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Experimental Set-Up for Evaluating Operator Performance through Operations Control Room Simulation in the Oil and Gas Industry

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Automation in the oil and gas industries has increased over the years. Nonetheless, human input still plays a critical role in the operation of process plants, where automation does not completely replace humans but rather provides new ways for operators to interact with the system. Some ways of accessing human performance are through human reliability analysis and human factors studies. Both disciplines have been discussing human performance in automated systems and issues are pointed out in recent literature, particularly in the development and evaluation of Human Machine Interface (HMI) in different automation modes. In addition, a way of evaluating human performance is through experiments/simulations. Therefore, we propose an experimental set-up to observe human performance in automated systems through simulation in an operations control room. In this experimental setup, some errors are assessed through human factors. Also, we recommend an artificial intelligence model using webcam information to detect inattention to monitoring.

Keywords: Automated systems, Oil and gas industries, human performance, HMI, simulation, experiment.

1. Introduction

Automation in energy industry processes has increased over the years. It has not been different in the oil and gas (O&G) sector (Camponogara et al. 2010). Nonetheless, human input still plays a critical role in the operation of process plants. Automation does not completely replace humans but provides new ways for operators to interact with the system (Peng, Zhen, and Huang 2023; Ramos et al. 2022a). Hence, it is still critical to ensure adequate human performance during operation. Human error has contributed to significant accidents in the O&G sector, such as the Piper Alpha explosion in 1988, the Texas City refinery fire in 2005, and the Deepwater Horizon explosion in 2010 (Almeida and Vinnem 2020).

With changes in the human role within a more automated process, new challenges may emerge (Maurer et al. 2016). Operators will play a more active role in monitoring, will share control with the system, and can serve as the final safety barrier if the autonomous system fails (Ramos and Mosleh 2021).

The fields of human reliability analysis (HRA) and human factors (HF) have been discussing how more automated systems impact human performance and human error (Bye 2023; Theophilus et al. 2017; Tinga et al. 2023). In this context, authors have pointed the potential impact of boredom arising from long monitoring times, over-reliance or under-reliance on automation, lack of situation assessment, and low automation transparency (Boring et al. 2019; Park et al. 2022). However, given the recency of highly automated systems in many industries, the quantitative impact of these and other factors on human performance is still unclear.

Data collection on human error and human performance using simulators is a recent advance in the field of HRA. Examples include large-scale efforts in the Nuclear Industry, such as SACADA (Scenario Authoring, Characterization, And Debriefing Application) and HuREX (Human Reliability data EXtraction) (Chang et al. 2022), and studies using lower fidelity simulators, such as Microworld (Park et al. 2022).

Analyzing human performance through simulators allows researchers to study how individuals interact with complex systems in a controlled and repetitive setting (Ballingall, Sarvi, and Sweatman 2022). It is possible to examine human performance through low or high-fidelity simulations. Despite reproducing the systems with a high level of detail, the latter requires high configuration costs and numerous specialists to secure a full-scope facility, which demands intensive resources and time and limit the use to few organizations able to satisfy these conditions (Park et al. 2022). In contrast, simplified simulators present a greater opportunity for control, providing a flexible and adaptable tool, in addition to being a cost-effective way of exploring complex systems (Boring et al. 2019).

Hence, this paper discusses the challenges related to automation and human performance and the potential solutions offered by simulator studies. We propose an experimental setup for analyzing human performance of control room operations of automated O&G operations. The setup includes a low-fidelity simulation of a refinery process considering factors such as task complexity, execution time/screen fatigue, and automation failures. Furthermore, we recommend an artificial intelligence model for detecting inattention in monitoring tasks through a non-intrusive method.

The remainder of the paper is organized as follows. Section 2 describes general information of human performance in automated systems, as well as use of simulators to evaluate of these performances. Section 3 describes the experiment and its features, the software used and the variables for measuring human errors. Section 4 discusses the methodological aspects proposed for the experiment followed by conclusions in Section 5.

