# Advanced Applications in Process Control and Training Needs of Field and Control Room Operators

**Annette Kluge,[1,*] Salman Nazir,[2] and Davide Manca[2]**

[1]Industrial, Organizational, and Business Psychology, Faculty of Psychology, Ruhr University Bochum, 44780 Bochum, Germany

[2]Department of Chemical Engineering, Politecnico di Milano, Italy

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*Corresponding author. E-mail: annette.kluge@rub.de

## IMPACT ON OPERATORS' COGNITIVE WORK BY ADVANCED CONTROL TECHNIQUES AND AUTOMATION

The last two decades have witnessed a large increase in the automation of industrial plants. With reference to an increase in systems for on-line control of chemical and petrochemical plants, mainly around the United States, Europe, and Asia-Pacific areas (Jämsä-Jounela, 2007), there has been a progressive introduction of advanced tools to monitor, support, and enhance the operation and performance of the process. After the introduction of automated control algorithms (1960s), deployment of distributed control systems (DCSs; 1970s), and the installation of seminal on-line optimization solutions for chemical processes (1980s), the progressive availability of high-performing central processing units (CPUs) and robust operating systems, together with improved mathematical algorithms and routines, have been the prerequisites for the widespread diffusion of advanced solutions (1990s).

This technological advancement and automation has significantly changed the nature of work for industrial operators. Indeed, at the beginning of the automation era, the control loops operated directly in the field or were concentrated in local control rooms. Consequently, in the past, fewer and concentrated actions in the field were sufficient to gather the process information and to make process adjustments (Emigholz, 1996). By contrast, the operators of modern industrial plants face different challenges due to handling, analyzing, and interpreting large amounts of distributed information simultaneously.

Although some advanced control techniques (e.g., dynamic matrix control, model algorithmic control) had their origins in the industry from some enlightened development groups (e.g., Shell, IDCOM), the formalization and systemization of these techniques was conceived, conducted, and finalized by academia through a rather long incubation period (see Morari & Lee [1999] for a detailed review). Eventually, starting from the 1990s, the availability of robust software environments and fast hardware, both reasonably priced, allowed the seminal model-based techniques (still too theoretical and simplified) to be transposed into stable and complex algorithms, such as model predictive control (MPC) and real-time optimization (RTO; De Souza et al., 2010).

MPC and RTO enabled the industries to implement models and solutions into their systems by optimizing the process parameters to maximize the production according to minimum energy usage, and/or minimum raw materials consumption, and/or minimum environmental impact. The growth and implementation of these optimization techniques can be judged by a prediction made by the ARC advisory group, that the RTO market will reach more than US$1.5 billion in 2015 (Abel, 2011).

## Contribution to Complexity of MPC and RTO

MPC and RTO are means to achieve a continuous optimal production of industrial processes. MPC uses model-based algorithms, holistic controllers, and sophisticated optimization techniques to predict future dynamic behaviors of the process. RTO incorporates the maximization of a suitable economic objective function, where the degrees of freedom are compositions, flow rates, efficiencies, and more general setpoints of operating conditions, which are optimized periodically in real time (De Souza et al., 2010).

If, on one hand, these automated algorithms and procedures seem to relieve the operator's burden by running in the background, on the other hand, and in reality, they call for a higher level of mental representation, understanding, and awareness by the operator. The operator stands at the last level of the control/optimization hierarchy. Consequently, he/she is responsible for the supervision of the process and the related control/optimization procedures. An industrial operator has to manage the automation and control loops on a more frequent and articulate basis than that of the pilot who has to understand the interconnections and control loops of a flight management system (FMS; Jamieson & Guerlian, 2000). Complex chemical plants can have several thousands of control loops where the corresponding controlled variables are affected by a proportional number of manipulated variables. The coupling and pairing of these process variables is quite intricate. These features call for an in-depth knowledge of the dynamic response of the system to either deterministic modifications by manipulated variables or stochastic variations by external disturbances.

Commercial producers of DCSs offer specific and customizable packages for MPC and RTO. These are seldom introduced into the fully automated control flow of the plant, but rather, have to be monitored actively, considered and checked, and finally implemented by the human operator (i.e., the control room operators [CROPs]) to reduce the risks involved by a fully automated algorithm. Consequently, the need for the operator to understand the control loops of MPC is essential and affects his/her cognitive information processing resources (Jamieson & Guerlain, 2000). Interestingly, from a human factors perspective, as many as 60% of the automated control loops among the plants worldwide are either underperforming or inefficient, because they are not well understood and handled by the operators (Thwaites, 2008). This result indicates the challenges in training operators to use advanced control techniques adequately.

## Cognitive Requirements of CROP as Challenged by Advanced Control Techniques

As the CROPs acronym recalls, these operators work in control rooms and are required to observe, monitor, control, and optimize the process variables with the help of synoptic diagrams displayed on the DCS (Fig. 1).

To validate the results proposed by the MPC and RTO tools, operators draw on their mental models to integrate separate indications and account for the required data. To either anticipate future states of the plant or evaluate plant performance under various configurations (Vicente et al., 2004), they need to:

- develop cause-and-effect relationships when explaining plant behavior and indications,
- perform internal experiments (Rasmussen & Goodstein, 1985),
- and "run" mental simulations of the plant.

