate the strategic reasoning process, for each of the factors a translation to power needs to be made. Table 1 shows a mapping from the dedicated values for the parameters in the model to an equivalent value which expresses the actual power value.

Table 1. Mapping of model parameter values to power

Parameter	**Values**	**Power equivalents**
threshold	[0,1]	[*max_threshold_cost*, 0]
reasoning time	[0, number_of_connections]	[0, number_of_connections · *power_per_connection*]
working memory observations	[0, $\sum_{\forall o:observations}$ cost(o)]	[0, $\sum_{\forall o:observations}$ cost(o)]
rationality factor	[0,1]	[0, *full_rationality_cost*]

It can be seen that the threshold normally has a value between 0 and 1, whereby 0 indicates that for all beliefs the connections should be considered whereas 1 expresses that this should only be done for beliefs that are completely activated. The power equivalent is precisely the opposite: the higher the threshold, the less power it costs (since fewer connections need to be considered). The maximum cost (performing all calculations) in terms of power is a constant which is called *max_threshold_cost*. The reasoning time to perform updates is expressed in the number of cycles that are being passed, which is limited to the number of connections. It is assumed that for each cycle (i.e. each connection that is being calculated) a certain power (*power_per_connection*) is required to obtain a mapping to a power value. With respect to the working memory for observations a cost value is already associated with each observation (in terms of power), and the maximum value is simply the sum of all cost of all possible observations. Finally, for the rationality factor in the decision making process, a value between 0 and 1 is possible, expressing fully non-rational decision making (which is assumed to cost no power) and fully rational decision making. Full rational decision making is assumed to be associated with a power of *full_rationality_cost*.

Given that these mappings are present, the agent first of all needs to determine how to spread the total power it has decided to spend on the task across the various parameters. Currently, a simple algorithm is assumed which simply assigns fixed weights to the different parameters: $w_{threshold}$, $w_{reasoning\_time}$, $w_{wm\_observations}$, $w_{rationality}$. Hereby, the sum of the weights is required to be 1. Once the total power $p(t)$ has been derived, the power spent on the various aspects is calculated by a simple multiplication:

$$p_{threshold}(t) = w_{threshold} \cdot p(t)$$
$$p_{reasoning\_time}(t) = w_{reasoning\_time} \cdot p(t)$$
$$p_{wm\_observations}(t) = w_{wm\_observations} \cdot p(t)$$
$$p_{rationality}(t) = w_{rationality} \cdot p(t)$$

In the next step, a translation of these values to an appropriate parameter value can take place.

$$v_{threshold}(t) = 1 - (p_{threshold}(t)/max\_threshold\_cost)$$
$$v_{reasoning\_time} = p_{reasoning\_time}(t)/power\_per\_connection$$
$$v_{wm\_observation}(t) = p_{wm\_observation}(t)$$
$$v_{rationality}(t) = (p_{rationality}(t)/full\_rationality\_cost)$$

Also within the strategic component more advanced strategies can be deployed such as a sensitivity-based approach whereby the weight of the parameter in the weighed sum expressed above is determined by the sensitivity of that parameter. For the sake of brevity, this option has however not been explored within this paper.

5 Simulation

In this Section, an extensive case study is conducted to evaluate the behavior of the integrated model. First, the case study itself is described, followed by the results of the application of the model.

5.1 Case Study Description

In this case, the case study concerns a military scenario obtained from domain experts. In the scenario a pilot has to detect whether (enemy) contacts (i.e. other planes in this case) are near and if so, what kind of threat these contacts pose. As a result, the pilot has to decide what action to undertake. The detection of the other planes is performed by means of a radar warning receiver, which can provide a number of *observations*, including certain intensities of beeps coming from the receiver (expressing for instance whether the enemy is near, or has the ability to fire a missile due to a locked radar), the direction of the other plane. The more detailed mental model used in the situation awareness model that relates these observations into judgments on the current situation is expressed in Appendix A[1]. Complex beliefs that are formed involve element such as whether the plane is a possible target of a hostile attack.

[1] `http://www.cs.vu.nl/~mhoogen/sa/sa_appendix_A.pdf`

Given that the agent is aware of the situation, there are 5 possible decisions available in this scenario: *fly cap* (start flying in a circle to patrol a certain dedicated area) *beam* (maneuver to prevent enemy radar detection), *beam dive* (beam and dive to a lower altitude) *run* (move away from the potentially hostile plane) and *maintain cap* (remain flying the cap). In order to decide upon these actions, five different goals can be active within the agent: *fly cap* (patrolling a certain area), *avoid detected* (avoid an enemy plane from detecting you), *avoid track* (avoid an enemy plane from tracking your positions), *avoid lock* (avoid an enemy plane from locking a radar upon you, resulting in the possibility of firing a missile), *defeat missile* (try to defeat a missile being fired at you). Given this scenario, two elements are set dynamically, namely the goals (see Section 5.1.1 on the approach used), and the world model itself (i.e. how do action influence, the world, and how are observations obtained from this world), presented in Section 5.1.2.