2. Theoretical background

2.1. *Human performance in the automated environment*

Automating processes and tasks previously performed by humans has helped improve the efficiency and safety of many organizations, reducing human error in high-risk sectors such as the O&G industry (Camponogara et al. 2010). However, automation is imperfect, and many operators who have switched from active participants in the task to passive monitors may experience degraded performance (Rovira, McGarry, and Parasuraman 2007). Human performance in automated environments is influenced by several factors that must be considered to ensure the safety and effectiveness of these systems (Ballingall, Sarvi, and Sweatman 2022). These factors include experience and training, understanding and trust in the system, and psychological factors (Bahner, Hüper, and Manzey 2008).

Experience and training are linked to the minimum guarantee of skills that a user must have to interact with the system efficiently and safely. Training should include understanding the system, practicing operating procedures, and troubleshooting. Indeed, users need to understand how the system works and how to interact with it to effectively use its functionalities (Merriman et al. 2021), which is also linked to the understanding of the Human Machine Interface (HMI), and the operator's confidence in it (Tinga et al. 2023).

Furthermore, internal factors such as attention, emotion, and stress can affect the effectiveness of human performance in automated environments. A highly discussed factor is automation complacency, when a user of an automated system becomes overly confident in the system (Ferraro and Mouloua 2021). Thus, these individuals do not monitor the systems sufficiently, which can lead to a loss of situation awareness and an increased risk of failing to detect and manage automation failures in time (Bahner, Hüper, and Manzey 2008).

2.2. *The use of simulators to evaluate human performance*

Measuring human errors in automated systems operations can be useful to identify areas for improvement, enhance usability, and ensure the safety of the system. In this case, several techniques can be; however, the use of simulators has been promising for safety-critical systems (Wen et al. 2022).

The use of simulators is particularly interesting for recent autonomous systems and more automated ones, which do not have sufficient historical operational data yet. In addition, by providing a controlled and reproducible environment, simulations allow the assessment of human performance in a variety of ways. For instance, simulation enable organization to conduct risk assessment and identify potential risks, subsequently taking steps to mitigate them. Simulations also aid in the assessment of decision-making in specific situations, allowing researchers to identify possible operator errors, as well as training these operators in various tasks and skills (Boring et al. 2019; Chang et al. 2022) .

Full-scope simulations ensure a high degree of fidelity when the system emulates as closely as possible a real environment. However, in the full-scope simulator, it may be challenging to produce testing differences caused by design elements in the HMI, as changing a design that has already been configured and programmed into the simulator is relatively restrictive. The complexity of control system, also has conflicting implications on data collecting, possibly making it challenging to extract simple contextualization for human errors. The SACADA and HuREX studies had similar issues with this limitation (Park et al. 2022). Furthermore, shortcomings such as dependence on the simulation software; the use of many resources (experts and time) to prepare the installation, develop scenarios; and excessive complexity (requiring significant computational resources) may be considered (Shahsavari et al. 2021).

Hence, the use of a simplified simulator offers a complementary approach (not a substitute) to full-scope simulations, with reduced HRA data collection entry points, mitigation of confusion due to simulator complexity, and a greater degree of freedom when designing experiments with reasonable cost and labor (Park et al. 2022). Simulations allow researchers to manipulate various factors and variables to understand how they impact human performance, using that knowledge to develop interventions and strategies to improve performance in real-world contexts.

3. Experimental Setup

This section describes the proposed experiment on human performance of control room operators of automated O&G operations. The experiment aims to evaluate the impact of automation-related factors on operator performance based on a microworld simulation, with variables controlled and measured. The experiment in an O&G process aims to investigate whether operators can maintain a water level within the pre-established limits in order to have an acceptable vapor pressure level in the High Pressure (HP), Medium Pressure (MP) and Low Pressure (LP) steam collectors. Additionally, the experiment aims to collect information on automation complacency, human errors, and assess the level of attention/drowsiness among operators.

3.1. *Experiment description*

The experiment inspired by real refineries, simulates a hypothetical refinery steam system comprising two gas turbines with dedicated heat recovery steam generators (HRSG) and a three-pressure steam distribution system. In addition, the system includes a steam generator boiler, a boiler drum supply and drain system, a burning system, and a heated gas output system.

