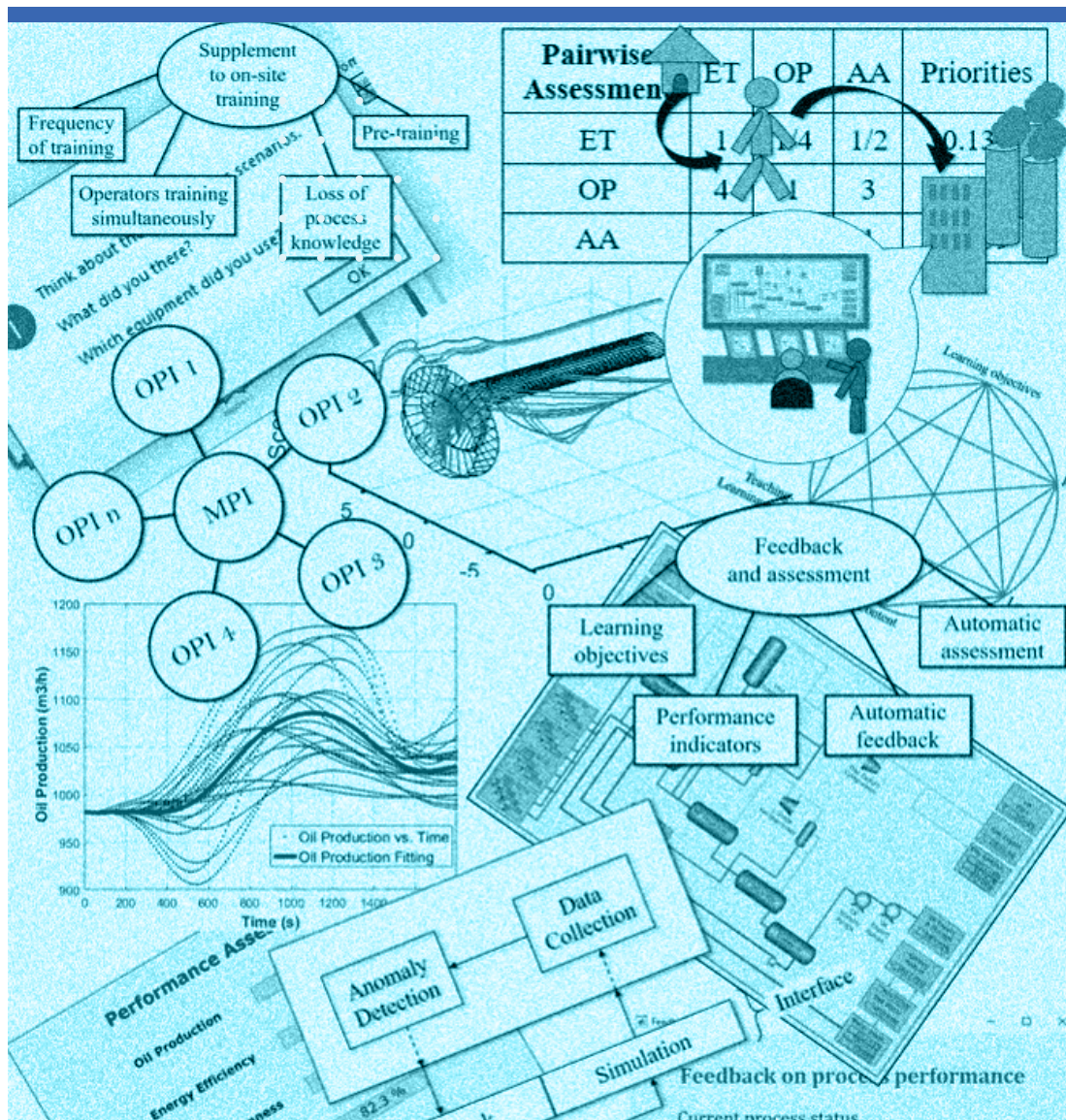


Laura Andreína Marcano Canelones

On Process Simulation and Learning Technologies





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On Process Simulation and Learning Technologies