Modern DCSs can comprise thousands of control variables organized into hundreds of synoptic views of the plant and divided into physical subsections. As discussed in the previous section, the intrinsic multidimensionality of the DCS and of the related MPC/

**FIGURE 1** Typical example of a CROP's activity.

RTO solutions plays a challenging role where the activity of operators is concerned, because

- couplings and interconnections (Kluge, 2008; Moray, 1997; Vicente, 2007; Wickens & Hollands, 2000) *require the operator to simultaneously process the interplay of cross-coupled variables to either assess a process state or predict the dynamic evolution of the plant*;
- dynamic effects (Kluge, 2008; Vicente, 1999; Walker, Stanton, Salmon, Jenkins, & Rafferty, 2010) *require the operator to mentally process and envisage the change rates of cross-coupled variables and to develop sensitivity for the right timing of decisions to be successful*;
- non-transparency (Funke, 2010; Kluge, 2014; Vicente, 1999; Woods, Roth, Stubler, & Mumaw, 1990) *requires the operator to work with more or less abstract visual cues that need to be composed into a mental representation and need to be compared with the operator's mental model*;
- multiple or conflicting goals (Brehmer & Dörner, 1993; Funke, 2010; Kluge, 2008; Reason, 2008; Verschuur, Hudson, & Parker, 1996; Wickens & Hollands, 2000) *require the operators either to balance management intentions or to decide on priorities in case of goal conflicts in the decision-making process, e.g., which course of actions to take*;
- comprehension of MPC and RTO philosophies is required, making sure that *CROPs understand the advanced control and optimization philosophies that are at the basis of MPC and RTO, since they have to validate the proposed results before accepting/rejecting their implementation in the on-line control strategy*; and
- crew-coordination complexity (Kluge, 2014; Woods et al., 1990) incorporates small crews, e.g., CROPs, field operators (FOPs), and supervisors, that are responsible for overall system operations (Reinartz, 1993; Reinartz & Reinartz, 1993; Carvallo et al., 2005; Vicente et al., 2004) *and calls for the operators to concurrently interact with team members to orchestrate individual actions into a coordinated flow of actions to either assess the situation or choose a course of actions.*

Finally, another challenge that CROPs have to face is alarm flooding. Actually, the highly automated alarm management system may produce a large number of alarms close together in cases of abnormal situations, which may bring about undesired and impracticable cascades. In an *abnormal* situation, a disturbance or series of disturbances in a process make plant operations deviate from their normal operating condition (Kluge, 2014). Instead of assisting and de-loading the CROP, alarm flooding takes the operators to conditions of high "stress" and information overload (Orasanu & Backer, 1996; Kontogiannis, 1999). In turn, these conditions lead to a loss of cognitive efficiency and strongly affect the capacity of CROPs to organize well-thought-out decisions due to overabundant information, sensory overload, ambiguity, time pressure, and unpredictability (Moore et al., 2012). The occurrence of abnormal situations in process industry is not a rare event. In fact, a report by Honeywell (Patrick et al., 2011) indicated that US$10 billion is lost every year because of abnormal situations. Among the attributes triggering these abnormal situations, the contribution of human errors was found to be 50% (Patrick et al., 2011).

Reflecting common practice critically, DCS designers seem to be focused strongly on improving and enhancing the performance efficiency of their products but without adequately addressing the cognitive constraints (Vicente, 1999), such as working memory capacity. As outlined above, this is a major human factors challenge, because the information handling required by the operators to assess the situation adequately necessitates the simultaneous processing of the interconnected variables, their dynamics, and side effects. Specifically, simultaneous processing leads to:

- an increased demand in terms of mental workload to correctly assess the situation, based on the operators' mental model (Bainbridge, 1992; Kragt & Landweert, 1974; Vicente et al., 2004), to reach correct decisions (contextual control model [COCOM] by Hollnagel 2007; Hollnagel & Woods 2005; Kluge, 2014); and
- high stress on the CROP in abnormal situations, when uncertainties are introduced to the system requiring non-routine decisions/actions, and when alarm flooding distracts from or impedes a correct decision-making process; consequently, risky decisions are made, skilled performance declines, and crucial information is ignored (Kontogiannis, 1996, 1999).

## Task of FOP

Focus thus far has been on the CROP's task, but CROPs are working in a crew with FOPs. As shown in Fig. 2, FOPs generally work at the plant site, in contact with the equipment, where the real process is in operation. The main task of an FOP is interacting with physical devices that are distributed throughout the plant, which can require the uses of different senses (i.e., sight, sound, and touch but seldom smell and very seldom taste) to crosscheck the perception that is formed by the interpretation of field data from sensors.

The challenges faced by FOPs are different from those faced by CROPs. Because of their work outside at the plant (e.g., to inspect the plant, observe malfunctions or leakages in the field), FOPs have to cope with challenges related to external factors that are mostly out of their control, such as weather conditions (rain, snow, wind, storms), shift timing (day or night), visibility conditions (fog, smokes, moisture, dust), different noise conditions, vibrations, altitude (working on a distillation column whose height can be up to 175 feet), odors (sometimes pungent), etc. The work of FOPs is additionally hindered by the fact that they are required to wear technical uniforms and protective equipment during their working hours.