The fired boiler is part of a process in which a liquid is heated to vaporize it. Normally, water is the working fluid used in boilers is the separation on liquid water and steam occurs in the boiler drum. In this type of process, it is extremely important to control the water level in the boiler drum, which cannot be too high or too low. Thus, for our simulation, some simplified scenarios were proposed.

- If the water level is low: the circulation of steam throughout the process may be affected and, therefore, the pipes may be affected;
- If the water level is extremely low: the boiler can run dry, causing mechanical damage to the equipment and not taking steam to the parts needed in the rest of the process (causing major consequences);
- If the water level is high, it can affect the steam's purity and result in more water droplets entering the superheater with the saturated steam. To vaporize these water droplets, more heat will be required, increasing the thermal load. Also implying the useful life of the tubes;
- If the water level is extremely high, some amounts of liquid may be carried downstream and damage the equipment.

Thus, the operator and/or the system must act to maintain standard operational control. Keeping the boiler drum level at 50% during operation is normally standard. Thus, the actions taken are presented in Table 1 depending on the type of existing scenario.

Table 1. Summary of scenarios, consequences and actions that should be taken.

Scenarios	Consequences	Actions
Low water level	tubes can be affected by a lack of optimal steam circulation;	Open water injection valve
Water level too low	boiler running dry, causing mechanical damage to the equipment;	Open water injection valve
High water level	steam purity is affected, increased heat load to vaporize water droplets, pipes affected;	Open drain valve
Water level too high	Transported liquids causing mechanical damage to the equipment.	Open drain valve

3.2. *Process Plant Simulation*

The plant is simulated using AVEVA, a dynamic simulation software (AVEVA 2020). AVEVA focuses on dynamic simulation studies and emphasizes key modeling assumptions and expected results. Among the thirteen default processes available in the software, we specifically utilize the Steam Drum Three Element Control simulation for our study.

A gas turbine generator/heat recovery steam generator (GTG/HRSG) is shown in Fig. 1. High-pressure steam is produced in the HRSG and sent to the Refinery North End via the gas turbine exhaust, which has a temperature of 958ºF. A superheater, a boiler, an economizer, and a steam drum constitute the HRSG. The HRSG supports the supplemental firing of natural gas using the excess oxygen in the gas turbine exhaust. The steam drum level is maintained with a three-element control system.

3.3. *Human-System Interface*

The system is considered a highly automated one that still needs to be monitored by an operator. The control and management of a system in a petrochemical industry can be performed with a graphical user interface known as a control panel or dashboard. Thus, we implemented through Wonderware InduSoft web studio software(AVEVA 2023) a control panel that schematizes the simulation Fig. 2.

In this type of control mechanism, water is fed into the boiler drum through one or more pipes and, therefore through one or more control valves.

Only the water level in the drum is measured using a level transmitter and the information is sent to the controller. The information is compared with the set point and then the control valves are manipulated to increase or decrease the flow of water inside the boiler drum.

3.4. *Control and measurement variables of the experiment*

The experiment aims at assessing the impact of certain factors related to an automated system on human performance. Firstly, human performance must be defined in the context of the task. In this task, an adequate performance is to open or close the