A PhD dissertation in
Process, Energy and Automation Engineering

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*A mi hermosa Venezuela, tierra maravillosa que me vio nacer...
Este es mi granito de arena para mantener tu nombre en alto,
para que un día logremos que seas tan grande como puedes y mereces ser.*

*To my beautiful Venezuela, wonderful land that cradled me at birth...
This is my bit to keep your name high, so that one day
we will make you as great as you can and deserve to be.*

*Til mitt kjære Venezuela, din vakre favn har vugget meg siden fødselen...
Dette er mitt bidrag til å holde navnet ditt høyt, i håp om at
vi en dag får se deg skinne slik som du fortjener.*

Preface

This thesis is submitted as partial fulfilment of the requirements for the degree of Doctor of Philosophy (PhD) at the University of South-Eastern Norway (USN). This work was funded by OsloMet – Oslo Metropolitan University, where I had the great opportunity of working as a PhD candidate in the Department of Mechanical, Electronics and Chemical Engineering (MEK) from September 2015 to August 2019.

The PhD road has been one of the most intense experiences that I have ever lived. It was not easy, but even though, it was great. The work described in this dissertation would not have been possible without the support of many intelligent, skillful, and above all kind people. Therefore, I would like to take the opportunity to express my gratitude to them:

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Marielviz and Sandalio, my parents, everything I am is thanks to them, thanks to their effort and hard work, thanks to their constant support and encouragement, and thanks most of all to their endless love. You both are my biggest motivation; I love you!

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Ana Sophia, the queen of my heart, your existence, little girl, makes everything worth it!

Oslo, 9th June 2019

Laura Andreína Marcano Canelones

Abstract

This thesis provides additional insights into the field of simulator training. Although numerous studies have identified how to improve simulator technologies and team training practices, little analytic attention has been paid to how to enable more independent training. In this PhD work, different methodologies and technologies were tested to evaluate their effect on trainees independence during simulator training.

Simulator training is widely implemented in different industries and academia as a training tool. Usually, in a simulator training session there is an expert instructor who guides the users through the learning process with the simulator by giving verbal feedback, pausing the scenarios if necessary, and sometimes by developing evaluations. The presence of an expert instructor during simulator training is of great importance for the trainees, if not indispensable, trainees rely on the instructor's support. This dependency on instructors has become a significant challenge both in the industry and academia, given that there is a deficit of instructors, either because of retirement or because of the continually increasing training demand. Therefore, it is critical to develop new technologies and methodologies that can help trainees be more independent and rely less on the instructor, which in turn will also decrease the load of the available instructors.

The main objective of this PhD thesis is to contribute to a solution to the challenge associated with the deficit of expert instructors in simulator training. Feedback is what makes the instructor so valuable. Therefore, it is the main focus of this work, developing a technology able to provide automatic feedback to trainees for improving individual technical skills, so that they can be more independent from the instructor's help.

Three different automatic feedback methods were developed, two based on Operator Performance Indicator values and one based on data mining. All the methods were developed using the dynamic simulator K-Spice, from Kongsberg Digital. The first method is an automatic assessment tool that provides numeric feedback. The second method gives prompt feedback in the form of pop-up windows. The third method is an online automatic feedback tool that provides information about the process status and offers a suggestion if it is requested. For the testing of each automatic feedback method, three simulator training modules were planned. The data gathered from each experiment consisted of observation notes, questionnaires, and pretest and posttest results. The participants of the study were master's students from the University of South-Eastern Norway and bachelor students from OsloMet – Oslo Metropolitan University.