In case of abnormal situations, a set of process variables moves toward unsafe values. Consequently, FOPs and CROPs have to coordinate and operate both individually and as a distributed group to take the process back to the safe domain. In these situations, the communication between the CROPs and FOPs increases significantly and covers both the information side about plant conditions and the action side about remote and in-the-field operations on valves, switches, and levers.

In such abnormal situations, an essential prerequisite for effective teamwork is shared cognition (Patrick & Morgan, 2010; Nazir, Johnstone Sorensen, Øvergård, & Manca, 2015) to facilitate the FOP–CROP communication and coordination. For example, an abnormal situation observed by an FOP in the field using his/her physical senses must be coordinated with the CROP for necessary actions and instructions (Nazir et al., 2012). This can be achieved by maintaining an adequate distributed situation awareness (Salmon et al., 2009). Operators are required to monitor recurrently the dynamics of the process without seeing directly what the other colleagues can perceive. This happens because operators are usually far from each other. Information exchange and a mental representation of the process dynamics are required to make timely, correct decisions based on a mutual comprehension.

**FIGURE 2** FOP in the field.

## OPERATORS' TASK PREPARATION

### Common Practice

In many plants in the United Staes and Europe, it is common practice that CROPs worked as FOPs before being assigned to control room tasks. CROPs observed in a study by Yin and Laberge (2010) attributed much of their system and process knowledge, included in their mental model, to their many years of practical experience working as FOPs. This means that major sources for deriving and developing the CROPs mental models are the field experience, incidents, and upsets that have occurred (Yin & Laberge, 2010). These include, for instance, spatial knowledge about the line-up, the layout of the plant, how the process works internally, why the equipment is at certain places, what is happening in/at each process unit, and what are the operating procedures. The preparation of FOPs in most industrial plants is accompanied by class-based preliminary formation with conventional written procedures and ex-cathedra lessons, the duration of which is often reduced to a few weeks before the FOP is placed alongside with experienced operators who, to some extent, play the role of on-the-job trainers (Manca et al., 2013a).

This kind of on-the-job experiential learning (Kolb, 1984) in the field is assumed to be effective particularly for the acquisition, elaboration, and differentiation of a mental model, but it leaves the acquisition of an accurate mental model somewhat to chance, depending on the situations experienced in the field. This means that the ways in which FOPs are assumed to acquire a mental model, and which seems essential for their later work as a CROP, are quite diverse and rarely based on what is known in training science about how to develop training programs (e.g., based on a cognitive task analysis; e.g., Cascio & Aguinis, 2011; Coultas et al., 2012). These deliberately designed training programs raise the likelihood of the *acquisition of an adequate mental model* that aids the CROPs and FOPs in decision making under normal and abnormal situations. For instance, in some countries where vocational training is less formalized, FOPs with diverse educational backgrounds are trained mainly on the job and informally (Cheetham & Chivers, 2005) and with a rather short introductory course before they are allowed to work in the plant. In contrast, in countries with more formalized vocational training systems, refinery FOPs receive a very formalized 3.5 years of information-based and demonstration-based (Salas & Cannon-Bowers, 1997) vocational training after high school, which includes theory and practical work in a technical center.

As far as training of CROPs is concerned, it is common practice that operator training simulators (OTSs) are used (Kluge et al., 2009; Patle et al., 2014). An OTS includes a main process model and a simulated DCS that allows for performing a realistic hands-on training of normal operations, start-ups and shutdowns, as well as upsets and emergency situations (Komulainen et al., 2012). These authors and several others (Reinig et al., 1997; Balaton et al., 2013; Patle & Ahmad, 2013; Vellaithurai et al., 2013) claim that to improve the skills of operators, OTSs have been widely applied since the 1990s (Patle et al., 2014). Nevertheless, from a human factors perspective, it is unclear what rationale is used to decide when, how, and how often to integrate the OTS in the training. Regrettably, nothing is said in the study by Komulainen et al. (2012), or the recent review by Patle et al. (2014), about a possible rational training-course development referred to the design process (i.e., how these scenarios are selected and how the simulator-based learning experience is exploited to support the acquisition of an accurate mental model).

Missing in the literature is a necessary clear and explicit link (Salas et al., 2012) between a cognitive task analysis (e.g., Crandall et al., 2006; Roth, 2008), as listed above, and the selection and development of a scenario that deliberately supports the acquisition of knowledge, mental model, and cognitive skills to proficiently execute these cognitive tasks. It is assumed that one reason for the missing link between the cognitive task analysis of CROP and FOP tasks and training design is also that recent literature on learning processes is not capitalized upon (Bell et al., 2008).

## "New Problems Demand New Approaches"

Vicente (1999) suggested that "new problems demand new approaches" (p. 17) and raised doubts concerning human capacity to utilize effectively the above-discussed technology of DCSs, such as MPC and RTO, by asking, "Do we know how to use it?" (p. 19). Here it is argued optimistically that the human operator is able to use the technology effectively but needs to be prepared and trained accordingly by practice-based training with respect to technical and crew-coordination complexity. However, based on other results (e.g., Kluge et al., 2009), it must be conceded that many current information-based and demonstration-based training practices (Salas & Cannon-Bowers, 1997) do not match yet the learning objectives derived from the above-outlined work demands and do not prepare operators as optimally as they could to handle complex systems based on learning theories. From this perspective, these current training arrangements ignore

- recent results from learning and training research (e.g., Gonzales et al., 2003; Sun et al., 2005; Kluge, 2014) on how operators actually learn and acquire mental models by experiential learning for handling routine and stressful abnormal situations and
- crew-coordination complexity, as outlined above, which results from the interconnectedness among multiple agents through coordination requirements (Roth & Woods, 1988; Waller et al., 2004; Hagemann et al., 2012).