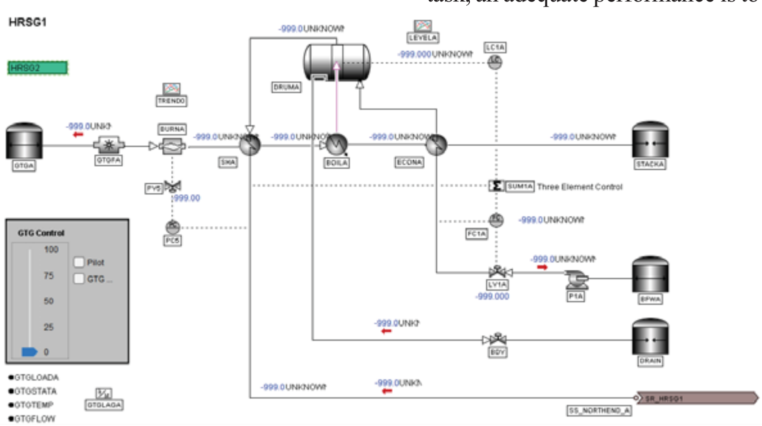

Fig. 1. Dynamic simulation refinery steam from AVEVA

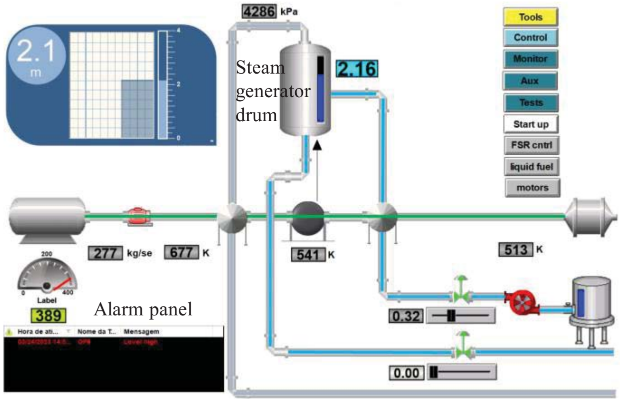

Fig. 2. Preliminary dashboard proposed in InduSoft

valves when needed by the plant (i.e., when the water level is too high or too low). Human Failure Events (HFEs) in this task are: (1) opening/closing the valve too early to too late, (2) manipulating the incorrect equipment, or (3) not performing the action. These HFEs are translated into measurable variables: reaction time and correct action (Table 2). Note that "no action" is included in reaction time, in which the time for reaction surpasses the available time the operator has. Secondly, the factors to be analyzed must be translated into control variables. These variables are Simulation time, task complexity, and failure in automation, further described in following sub-sections.

Table 2. Experiment's control and measurable variables

Control variables	Simulation time
	Task complexity
	Failures in automation
Measurable variables	Reaction time
	Correct action

3.4.1. *Monitoring time*

In automated operations, it is common for operators to go for extended periods without any actions required on their part, leading to a potential decrease in situational awareness. The lack of immediate stimuli or occurrences can cause complacency, making it challenging to be prepared to quickly recognize newly emerging problems. When monitoring automation, it frequently takes people a long time to notice that a situation calls for action, and even longer to fully comprehend it and respond appropriately (Endsley 2017). This gap between problem detection and action can result in critical delays and negatively impact the effectiveness of needed interventions. Therefore, it is essential to adopt strategies to mitigate the decrease in situational awareness.

3.4.2. *Task complexity*

In general, procedures lessen the likelihood that human operators would forget or skip an activity they need to do, reduce their physical and/or cognitive workload by providing explicit instructions, and maintain their performance over time. However, complicated procedures (i.e., incomplete, inaccurate, inconsistent, or difficult to understand) reduce human performance, suggesting that tasks' complexity has an impact on it (Jang, Kim, and Park 2021).

The level of complexity also can negatively affect human performance in tasks that require a high level of concentration and attention. Hence, there are points of attention that the operator must focus on, however, there are several other boxes that bring information about the system but do not necessarily impact its action. For example, when the water level is rising (or decreasing), the operator can see the variation in the dashboard display (right side of the steam generator drum) and in the water level over time (left side of the steam generator drum) show in Fig. 2. The system is also proposed to alarm (box at the bottom left) if the level exceeds certain pre-established limits. However, other markers can draw attention.

3.4.3. *Automation complacency*

Automation complacency is a critical topic in automation safety. Complacency manifests in inadequate monitoring and checking of automated functions, as exemplified by pilots who overly rely on their autopilot's proper functioning and consequently fail to monitor and check it appropriately (Bahner, Hüper, and Manzey 2008). According to Parasuraman and Manzey (2010), automation complacency is found for both naive and experts participants and cannot be overcome with simple training practice, and can affect decision-making in individuals as well as in teams.