Further, the effect of trainees' preparation before attending the simulator training session was also evaluated, this with the aim of studying whether preparation allows

trainees to be more independent and request the instructor's help less often than trainees who do not prepare. It was noticed that trainees who prepared themselves for the simulator training session considered they needed the instructor's help less frequently than the trainees who did not prepare. Moreover, trainees that prepared for the session had a better performance in the pretest than those who did not.

The overall results show that automatic feedback does have a positive impact on trainees performance. However, it could not be demonstrated that, in fact, it allows trainees to be more independent. Nonetheless, in the case of the online automated feedback tool, it did make trainees who use it feel more confident than those who did not. It is concluded that an effective automatic feedback tool is one that can match as much as possible the feedback that would be given by an actual instructor.

List of Publications

1. L. Marcano, F. A. Haugen, R. Sannerud, and T. Komulainen, “Review of simulator training practices for industrial operators: How can individual simulator training be enabled?,” *Safety Science*, vol. 115, pp. 414-424, 2019. doi: <https://doi.org/10.1016/j.ssci.2019.02.019>
2. L. Marcano and T. Komulainen, “Constructive Assessment Method for Simulator Training,” in *Proceedings of The 9th EUROSIM Congress on Modelling and Simulation, EUROSIM 2016, The 57th SIMS Conference on Simulation and Modelling SIMS 2016*, 2018, no. 142, pp. 395-402: Linköping University Electronic Press. doi: 10.3384/ecp17142395
3. L. Marcano, T. M. Komulainen, and F. A. Haugen, “Implementation of performance indicators for automatic assessment,” in *Computer Aided Chemical Engineering*, vol. 40, M. G. Antonio Espuña and P. Luis, Eds.: Elsevier, 2017, pp. 2971-2976. doi: <https://doi.org/10.1016/B978-0-444-63965-3.50497-9>
4. L. Marcano, F. A. Haugen, R. Sannerud, and T. Komulainen, “Effect of Automatic Feedback on Large-Scale Simulator Training,” Submitted for publication in *IEEE Transactions on Learning Technologies*, IEEE, 2019.
5. L. Marcano, A. Yazidi, D. Manca, and T. M. Komulainen, “Using the concept of data enclosing tunnel as an online feedback tool for simulator training,” in *The 59th Conference on Simulation and Modelling (SIMS 59)*, Oslo Metropolitan University, Norway, 2018, pp. 132-139: Linköping University Electronic Press. doi: 10.3384/ecp18153132
6. L. Marcano, A. Yazidi, D. Manca, and T. M. Komulainen, “Methodology for Building a Data-Enclosing Tunnel for Automated Online-Feedback in Simulator Training,” Submitted for publication in *Computers & Chemical Engineering*, Elsevier, 2019.

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Acronyms

Acronym	Description
AHP	Analytic Hierarchy Process
CROP	Control Room Operator
DCS	Distributed Control System
DTW	Dynamic Time Warping
FM	Feedback Method
FN	False Negatives
FP	False Positives
GUI	Graphical User Interface
KPI	Key Performance Indicator
MEC	Minimum Enclosing Circle
MPI	Main Performance Indicator
OPI	Operator Performance Indicator
PAA	Piecewise Aggregate Approximation
PCA	Principal Component Analysis
SAX	Symbolic Aggregate Approximation
STM	Simulator Training Module
TN	True Negatives
TP	True Positives

1 Introduction

1.1 Background

Simulator training refers to the implementation of models that represent real phenomena and processes as a learning tool; it enables the possibility of training under realistic and engaging settings, to practice relevant skills as many times as needed, and it provides safe environments for practicing tasks that are dangerous to perform in the real world, or that rarely occur [1], [2]. Simulators have been used for training in different fields for decades. Two relevant fields that rely on simulator training are the industry, where simulators are used for personnel training, and academia, where simulators are used to reinforce students' education.