The following section refers to recent research to address the following question: How do operators actually learn and acquire mental models and skills to coordinate in a team?

## Recent Results from Learning Research

Concerning the *acquisition of a mental model*, learning to control a complex system takes place through the accumulation of knowledge about so-called instances (Gilboa & Schmeidler, 2000; Logan, 2002;

Gonzales et al., 2003; Gonzales, 2012). Instances are situation-decision-utility (SDU) chunks, consisting of environmental cues named the *situation* (*S*; for example, indicators on the screen, alarms, warnings) of a set of actions applicable to the situation named *decision* (*D*; for example, a number of standardized operating procedures [SOPs] required) and the evaluation of the goodness of a decision in that particular situation (*U*; Gonzales et al., 2003). The acquisition of mental models accumulates only with job experience or is substituted by practice-based training (e.g., Kluge & Schüler, 2007; Nazir et al., 2013a). Practice-based training allows learning about situational cues, capturing the selected courses of action, and enhancing the results accuracy in the achievement of organizational goals (Kluge, 2014) for later cue recognition based application of the instance-based knowledge.

The perception of similarity among situations increases with experience and practice-based training on the task (Gonzales et al., 2003). This supports attention management for relevant task cues (Kolodner, 1983; Vicente et al., 2004), which is extremely important in cases of alarm flooding and abnormal situations. In summary, extensive practice-based experiential training is the essential prerequisite for initiating learning processes to prepare operators to handle complex systems.

Thus, in common practice, in process industries the following aspects of instance-based learning are lacking and should include:

- the possibility to acquire instances (SDU chunks);
- the possibility to learn about the methods, algorithms, and conceptual contents of MPC and RTO and to integrate these insights into the mental model;
- the possibility to simulate a large number of unanticipated/abnormal situations, *to learn about situational cues, which prompt for the emergence of an abnormal situation and the possibility to learn how to handle stressors*;
- the possibility to simulate accident events and observe the possible consequences *to acquire feedback about the utility of a decision*; and
- the possibility to be exposed to unexpected alarm sequences and possibly to alarm flooding *to learn to focus attention on task-relevant aspects*.

Concerning *crew-coordination complexity* in abnormal situations, it is assumed that teamwork is also learned through the accumulation of instances of teamwork episodes (e.g., Rentsch et al., 1994; Reagans et al., 2005; Edmondson et al., 2008; Mathieu et al., 2008; Kluge, 2014). This is because most of the things one knows about teamwork are procedural and implicitly stored, and with everyday experience and increasing job experience, explicit and rule-based knowledge is extracted (Sun, Slusarz, & Terry, 2005). By "doing" teamwork, it can be assumed that team knowledge (Wildman et al., 2012) also develops in a similar way to system knowledge. Team knowledge (Wildman et al., 2012) consists of task-related, team-related, process-related, and goal-related static knowledge (task knowledge, expertise location, teamwork mental models, and shared vision) as well as dynamic knowledge (e.g., distributed situation awareness, situation models). In recent literature (Rentsch et al., 1994; Reagans et al., 2005; Edmondson et al., 2008; Mathieu et al.; 2008), it is assumed that for teamwork as well (in addition to task work), SDU chunks are acquired and differentiated through work experience and practice-based training.

Concerning the requirement of handling crew-coordination complexity, current training arrangements are lacking and should include such aspects as

- the possibility to practice crew-coordination skills *to deal with concurrent task work and teamwork demands that need to be interleaved*;
- the possibility to learn to handle additional cognitive demands caused by teamwork *to achieve a smoothly coordinated multi-agent workflow*;
- the possibility of developing shared mental modeling/mapping among FOPs and CROPs *to implicitly coordinate multi-agent action steps*; and
- the possibility to perform coordinated actions among FOPs (where both CROPs and FOPs have to perform their own actions in a timely coordinated and consistent way) *to practice the timing issues in coordination*.

After having summarized the current state-of-art concerning learning theories, the next section gives an idea of how cognitive and team task analysis results can be linked to training methods to prepare CROPs and FOPs for their work in highly technical and crew-coordination complex environments.

### Integration of Cognitive Requirement Analysis, Training Objectives, and Learning Theory

Table 1 presents a synopsis of what has been outlined so far in the first two sections. In the first column (from the left), aspects contributing to complexity, cognitive requirements, and learning objectives are summarized, as introduced in the first two sections. The column on training methods integrates the propositions of the second section and adds principles from experiential learning theory (see Fig. 3) by Kolb (1984). Due to the hazardous potential of experiential learning during normal operations and workers' shifts, and the rare occurrence of abnormal situations (upon which to train), substantial simulated practice-based training is suggested as a substitute for work experience. This has the potential to enable workers to acquire instances and a mental model that incorporates knowledge about process dynamics, as well as the possibility to enable them to attain better attention management and to acquire situational cues and mental mapping.

