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Enabling swifter operator response in the event of a fault initiation through adaptive automation

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Abstract

The increasing size and operational complexity of Dynamic Positioning (DP) platforms and the continuous increase in number of DP incidents has driven the need to further improve the safety and reliability of DP operations. A large portion of so-called 'operator error' is explained by increasing automation of operator tasks, pushing bridge teams into a more and more passive supervisory role, a role for which humans are not very well suited. For instance, a supervisory role may undermine the team's ability to develop and maintain sufficient situation awareness during DP operations. The ambition of The Netherlands Organisation of Applied Scientific Research, or TNO in short, is to develop, together with the industry, a transparent (human-in-the-loop) adaptive automation platform, or *adaptive automation*, that substantially improves safety for maneuvering and control tasks. Ideally, this automation is based on a *computational model* that is able to assess the current and predicted state of the system, environment, and operator. For instance, when a drop in operator attention is detected, the computational model could decide to involve the bridge team to a greater extent in the DP process, reducing the chance for operator error and enabling a swifter response in the event of a fault initiation. Moreover, with adaptive automation, there may be less need for continuous human supervision of DP systems, leaving room for ship designers to reduce ship manning requirements. This paper describes the requirements of the computational model, how it could be made adaptive, and how measuring and modeling system, environment and operator state drives the actions of the adaptive automation platform.

Introduction

The manning of a ship is a major driver of total ownership cost. The U.S. Government Accounting Office (GAO) states that "the cost of the ship's crew is the largest expense incurred over the ship's lifetime" (GAO. p. 54, 2003). There are a number of options available to ship designers to reduce ship manning requirements. These options include automation of human operator functions (Scofield, & Brown, 2007). Manning reduction is not the only driver for automation of human operator functions aboard of ships. Automation is often applied in order to increase cost-effectiveness, as well as quality, reliability and safety of ship operations.

The automation of operator tasks, however, may also have unwanted and unforeseen detrimental consequences for the reliability and safety of ship operations. Several major incidents in the past years have been attributed to conditions that stem from automation. For instance, automation may undermine the team's ability to develop and maintain sufficient situation awareness (SA) during operations (Øvergård, Sorensen, Nazir, & Martinsen, 2014). This continuing automation of operator functions increases the risk that incident numbers might increase over the coming years. Indeed, a series of incident report publications of the International Marine Contractors Association (IMCA) shows a steady increase in the number of DP operator related incidents (see, for example, IMCA, 2009).

Our ambition is to develop smarter automation, by shifting tasks between humans and machines dynamically, depending on environmental factors, operator state, and system performance. The goal of this automation should be to help bridge teams in their work, instead of pushing them out of the loop. We envisage a transparent (human-in-the-loop) adaptive computational system that substantially improves the safety and reliability of DP operations. This system is based not only on system and environmental state models, but also on an operator state model to assess current and predicted levels of operator state, for instance regarding the operator's level of SA. A second ambition is that knowledge development and breakthroughs go hand in hand with applicability. To ensure this, and to ensure the emergence of research ecosystems, i.e. collaboration between business, universities and research institutes, the knowledge development and innovation takes place in so-called use cases, i.e. specific operational domains for application.

Dynamic positioning

Dynamic Positioning is a computer-controlled system to automatically keep a floating vessel at a specific position or to follow a pre-defined path (tracking) by using its own propellers and thrusters. Applications include shuttle tanker operations, deep water drilling (drilling rigs), diving and ROV support operations, dredging and rock dumping, pipe laying and pipe trenching operations, cable lay and repair operations, but also military operations (e.g., mine countermeasures) (see also Fossen, 1994). The number of vessels with DP systems has increased in recent years. This is due mainly to increased oil and gas exploration at sea, as well as offshore operations, such as drilling, diving support, and anchor handling. DP systems have been increasingly applied to shuttle tankers during offloading operations with FPSO (Floating Production Storage and Offloading). FPSO installations are oil tankers that mine and store crude oil. The oil is regularly loaded into a shuttle tanker for transport. FPSOs can be brought quickly to new operations, so it is very useful for small oilfields and to operate the first wells before a final platform is ready. Critical is the positioning at a well and a shuttle tanker. Figure 1 depicts an FPSO installation.