5.1.1 Goals

The activity value of each goal is determined at each point in time, taking the activity value of complex beliefs into account, such that the agent adjusts its goals based on the situation. The influences of each complex belief to the available goals are known to the agent beforehand:

influences_goal(complex_belief, goal, t)

And the total influence of all complex beliefs to a goal is calculated by taking into account this influence and the activation value of all complex beliefs:

total_goal_influence(goal, t) =
$\sum_{CB:Complex\ Beliefs}$ complex_belief_activation_level(complex_belief, t) ·influences_goal(complex_belief, goal, t)

Finally, the relative activation value of each goal is calculated by dividing the total_goal_influence by the sum of the total goal influences for all goals.

goal_activation_level(goal, t)= (total_goal_influence(goal, t)/ ($\sum_{G:Goal:}$ total_goal_influence(goal, t))*2

5.1.2 World Model

A world model has been developed to complete the cycle from actions derived by the agents to observations in the world. The world model has been developed in two parts. First of all, there is a standard development of the world (in this case the enemy taking the necessary steps to perform a full attack). This standard development consists of a table which indicates how observations contribute to other observations (e.g. an observation of another pilot having a lock on the plane will contribute to the observation that a missile is fired). This consists of numbers on the interval [-1, 1] where -1 indicates a very negative influence whereas 1 expresses a positive influence. Assume two observations o_1 and o_2 whereby the influence of o_1 upon o_2 is calculated. The new value for o_2 is then calculated as follows:

activation_value(o_2, t + Δt) = activation_value(o_2, t) +
(Pos((1- activation_value(o_2, t) · activation_value(o_1, t) · influence_value(o_1, o_2, t) +
Neg(activation_value(o_2, t) · activation_value(o_1, t) · influence_value(o_1, o_2, t)·Δt

First, a single observation is selected, after which the above equation is sequentially applied for each of the influencing observations, followed by the second observation being selected for recalculation, etcetera.

The agent can of course influence this standard development by means of performing certain actions in the world, which is the second part of the world model. This expresses how actions influence observations (e.g. a dive results in a negative influence on an observation of a lock on the plane). This is done in an identical manner as presented before for the standard development (except that it of course now concerns actions that influence the observations). The combination of the standard development with the actions then results in appropriate observation results for the agent.

5.2 Simulation Settings

In this section, some simulations are presented. First, the setting of the key values are presented, followed by the results. Note that due to the fact that not all details of the individual models have been presented, some model specific parameters for these models are not explained further. In all simulations that are shown, the weights in the strategic component were divided based upon the following weight values: $w_{threshold}$ and $w_{reasoning\_time}$ were both set to 0.4 and $w_{rationality}$ and $w_{wm\_observations}$ were both 0.1. In the translation of the power values to parameter values, the following model settings were used: *max_threshold_cost = 6*, *power_per_connection = 0.15*, *full_rationality_cost = 5*. Furthermore, the exhaustion budget (the maximum amount of exhaustion that can build up in the functional state) has been set to 1000 and no recovery was allowed (according to the FS model, exhaustion builds up with the extra power provided).

Simulations were performed varying the basic power between 0 and 100 and the desired performance quality between 0.5 and 1. Graphs of simulation results are presented that best represent the integrated model behavior in Figs 2 to 6). Fig. 2 and 3 present simulations with a relatively high desired performance quality of 0.8. In the situation where the basic power is low (Fig. 2), the extra power that is contributed increases each point in time as the current performance quality is always lower than the desired PQ. After time point 32, no more extra power can be contributed because the maximum exhaustion budget of 1000 is reached. When the basic power is high (Fig. 3), this is not the case as only a low amount of P_{extra} needs to be contributed in order to achieve the desired Performance Quality.