The experiential learning approach consists of four elements and is compatible with instance-based learning (Gonzales et al., 2003) and theoretical assumptions about the CROPs tasks as outlined in the COCOM by Hollnagel (2007) and Hollnagel and Woods (2005). The learning process is initiated by carrying out a particular action, experiencing, and then seeing the effect of the action in this situation. The second element consists of understanding these effects in a particular instance, to build up a mental model of the interconnections, coupling, dynamic effects, etc., to form later a model-based mental expectation of what would follow from a particular action (e.g., in predicting future states of the plant). According to the experiential learning circle, the subsequent elements consist of reflecting and understanding the general principle under which the particular instance falls and forming an abstract concept and mental representation of similarities and differences between experienced instances that allow for a flexible use to mentally envision and simulate the dynamics of the plant.

## SELECTING THE MOST SUPPORTIVE LEARNING ENVIRONMENT

As denoted above, due to the hazardous potential of experiential learning during normal operations and the rare occurrence of abnormal situations (Patle et al., 2014), simulated practice-based training is suggested as a substitute for work experience to achieve the training objectives of FOPs and CROPs. For simulated practice-based training, different learning environments can be employed, such as (i) OTSs as briefly introduced above and which already has a long history in training practice and (ii) virtual reality training simulators (VRTSs), which are new in training practice.

### OTSs

As introduced above, OTSs have been widely deployed in the chemical industry since the 1990s. Typically, the OTS is a software tool that is able to simulate chemical processes in real time and is installed in a dedicated room that replicates the control room with all its necessary furniture and features. The synoptic panels of OTSs resemble/replicate process flow diagrams (PFDs) of the process, which allow the operator to understand and learn the process details and optimal operating conditions.

Focusing on the CROPs as the target group, the *benefits* of OTS include learning, understanding, and experiencing real DCSs, operating conditions, parameters, interconnections among control loops, control algorithms (e.g., MPC, RTO) start-up and shut-down procedures, as well as simulated abnormal situations and alarm flooding. The control loops, algorithms, and tools are assumed to be well understood in this (2D) environment with the help of PFDs and the dynamic simulation performed by a conventional OTS, as they are exact replica of control rooms. This means that the OTS enables practice-based experiential learning and supports instance-based learning of the CROPs. The identical elements replicated between the control room and OTS provide the operator with exactly similar instances that he/she faces in real control room during normal operations and in abnormal situations (Kluge et al., 2009).

There are some limitations of OTSs, though, for achieving the above-derived training objective. The complexity of crew coordination between CROPs and FOPs is not considered in the conceptualization of an OTS. Nonetheless, both under conventional (e.g., start-ups, shut-downs) and abnormal situations (e.g., alarms, near misses, incidents, accidents), the intervention of FOPs is usually required at the plant site. In these situations, the automated control

**TABLE 1** **Linking cognitive requirements, learning objectives, training methods, and environments**

| Aspects contributing to complexity | Cognitive requirements | Learning objectives | Training method derived from learning theories |
|---|---|---|---|
| Couplings and interconnections (Moray, 1997; Wickens & Hollands, 2000; Vicente, 2007; Kluge, 2008) | Requires the operator to simultaneously process the interplay of cross-coupled variables to either assess a process state or predict the dynamic evolution of the plant | Acquisition of instances (SDU chunks); acquisition of feedback about the utility of a decision; acquisition of situational cues that prompt the emergence of an abnormal situation and the possibility to learn how to handle stressors | Experiencing accident events and observing possible consequences; experiencing a large number of unanticipated/abnormal situations |
| Dynamic effects (Vicente, 1999; Kluge, 2008; Walker et al., 2010) | Requires the operator to mentally process and envisage the change rates of cross-coupled variables and to develop a sensitivity for the right timing of decisions to be successful | Acquisition of instances (SDU chunks); acquisition of feedback about the utility of a decision; acquisition of situational cues that prompt the emergence of an abnormal situation and the possibility to learn how to handle stressors | Experiencing accident events and observing possible consequences; experiencing a large number of unanticipated/abnormal situations |
| Non-transparency (Woods et al., 1990; Vicente, 1999; Funke, 2010; Kluge, 2014) | Requires the operator to work with more or less abstract visual cues that need to be composed into a mental representation and need to be compared with the operator's mental model | Acquisition of instances (SDU chunks); acquisition of feedback about the utility of a decision; acquisition of situational cues that prompt the emergence of an abnormal situation and the possibility to learn how to handle stressors | Experiencing accident events and observing possible consequences; experiencing a large number of unanticipated/abnormal situations |
| Multiple or conflicting goals (Brehmer & Dörner, 1993; Verschuur et al., 1996; Wickens & Hollands, 2000; Kluge, 2008; Reason, 2008; Funke, 2010) | Requires the operators either to balance management intentions or to decide on priorities in case of goal conflicts in the decision-making process (e.g., which course of actions to take) | Acquisition of feedback about the utility of a decision | Experiencing situations with conflicting goals |
| MPC and RTO implementation | Requires CROPs to understand advanced control and optimization methods that are the basis of MPC and RTO since they have to validate the proposed results before accepting/rejecting their implementation in the on-line control strategy | Knowledge acquisition of methods, algorithms, conceptual contents of MPC and RTO; integration of insights into the mental model | Experiencing situations that emphasize the aspects of MPC and RTO; supported reflection and abstract conceptualization |

(*Continued on next page*)