Figure 1. FPSO installation

Safety and reliability of DP operations

The increasing size and operational complexity of DP platforms has fueled the need to further improve the safety and reliability of DP operations. Incidents may lead to considerable costs and must be prevented at all time (Payne, 2001). These costs include, but are not limited to, (1) injuries and fatalities, (2) severe equipment damage or destruction, (3) major pollution, and (4) rig downtime with significant loss of revenue and contractual problems. Moreover, IMCA (2009) reports a continued increase in the number of incident reports. As shown in figure 2, incident analyses point out operator error as the root cause of DP incidents again and again (IMCA M 181; IMCA M 198; Oltedal, 2012). The operator is not only a trigger by itself without a fault or failure occurring first, technical failures often need the operator to fail in some way for the fault to reach a position loss (IMCA M 181 p.10; see also Figure 2). Hence, operator error is part of each incident category by default.

Analyses of operator error shows that DP operators are often not able to react fast enough after the initiation of a drive-off incident (Tjallema, Van der Nat, Grimmelius, & Stapersma, 2007). Indeed, Oltedal (2012) found that a major cause of ship–platform collisions in the North Sea is the human deficiency to detect or interpret a technical state or error in time. The relatively slow reaction time of the operator indicates that either the fault detection is slow or the operator needs too much time to recognize the failure and to decide what action to take. For example, in 2007, a major loss of position occurred during a drilling operation when a DP operator's arm accidentally contacted the surge button on the DP console so that it was deselected (IMCA, 2009). The DP operator was operating other equipment adjacent to the DP console and incorrectly identified these activities as the main cause of the offset. At the time it was finally discovered that the drifting of the vessel was due to the deselection of the surge button, the offset was already 135 meters. Although no people were injured and no structural damage was caused in this incident, this example shows nicely how easily a position loss could occur, and how important it is to swiftly and correctly diagnose the fault.