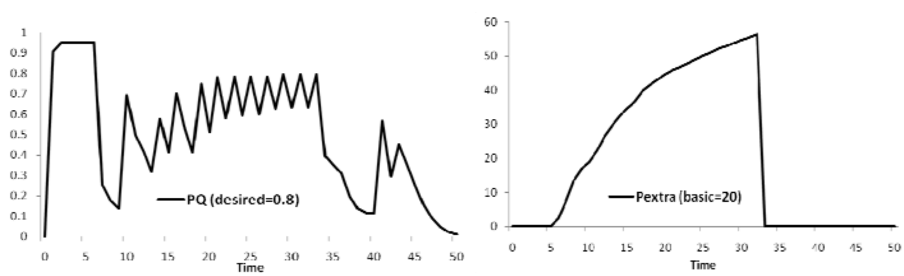

Fig. 2. Performance quality (a) and P_{extra} (b) with a desired PQ of 0.8 and a basic power of 20

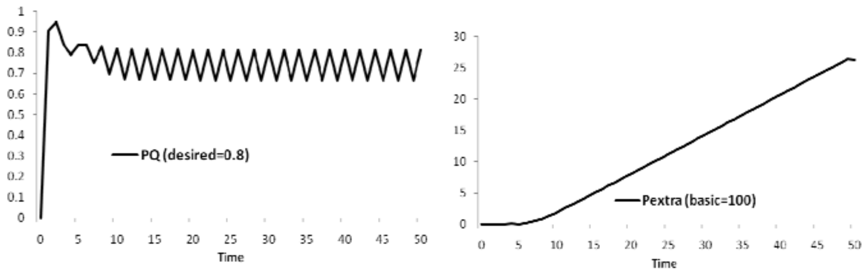

Fig. 3. Performance quality (a) and P_{extra} (b) with a desired PQ of 0.8 and a basic power of 100

In Fig. 4 it can be seen that when the desired performance quality is relatively low (i.e. 0.5), it is possible to achieve this level even though the basic power is low. Also, the extra power that is contributed is adjusted continuously, either downwards with the increase of performance quality or upwards with the decrease of performance quality. Fig. 5 shows the performance quality when the basic power is 100. In this case, no extra power needed to be contributed to achieve the desired performance quality of 0.5 (throughout the entire simulation, P_{extra} was zero).

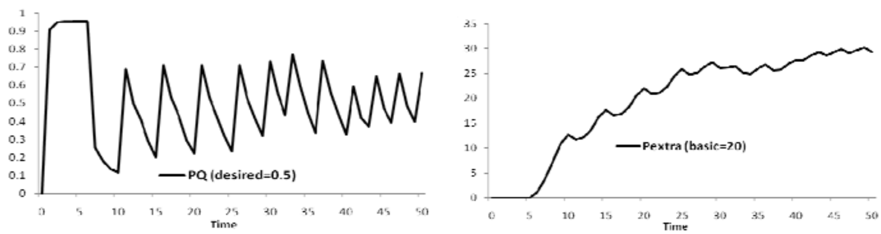

Fig. 4. Performance quality (a) and P_{extra} (b) with a desired PQ of 0.5 and a basic power of 20

In addition, a case was simulated where the basic power was very low (Fig. 6). The performance quality in this case stays very high, which shows the subjectivity of performance. As a consequence of the low power contribution, the agent's situation

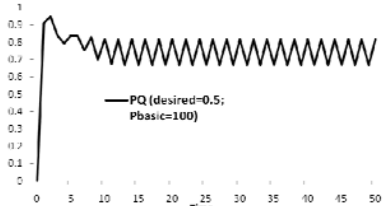

Fig. 5. Performance quality with a desired PQ of 0.5 and basic power of 100

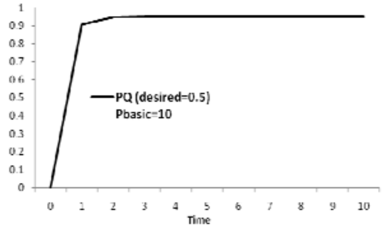

Fig. 6. Performance quality with a basic power of 10

awareness is very low, which results in a low awareness on its own performance qualtiy. Since this is the case, no extra power will be contributed to improve the agent's situation awareness.

6 Discussion

In this paper, an integrated agent model was presented addressing the dynamics of mutually interacting situation awareness (e.g., [2]) and functional state (e.g., [1], [3], [4]) in decision making. By a number of simulation scenarios it was shown how a human's exhaustion and power, affect situation awareness and decision making. Although models exist for situation awareness or functional state separately, no models exist addressing the integrated process in a decision making context, as far as the authors know.

The integrated agent model was developed in the context of the national project Smart Bandits in cooperation with the National Aerospace Laboratory (NLR), aimed at developing simulation-based training facilities for fighter pilots. As a next step on the basis of the presented model it is planned to develop a software agent that can act as an automated enemy fighter for a trainee.

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