In our example, the automation is designed to function correctly for a period, in order to build operators' confidence in the system, which may lead to complacency. However, we randomly induce an automation error over time, which can only be noticed when one of the events occurs and the alarm is not triggered. The event is implemented in the simulation itself, to induce a reduction in the water level, behaving like a leak.

In our simulation, the automation error may will be interpreted by a communication error between the control panel and the simulation, where even with the water level exceeding the pre-established limits, the alarm is not activated. However, the variation in the dashboard display (right side of the steam generator drum) and in the water level over time (left side of the steam generator drum) shown in Fig. 2 will continue to report correctly. We can assess participants' reaction time and actions to determine their perception of water level changes without relying on the alarm and evaluate their accuracy.

3.5. *Assessment of human performance*

To evaluate the performance of the proposed experiment, various measurable variables need to be computed. The performance will be observed using a webcam to track the operator's actions, and the system also collects reaction time and the accuracy of their actions in a quantitative way. Additionally, more sophisticated methods can be employed to assess performance, such as automated detection of attention and drowsiness.

3.5.1. *Computational vision to assess human performance*

Fatigue, which can be influenced by both human and task-related factors, has been identified in the literature as a factor that decreases overall employee performance and can lead to drowsiness. Drowsiness is associated with various accidents and is of particular interest to organizations operating critical safety systems, including the O&G industry. In this context, it is possible to monitor an operator's level of drowsiness using computer vision information, such as images or videos. Advanced machine and deep learning techniques have been used to speed up the training process and improve model efficiency. In this context, we will assess the suitability of an approach that uses visual information in a deep learning model known as InceptionV3 for drowsiness detection (Ramos et al. 2022b). More details about the model will be described in another study.

4. Discussion

Simulators can be used to analyze human performance and errors in various automated industries (e.g., O&G, nuclear, aviation). One of the advantages of simulators is that they can simulate dynamic processes that may be difficult to analyze in the real world.

The use of simulators for studying and collecting data on human performance requires several elements. The first element is the dynamic simulation of the plant. The second element is the human-system interface and the physical space, which should be as close to reality as possible. Low-fidelity simulators of control rooms can be as simple as adequate screens and control tools. Then, the desired human actions in the scenarios must be defined, along with the deriving human-failure events. Human failures must be observable and measurable. For instance, “degraded performance” needs to be assessed through observable factors, such as long reaction time (in which “long” needs to be defined). This step can leverage Task Analysis such as the Concurrent Task Analysis (CoTA) to identify human tasks under the system dynamics and failures and develop the criteria for the operator’s success (Ramos et al. 2020). The fourth element is the influencing factors, i.e., the factors that may impact human performance in the scenario. It is essential to translate the factors into control variables that can be manipulated and measured. For example, “safety culture” cannot be evaluated directly, so a surrogate variable that is measurable and manipulable must be identified.

Additional elements concern the post-experiment data collection and analysis. Post-experiment questionnaires are a valuable tool to assess factors not observed in the experiments, such as fatigue or motivation. It is also necessary to determine the required number of experiments to obtain statistically significant results. Moreover, human performance generally depends on interdependent factors, as much as the experimental setup attempts to isolate the factors. Bayesian modeling can help modelling interdependent factors. Finally, it is important to define the population to be studied, including age, gender, and other relevant factors in order to avoid biased analyses.

5. Conclusion

Automation has become increasingly prevalent in the energy industry, including the O&G sector, but human input remains critical in process plant operation. Human error can contribute to significant accidents in the industry, and as the human role changes with more automation, new challenges may arise. Operators will have a more active role in monitoring and can serve as the final safety barrier if autonomous systems fail. The impact of automation on human performance and error is a topic of discussion in the fields of HRA and HF, but the quantitative impact of influencing factors on human performance is still unclear.

This paper presented the experimental setup to observe and quantify the impact of certain factors associated with more automated operations in the context of O&G, through a low fidelity simulator. The experiments will be performed at the Center for Risk Analysis, Reliability Engineering and Environmental Modeling (CEERMA) at the Federal University of Pernambuco (UFPE), Brazil. The preliminary, simplified setup is expected to produce an initial assessment of the impact of those factors and requirements for more complex studies in the future.

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