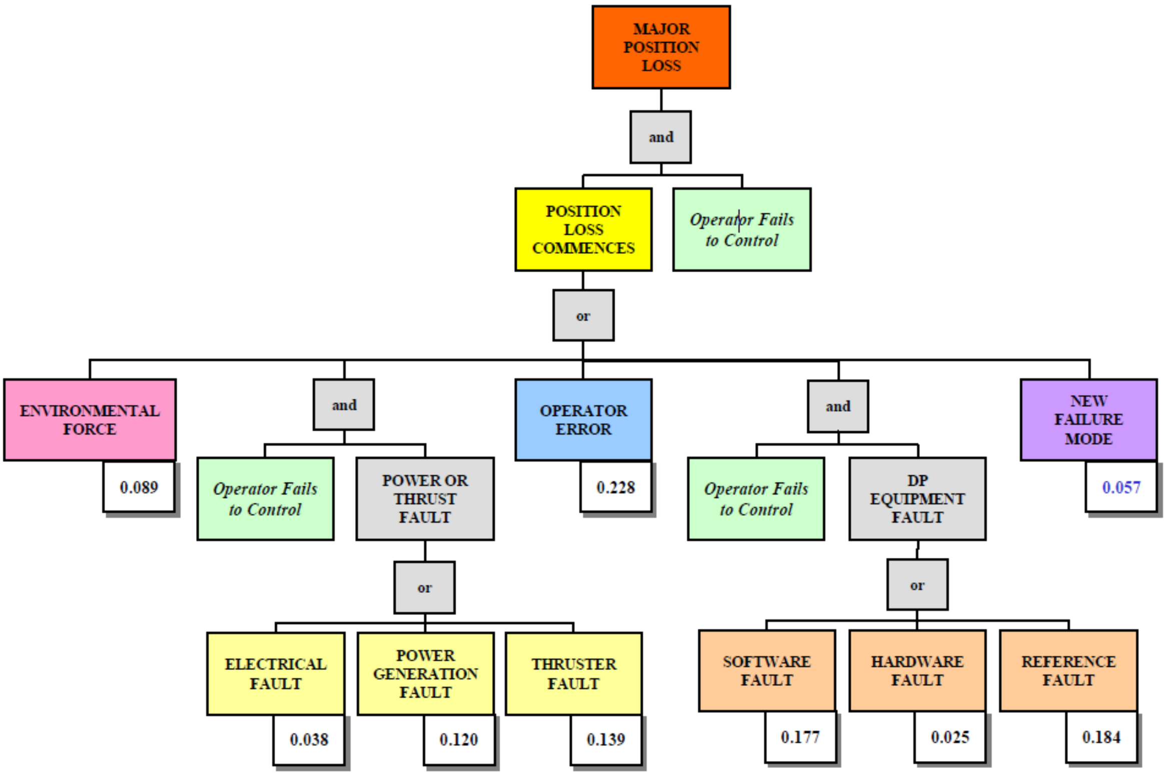

Figure 2. Major Loss of Position (LOP1) Incidents (taken from: IMCA M-181, 2006). Below the categories are listed the percentages of occurrence. Hence, 0.228 stands for 22.8%.

Causes of operator error

Several causes of operator error are identified in the literature (IMCA, 2006; Bray, 2008; Costa & Machado, 2006). Examples include, but are not limited to:

- (poor) Ergonomic design of the DP station;
- (poor) Employment conditions (e.g., low morale);
- (poor) Working conditions (e.g., noise, [low] workload, or distraction);
- Physical state of operator (e.g., fatigue, vigilance, attention);
- Data overload (largely irrelevant information);
- (insufficient) Operator training and competence;
- (inadequate) Short-term handover arrangement between DPO and Master;
- (irresponsible) Behaviour patterns (i.e. violating rules and procedures);
- (inadequate) Procedures, manuals and documentation;
- Misplaced trust in system (Class III invincibility error leading to complacency).

Many researchers and practitioners alike agree that a large portion of operator error may be or might have been reduced or eliminated by paying more attention to underlying human factors issues, such as procedures, working and employment conditions, system and interface design, ergonomic design of the DP station, training, and handover arrangement between DPO and Master (IMC, 2006; see also Olson, 2001; Costa & Machado, 2006; Bray, 2008; Sandhåland, Oltedal, Hystad, & Eid, 2015). There are several improvements that make for good quick wins for increased safety and reliability of operations. For example, Sandhåland et al. (2015) identified several practices regarding planning, communication, and management of interrupting elements, that would immediate and significantly decrease the chance for operator error. Olson (2001) identified training of operators in how to deal with human factors issues through simulator training as the way forward. A more difficult problem to tackle, besides the identified human factors issues, stems from the ongoing automation of operator tasks due to the ongoing development of DP technology, pushing the operator into a more and more passive supervisory role, or even a backup role, a role for which humans are not very well suited, as we will discuss in the next section.

The problem with automation

As was described, DP systems are basically automation, taking over tasks previously performed by people, with the intention of increasing safety, accuracy, and reliability (see also Parasuraman, Mouloua, & Molloy, 1996; Sheridan, 1992; Wickens, 1998). When automation is introduced into a system, or when there is an increase in the autonomy of automated systems, developers often assume that adding automation is a simple substitution of machine activity for human activity (Woods & Sarter, 2000). Empirical data on the relationship of people and technology suggest that this is not the case and that traditional automation has several negative performance and safety consequences associated with it stemming from the *human out-of-the-loop (OOL) performance problem* (Endsley & Kiris, 1995; Kaber & Endsley, 2004).