Whether in academia or industry, the ultimate goal of simulator training is for users to learn. However, there is a different approach depending on the area of implementation. In the industry, there is more emphasis in simulators to be a cost-effective learning tool, while in academic settings, the development of concepts has particular importance [3], meaning achieving learning goals and understanding of complex processes and systems. The following subsections describe simulator training in the industry, simulator training in academia and the importance of feedback in simulator training.

1.1.1 Industrial Simulator Training

The airline industry and the military are among the first areas that started to implement simulator training; the first flight simulator was designed in 1929 [4], [2]. The nuclear industry is also a long time user of training simulators; the first control room simulator was put in service in the 1970s [5]. Moreover, due to the high risks related to nuclear operations, in many jurisdictions simulator training has become a legal requirement for the plant operators [6], [5]. Later, in the early 1990s simulator training became a common practice in the chemical industry as well [7]. According to Kluge et al. [4] in the late 1970s oil and gas well-drilling simulators started to be in use for training rig personnel. Nowadays, in Norway, simulator training is a mandatory requirement by the Norwegian Law for petroleum process operators [8], [9]. In March 2019 a detailed market study on operator training simulators was published [10]. The report indicates that the operator training simulator market is expected to exceed USD 20 billion by 2025.

Industrial simulator training for operators mostly refers to on-site training for control room operators (CROPs). On-site training means that the operators need to travel to the training facilities. Commonly the training takes place in a room

1 Introduction

that replicates the actual process control room with all the necessary equipment (hardware and software) and furniture [11]. The training room also includes a user interface that shows a distributed control system (DCS) resembling the real process. Figure 1.1 shows the training room at Equinor ASA, Stjørdal. This allows the operator to learn and understand the process through hands-on training of normal operations, and different kind of scenarios such as start-ups and shutdown, malfunctions and troubleshooting, abnormal situations and emergencies [11], [12], [13], and all this without compromising the safety of the operators, of the process, or the environment.



Figure 1.1: Simulator Training Center - Equinor ASA, Stjørdal. Photographed by the author on December 01, 2015.

An expert instructor typically leads the industrial simulator-training. The instructor usually is an experienced operator, which is a significant advantage thanks to the broad knowledge they can share with the trainees. The instructor gives feedback to the trainees and guides them through the training scenarios. Therefore, the presence of the instructor during simulator training is essential. Furthermore, the instructor takes care of starting or pausing the training scenario. Commonly, the instructor also takes care of the assessment of the performance of the operators, once they have finished the training tasks. The instructor indicates what they did correct and what they did wrong [14]. Another important function of the instructor is to help trainees reflect on what they have done, and on how they could improve their performance and solve the scenarios more efficiently.

1.1.2 Academic Simulator Training

Simulators have also been widely used for academic purposes since early dates as the 1970s [15]. The implementation of simulators as a learning tool can be found in many different educational levels from high school [15], [16] to higher education [17], [18]. Also, academic simulator training can be found in many different fields such as science education [19], engineering [20], statistics [21] and healthcare [22].

The implementation of simulators in academia has a significant number of benefits certified by extensive research, hence its fast spread in so many academic fields.

Some of these benefits include the improvement of students understanding of difficult topics using realistic computer models, enhanced student awareness in designing of process units, and more practice-based learning that can even be remotely [17], [20], [23]. Research also shows positive results when implementing simulators as a pre-laboratory training; it is an effective way of extending the scope of laboratory work, and it gives insight to the selection of optimal process parameters since it works as a visualization tool [15], [18], [19]. Rutten et al. [19] indicate that simulations have a significant influence on the effectivity of real lab exercises when they are implemented as a preparatory activity for the lab. Moreover, the use of simulators represents an excellent alternative for schools with few resources that cannot afford actual laboratory equipment. With the use of simulators students do not have to miss the entire laboratory experience [16].