TABLE 1 **Linking cognitive requirements, learning objectives, training methods, and environments *(Continued)***

| Aspects contributing to complexity | Cognitive requirements | Learning objectives | Training method derived from learning theories |
|---|---|---|---|
| Crew-coordination complexity (Dörner, 1989/2003; Woods et al., 1990; Kluge, 2014) | Calls for operators to concurrently interact with team members to orchestrate individual actions into a coordinated flow of actions to either assess the situation or choose a course of actions | Acquisition of teamwork skills that support the interleaving of concurrent task work and teamwork demands; acquisition of skills to achieve a smoothly coordinated multi-agent workflow; acquisition of skills to implicitly coordinate multi-agent action steps; aacquisition of a shared mental model among FOPs and CROPs (for normal and possible abnormal operating conditions); acquisition of skills to coordinate timing issues | Practicing teamwork, team training in intact teams; practice to handle additional cognitive demands caused by teamwork; reflection and abstract conceptualization of teamwork practice; practice of coordinated actions among FOPs (where both CROPs and FOPs have to perform their own actions in a timely coordinated and consistent way) |
| Alarm flooding | Coping with alarm flooding conditions of high "stress" and information overload | Acquisition of skills to focus attention on task-relevant aspects | Practicing to cope with unexpected alarm sequences and possibly to alarm flooding |

valves, which are generally operated remotely from the control room, are converted to be operated manually in the field. It is the responsibility of CROPs to suggest the FOPs to operate the field-operated valves (FOVs) during these situations. A delay of few seconds or an error in selecting a specific valve can exacerbate the situation and lead to even worse conditions (Nazir et al., 2013a).

## VRTSs

The concept of using virtual reality in training simulators (VRTSs) has been discussed for several years (e.g., Dalgarno & Lee, 2010). Virtual reality is defined as "the

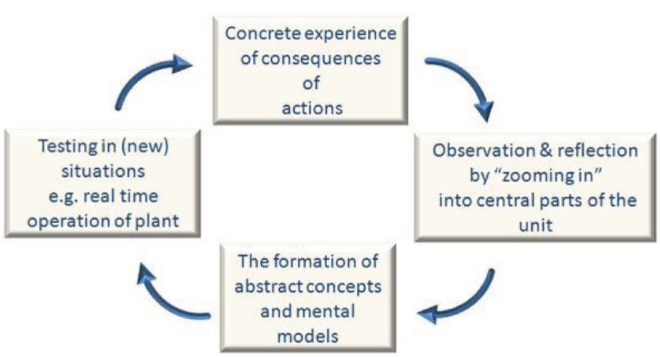


**FIGURE 3** **Instance-based learning based on experiential learning circle, adapted from Kolb (1984).**

ability to augment, replace, create, and/or manage a learner's actual experience with the world by providing realistic content and embedded instructional features" (Cannon-Bowers & Bowers, 2010, p. 230). Training simulators with virtual reality have been successfully employed in medical and surgical scenarios (Aggarwal et al., 2006), mechanical systems (Restivo et al., 2013), aviation (Rupasinghe et al., 2011), and the military (Lele, 2013). Adaption of virtual reality in training simulators for process industry can bring several benefits. VRTSs in process control can allow operators to become aware of the process units and understand their features and geometrical, spatial, and steric layout for future possible interventions in case of start-up, shutdown, grade change, malfunctions, abnormal situations, alarms, and incident/accident events.

Since FOPs work in the field, training should be capable of reproducing the spatial layout of the plant, which can be achieved with the help of VRTS. Some of the relevant advantages of VRTS with regard to the present article are that they simulate hard-to-visit places, simulate physical environments containing entities with dynamic behaviors, simulate dangerous or expensive environments for skill practice, and provide a "sense of place" (Dalgarno, 2002). A comparison of Figs. 4 and 5 exemplifies this concept, as it shows a 3D representation of a distillation column together with its auxiliary units, such as the reboiler, condenser, and reflux drum. Figure 4 shows a conventional DCS synoptic based on a standard 2D representation of a distillation column. It is worth observing how the schematic diagram of that unit reports the condenser at the top of the column, while a real condenser is usually installed at the ground for both stability and maintenance reasons. In addition, the simplified representation of Fig. 4 lacks the 3D details and auxiliary devices, such as pumps, inspection holes, flanges, automatic and manual valves, switches, pressure gauges, and flow-meters.

The detailed review on learning affordances of 3D environments by Dalgarno and Lee (2010) highlighted several empirical studies emphasizing the benefits for learning related to virtual environments. Virtual environments contribute to learning because they

- facilitate familiarization to inaccessible environments;
- facilitate learning tasks that lead to the development of enhanced spatial knowledge representation;
- facilitate task mastery through practice of dangerous or expensive tasks;
- improve transfer by situating learning in a realistic context;
- facilitate learning from mistakes without any damage/harm (Koźlak et al., 2013); and
- facilitate understanding of complex environments (Dalgarno, 2002; Dalgarno & Lee, 2010; Hedberg, Harper, & Dalgarno, 2002).

Training in a VRTS allows the operator to reach the equipment closely, experience the spatial sounds (which are associated with the equipment in process industry and also with certain processes), and learn various observable fault diagnoses (observable through the naked eye or with the help of some simple devices). Figures 6(a) and 6(b) are taken from the 3D model and show the visibility (which also means availability and usability) of a pressure gauge in a crude oil refinery at different hours of the day. It can be seen that visibility of the gauge varies, which can be only experienced in such scenarios. Any 2D representation of such gauges cannot represent the change in visibility, which varies dramatically with respect to the time of the day.