The operator has no direct need to constantly know what the status of all parts of the DP system is, because the DP system is controlling all components itself. Only after a failure arises the operator needs to take over this task and take appropriate action(s) to prevent the failure from harming the operation, or abort the operation in time to prevent accidents. Consequently, the low SA due to a high level of automation makes that the operator cannot intervene quickly and effectively if the automation fails. This is known as the OOL-performance problem, as the operator is not an active part of the process, (Parasuraman, Molloy & Singh, 1993; Tjallema et al., 2007). This is especially problematic in DP operations where the available time-window for reacting on a drive-off incident is in general very short, and the chances of preventing an accident decrease rapidly after the fault-initiation (Chen & Moan, 2003; Sandhåland et al. , 2015).

Our ambition is to develop, together with the industry, a transparent (human-in-the-loop) adaptive automation platform that substantially improves safety for manoeuvring and control tasks capable of assessing the operator’s need for support, based on the system, environment, and the current and predicted operator’s functional state, that is, the variable capacity of the operator for effective task performance in response to task and environmental demands. As mentioned, an important operator variable for safe and reliable DP operations is *situation awareness*, or SA in short. It is important that the operator’s level of SA is maintained at high levels.

The ambition we have set for the *computational model* behind the adaptive automation is that it needs to be able to assess the current and predicted levels of operator SA. When the detected or predicted levels of SA are low, the support system needs to intervene, for instance through involving the operator to a greater extent in the process, reducing the chance for operator error and enabling a swifter operator response in the event of a fault initiation. The purpose of this paper is to describe the requirements of this computational model, and how measuring and modelling operator SA drives the content, functionality and modality of the adaptive automation platform.

The OOL-performance problem prevents human operators of automated systems from taking over operations, for example in the event of automation failure (Endsley & Kiris, 1995), and has been attributed to a number of underlying factors, including human vigilance decrements (Billings, 1991), complacency (Parasuraman, Molly & Singh, 1993), skill degradation (Parasuraman, Sheridan & Wickens, 2000) and loss of operator SA (Endsley, 1995a; Endsley & Kiris, 1995; Nazir, Colombo & Manca, 2012). When a human operator is out of the loop, instances will occur, when s/he cannot maintain control over the system (Norman, 1990). A supervisory role requires a different set of cognitive skills than the role of control and intervention (Bainbridge, 1983). System design must take into consideration the elements that determine the quality of task performance (Woods & Roth, 1988). This requires an approach to the design of the automation that enables operators to better manage DP systems.

Human-automation collaboration

The way that the operator and the automation collaborate is of vital importance to the performance of the overall system. Human-automation collaboration can have many different forms. Between manual control and full automation, different levels of automaton can be distinguished. Well known classifications are made by Sheridan and Verplank (1978) and by Endsley and Kaber (1999), with different variations, but others exist. Adaptive systems are systems in which the locus of control varies over time. This can imply a mode change for the whole system, but also that the responsibility for a specific subtask moves from the automation to the operator or vice versa.

Operator, system, and environment models

For adaptive automation to be effective, it needs to be able to monitor operator-system-environment state. This enables the automation to intervene in case needed. For this purpose, the automation needs a computational model, which should be valid, as the automation might otherwise intervene at inappropriate moments and even worsen performance. Hence, a conceptual framework is required with operator-system-environment state as a basis, with a large focus on integrating system, environment and operator state monitoring.

Relevant operator states must be determined and added to the framework and broken down in several subtypes, such as fatigue, stress, distraction, workload, arousal, and vigilance. The state of the environment could also be described in several subtypes, indicating weather conditions, sea state, current, ship state, etc. Also the model needs to incorporate the interdependencies of these factors. However, since we also want to make a link with the DP system (since various levels of automation or operator support may be needed), a system state estimator is also required. In the next section we focus in more detail on the operator model.

Operator state & characteristics

There are many variables that influence the ability of the DP operator to maintain position or to control position loss in case of a fault (e.g., black out or drive off), human error or environmental force. These variables together represent the dynamic state in which the operator is situated. User variables are an important class of variables, since the operator is the subject of applications. In the remainder of the paper we use the term ‘controllability’ for this operator ability.

The most notably user variables are the user state and the user characteristics (see, for example, Feld & Müller, 2011). *User characteristics* are typical and more static user variables, such as demographics (i.e., age), physical properties (e.g. weight), abilities (i.e., eye sight) and personality traits (e.g., extraversion). For example, when an operator has a hearing problem, this may seriously hamper the controllability, for the operator may not hear all alarm signals. *User states* are more fluid, and are typically broken down in cognitive state (e.g., stress), emotional state (e.g., anxiety), and physiological state (e.g., fatigue). The user or operator state is a combination of factors that summarize the state of a human operator when performing a task (Bosse, Both, Hoogendoorn, Jaffry, Van Lambalgen, Oorburg, Sharpanskykh, Treur, & De Vos, 2011). A selection of the variables contained by operator state is depicted in figure 3.

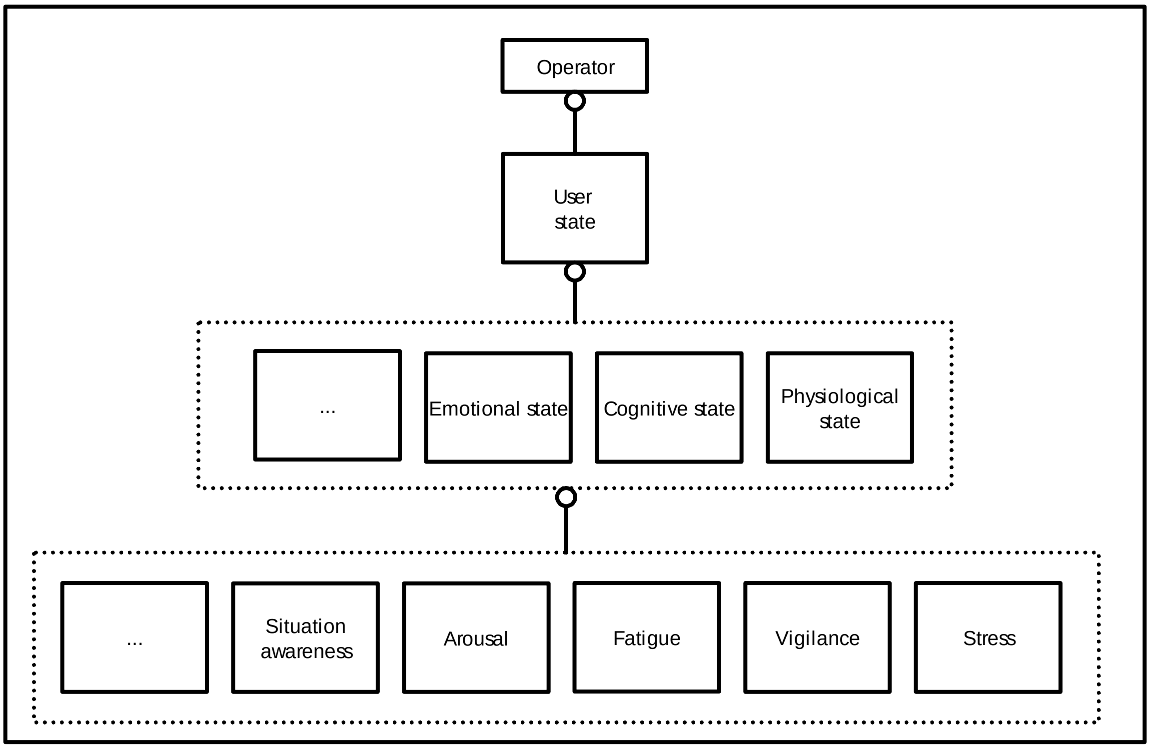

Figure 3. Selection of the operator model: user state.