Sometimes the leakage of gases is in very small flow rates (parts per million [ppm]), and therefore, it cannot be inferred in the control room at all. In VRTS, the

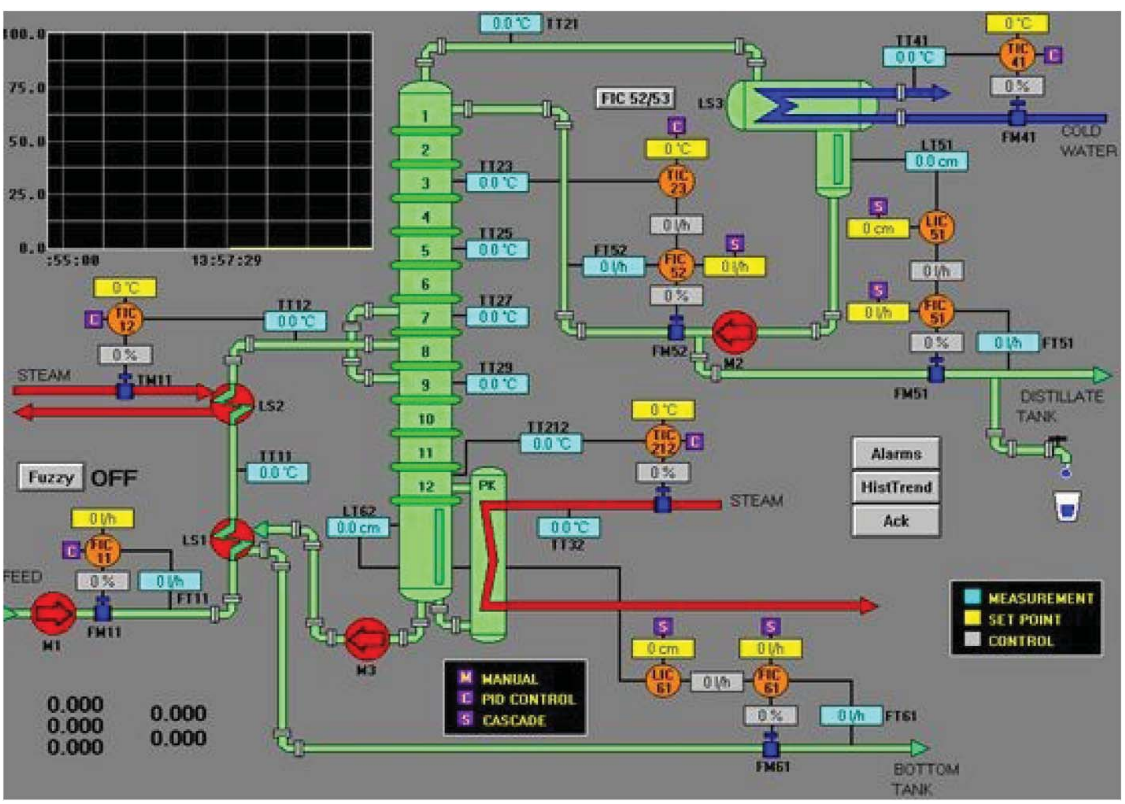


**FIGURE 4** **Conventional DCS synoptic of distillation column.**

**FIGURE 5** 3D representation of a distillation column (vertical cylinder on right) and of auxiliary process units, such as reboiler, condenser, and reflux drum (i.e., the three horizontal cylinders from left-bottom corner to center of figure).

FOPs can be provided with virtual detectors to perform an analysis in the virtual field on a frequent basis to practice the procedures to be performed at a high proficiency level. The concept of VRTS in the process industry has seen a development from theoretical background to a real training tool, such as in the form of the plant simulator (Manca et al., 2013a, 2013b; Nazir et al, 2013a). Figures 4 to 6 are snapshots taken from the plant simulator. The technical details of coupling process simulators into virtual environments were discussed in Manca et al. (2013a). Initial empirical evidence indicates that training the FOPs in VRTS and exposing them to some real stressors that they would face in both normal and abnormal situations makes achievement of the training objectives linked to handling those events more likely (Nazir et al., 2013b).