Adaptive automation computation model

In the previous chapter we have described specific variables that could drive the method of invocation of the adaptive automation. This section describes the working of the computational model and, more specifically, how the assessment of relevant variables from the system, the environment and the user could trigger the invocation of the automation. Figure 4 depicts the model as a classical feedback control loop. Feedback loops find their origins in control theory, that deals with the behaviour of dynamic systems with inputs, and how their behaviour is modified by feedback. The idea is that the automation takes supervisory control actions, through assessment of relevant current or predicted system, environment, or operator state variables (see also Sheridan, 2011).

An important aspect of the computational model is the control law. Our plan is to make the control law for the initiation of actions, as well as the assessment of user state, dependent on operator characteristics, as can be seen in in figure 4. Hence, we are striving for *personalized* automation. For example, less experienced operators may be equally effective in solving problems than expert operators, but require more SA. At the same time, the deterioration of SA over time probably goes slower for more experienced operators as compared to novices. Control actions are initiated when the measured or estimated user state is below a dynamic threshold, that is dependent on estimates of environment and task variables. For example, when the task becomes more complex or the environment gets more complicated due to extreme weather conditions, then the threshold will be raised to a new higher level. Hence, the control law is adaptable or changeable. The *adaptation* refers to the mapping of goal state and measured state into control actions (see also, Äström & Wittenmark, 1989). The system actions are applied as feedback to the input of the system, the user state, to bring the actual output closer to the reference, and eventually, improve the ability of the DP operator to maintain position or to control position loss in case of a fault, human error or environmental force. Hence, the control loop is closed.

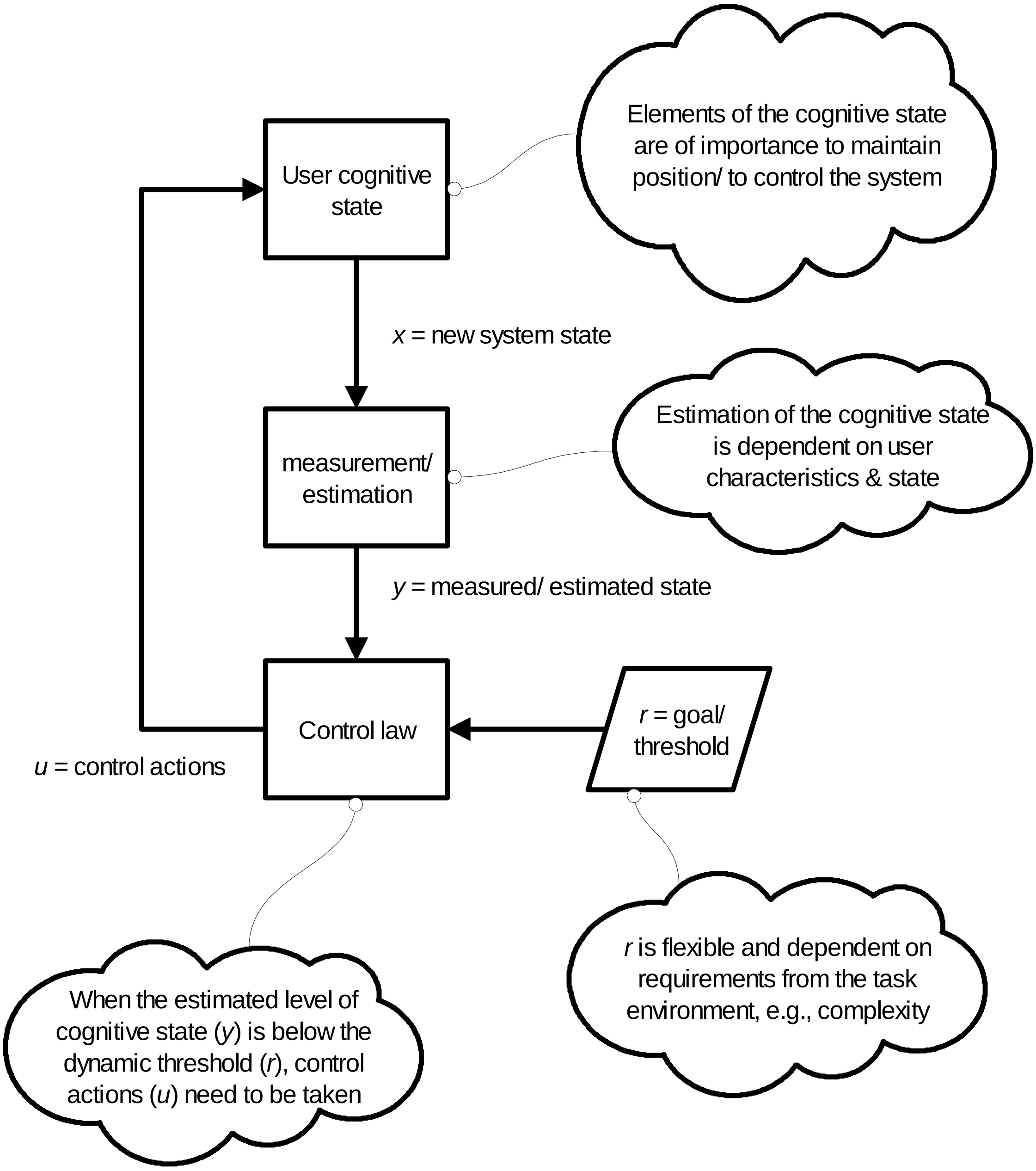

Figure 4. The computational model of the personalized (adaptive) automation platform.

As was mentioned, ongoing automation of DP tasks may seriously undermine the DP operator's ability to develop and maintain sufficient SA during operations. The ability to assess SA might therefore be especially critical for successful adaptive automation (see also, Kaber & Endsley, 2004). Fault analyses show that low levels of SA pose a threat to DP operations, for they may lead directly to operator error, or prevent the timely control of other faults. Hence, we agree with Pfaff, Klein, Drury, Pil Moon, Liu, and Entezari (2013), that in the given domain, besides SA, the perception and comprehension of the relative desirability of available *options*, as well the underlying factors and trade-offs that explain that desirability, is of equal importance. Pfaff and colleagues have defined this state as *option awareness* (OA). Although there is no reporting at this time of insufficient OA being the cause of DP incidents, the importance of selecting and implementing a course of action after the initiation of a fault, justifies, at least in our opinion, research into the role of OA in DP. We have therefore chosen to focus the supervisory control actions of our computational model, and our ongoing research efforts, on the assessment of the operator's level of awareness of the situation *and* relevant options to control the situation.

Discussion & way ahead

In order to develop a transparent (human-in-the-loop) adaptive automation platform, or *adaptive automation*, that supports DP operators in demanding circumstances, reducing the chance for operator error, a *computational model* is required. This model describes the interplay between an individual operator's cognitive state, system performance and the environment. This paper presented such a model. This model will serve as guidance for our ongoing work together with industry.

The computational model takes user state as input and determines how user characteristics, task demand and situational aspects initiate the need for control actions. The ability of the model to allow for changes to the control law makes it adaptive in nature. The rationale for adaptive control is to cope with the fact that many of the parameters to maintain position or to control position loss in case of a fault, human error or environmental force, are slowly time-varying or uncertain in nature (cf. Sheridan, 2011, p. 665). For example, during DP operations, currents or weather conditions may change, imposing the need for more operator attention. Task complexity may also increase, for instance when shuttle tanker loading operations must be coordinated, again creating a more stringent need on operator resources through the control law.