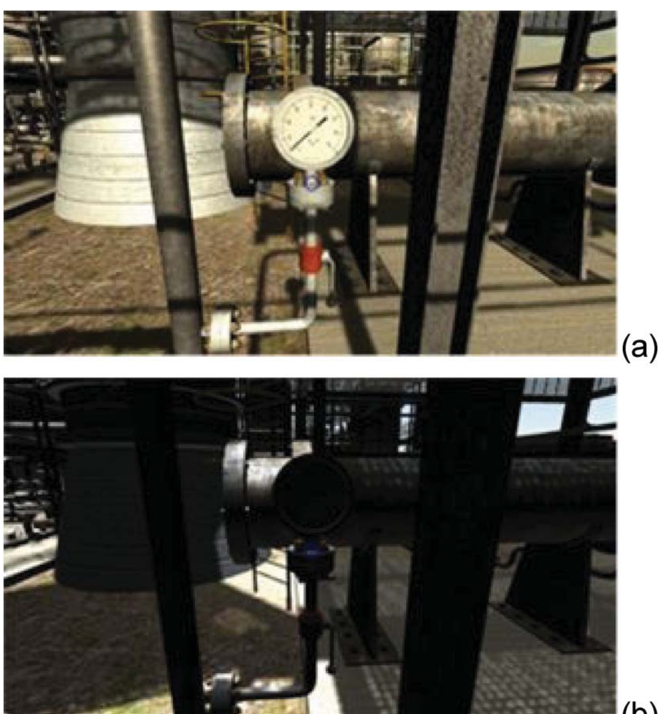


**FIGURE 6** Pressure gauge in a crude oil refinery appears to be different: (a) at midday and (b) at sunset.

Finally, concerning crew-coordination complexity, VRTS allows the crew of operators to experience a stressful situation and resolve it by working in teams, replicating exactly the same working procedures adapted in real plants (Kontogiannis, 1996; Driskell & Johnston, 1998/2006; Kluge, 2014). In such a VRTS training scenario, a crew of operators trains how to communicate the abnormality, to weigh and analyze the parameters, and to develop a shared mental model to reach correct decisions capable of averting the impact of the simulated accident under time pressure (Nazir et al., 2013b).

In summary, several—regrettably unrelated—studies have shown that the use of VRTS has advantages over other training environments as listed above, but a comprehensive (e.g., meta-analytic) approach is missing, and the field is still relatively young compared to the use of OTS, which has existed for decades. Further efforts to determine the long-term benefits of using VRTS, as well as the impact on HF constructs of general interest, are still needed.

As introduced in the section on OTS, there are challenges in the use of VRTS as well. One is the unclear benefits associated with this training method at the managerial level. This lack of evidence may lead to an inadequate use of VRTS without much consideration of what has been learned about cognition, factors affecting the learning process, and how to best support skills acquisition effectively (Salas et al., 1998). Although some advantages were highlighted, the learning process has to be carefully designed based on what is known about the cognitive load (Wickens, 1992; Sweller, 2006) that might be imposed on the learner while learning in the VRTS and which is detrimental to an efficient acquisition of skill (Wickens, 1992; Sebok et al., 2002). Thus, it is not simply VR technology that contributes to effective learning (Sebok et al., 2002) but the comprehensive application of principles that underlie the science of training (Salas & Cannon-Bowers, 1997), such as guided versus non-guided training, and active versus passive learning and presence (Sebok et al., 2002; Frank & Kluge, 2014). Additionally, the VRTS environment might be used, or even misused, if not properly designed for integrating with many training objectives at the same time, such as the acquisition of a mental model, reducing the mental workload, and enhancing the distributed situation awareness. VRTS incorporates the possibilities to achieve the objectives listed in Table 1, but training sessions need to be purposefully and subsequently designed such that learners are not overwhelmed by too many tasks to be managed in parallel.

In that respect, operators need to be pre-trained, for example, to become familiar with the use of the interactivity, immersivity, and spatial features. In studies conducted by Nazir et al. (2013b, 2014), where VRTS was used, most participants indicated that a more extensive pre-training session for interactivity might have improved their performance and associated learning benefits. The issues raised indicated that the use of VRTS does not "guarantee" a valid training per se but depends on several considerations, such as balancing the cognitive load of the learning task in relation to the learner's prior experience. This requires, for example, the use of scenario design parameters that support psychological fidelity, which is the extent to which the training environment prompts the essential underlying psychological processes relevant to key performance characteristics in the real-world setting (Kozlowski & DeShon, 2004) but without putting too much stress on the learner. A balanced integration between existing OTS and modern VRTS has yet to be developed that can facilitate the training objectives highlighted in this work without over-demanding the cognitive resources of the trainees.

Thus, OTS and VRTS have associated advantages and disadvantages in light of the learning theories and arguments aforementioned, and it is not easy to recommend either of these as the ultimate training solution to fill the void between training affordances and operator's demands.

## CONCLUSIONS

The purpose of this article was to point out the missing link between training needs of industrial operators, existing learning theories, and current training practice, as well as to highlight possible resolutions. A "one-size-fits-all" approach is not the solution for training in the process industry, as there are several parameters/factors to consider before determining the optimal training for operators that face dynamic and complex tasks. It is proposed that the significant advancement in the applications of process control techniques calls for a new mindset in terms of training industrial operators. Advanced training methods and environments can be one way of helping the operator. This article may stimulate further research on these topics that can lead to answers to some of the research questions concerning the best compromise between OTS and VRTS. This compromise should be framed in terms of optimal operator preparation and reduction of mental workload to understand and operate both MPC and RTO. An optimal integration between OTS and VRTS would allow improving the quality of operator training with respect to a number of intrinsic features of plants/processes, such as of variables coupling, dynamic effects, non-transparency, conflicting goals, and crew coordination in both normal and abnormal situations.

Salas and Cannon-Bowers (1997) posed the question "Why should organizations care about the science of training?" (p. 75). Their answer was that training is a key component in building and maintaining an effective employee workforce, which, in turn, drives various metrics of corporate well-being. They concluded that much is known about training individuals and teams and that links effective training to improving performance, reducing errors, saving lives, and enhancing safety. Hopefully valuable arguments have been presented for implementing the science of training in the training practice of operators in process industries to help improve performance, reduce error, and enhance safety.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

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