For DP operations to be successful, in our opinion, the operator continuously needs to be aware of the unfolding situation *and* available control options. Our ambition for the following years is therefore to develop adaptive automation that is capable of assessing these elements of the operator state. Hence, the adaptive automation platform should be able to assess the operator's level of (a) awareness of the situation and (b) relevant options to control the situation. This poses a real challenge for the phases yet to come. We will explain below why.

First of all, we need an applicable definition of SA, for instance Endsley's (1995a) three level model of SA. Endsley defines SA as "the perception of the 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". However, several researchers have argued that the Endsley (1995a) model is not applicable to socio-technical systems (Hollnagel, 2001; Salmon, Stanton, Walker, & Green, 2006). Socio-technical systems can be described as systems where humans and machines interact or collaborate and together form the system as a whole. DP operations are basically a socio-technical system, since operator and system more or less collaborate to keep the vessel at its position or remain at track. To solve this problem, a new paradigm has emerged in the study of SA: *distributed situation awareness* (Stanton et al., 2006). Distributed situation awareness theory states that not only the human operator, but all agents in the system contain a certain amount of SA that together adds up to the total available SA.

The biggest challenge, however, resides in measuring SA of the operator. There are many techniques developed in the last decades. Some of these techniques are obtrusive, for example SAGAT (Endsley, 1988), meaning that operators are required to answer questions during periodic, randomly timed breaks. During these breaks operators are not able to perform their work. Other techniques are non-obtrusive, using eye tracking or physiological techniques. These techniques seem at first glance promising techniques for acquiring the required input for our adaptive automation, because these techniques do not disturb or hinder operators during their work. However, as was voiced by Endsley (1995b), "Physiological techniques, though providing useful data for other purposes ('determining whether information is registered correctly'), are not very promising for the measurement of SA *as a state of knowledge*." These measures are limited, according to Salmon, Stanton, Walker, Jenkins, Ladva, Rafferty and Young (2009), because they cannot determine how much information remains in memory, whether information is registered correctly, or what comprehension the subject has of those elements.

For the computational model to work correctly, the situation state, including task demands, need to be assessed as well. The user state is only meaningful to the model when it knows what demands there are from the task environment. When the demands are high, for instance due to high task complexity during offloading operation, the requirements for user resources increase. Meaning that the operator should be aware of the elements in the environment, have comprehension of their meaning and is able to project their status in the near future.

The next question to address is how to assess OA. OA is a relatively new and immature research topic. Hence, little is known about the workings of option awareness and the mechanism to which operators acquire awareness of this sort. More importantly, all experimentation to date determining the success of OA support, has used implicit measures of assessing the degree to which participants have attained OA, such as decision correctness, speed, confidence, and interface use (Pfaff et al., 2013). Perhaps, we should therefore lower our ambitions and focus on user state concepts that are sufficiently mature to be applied to the current use case. To put it simply: we should focus on one hurdle at a time. If we have cleared this first hurdle; then we must consider whether or not to include the other relevant variables in the computational model.

Then there is the issue of what the control law actions might look like. The idea is that the automation takes supervisory control actions, through assessment of relevant current or predicted system, environment, or operator state variables. The system actions are applied as feedback to the input of the system, the user state, to bring the actual output closer to the reference, and eventually, improve the ability of the DP operator to maintain position or to control position loss in case of a fault, human error or environmental force. As yet, it needs to be determined what these actions look like. When the system has determined that the requirements for operator SA are below the goal that was set, what actions should the platform initiate? How to provide the operator with sufficient situation awareness in a timely manner? Moreover, this brings us to the discussion of the functionality of the automation platform. Is its function to merely monitor the ability of the operator to control the DP system, and to take actions when this ability is below a dynamic threshold? Or is the automation merely another part of the DP system, making the operator even more redundant? Clearly, these questions need to be addressed as well when considering the potential success of the adaptive automation.

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