In general, the use of simulators in academia is perceived as a way to improve traditional instruction, as a supplement to conventional practices to enhance students learning outcomes. Further, learning with simulations allows students to practice under more realistic situations, which prepares them better for the actual work life. Wankat [24] indicates that since many commercial simulators are commonly used in work settings, it is necessary to ensure that simulators are included in engineering educations. In the case of highly industrialized countries, high-fidelity process simulators are an essential tool for process and automation engineering students since many of them will be working in the industry after graduation[23]. Therefore, academic simulator training also works in favour of the industrial community that seeks to employ significantly capable engineers [17]. Simulator training in academia can be of benefit for the industry since it leads to industry-ready graduates and it can develop collaboration between university and industry [25].

1.1.3 Feedback in Simulator Training

In simulator-training, feedback refers to any type of guidance that trainees may receive while using the simulator or after using the simulator and finishing a task. In the industry, trainees receive feedback mainly from the instructors. It is the instructor who evaluates the trainees and discusses with them their performance after the training is completed. In academia, the role of the instructor is usually taken by the teacher; the teacher guides the students through the simulation tasks and evaluates the their development. However, there are cases in which academic simulator training is implemented as an extra or secondary task and not as part of the curriculum. In these cases, students are usually asked to develop the simulation tasks by themselves, and it can be their peers or senior classmates who give them feedback [24].

Feedback is critical in simulator training; it is a remarkable fact already noticed from early research. Veenman et al. [26] indicate that “simulations can be a powerful tool if they incorporate instructional guidance.” Their results confirm that giving guidance to trainees, so they reflect on their actions during a simulation task, improves their performance. Nowadays, many studies continue emphasizing and demonstrating the importance of feedback in simulator training [2], [22], [27].

1 Introduction

One of the many advantages of simulator training is that it allows for practicing and repetition as much as needed. However, the benefits of practicing and learning from errors cannot be utterly leveraged if they are not combined with relevant feedback that guides the user to interpret their results [4], [2].

According to Kolb [28], learning is a four-stage cycle: concrete experience, reflective observations, abstract conceptualization, and active experimentation, as shown in Figure 1.2. Based on Kolb's experiential learning cycle, feedback takes place during the reflective observation stage. Feedback generates valuable information that helps trainees to assess deviations from the desired goal. It provides the basis for evaluating the consequences of an executed action and reflecting on whether or not the action taken was beneficial for reaching the desired goal. Hence, feedback plays an essential role in the learning process.

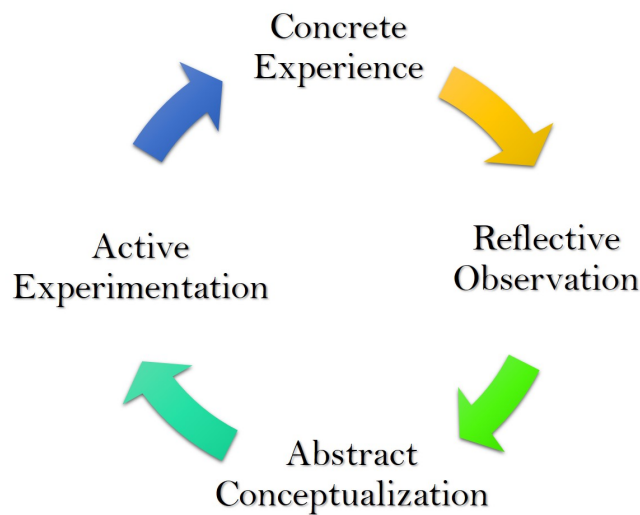


Figure 1.2: Kolb's Experiential Learning Cycle.

1.2 Problem Statement

Nowadays, continuous technological development and modernization come together with an increasing demand for training, so that trainees can understand and fully utilize all the advantages new technology brings. High demand for training equals a high demand for instructors and skilled people that can guide and teach novice users. Unfortunately, research shows that the amount of qualified instructors is not enough for fulfilling the training demand, not just in the industry [27], [29] but also in academia [30], [31]. A survey on simulator training in the Norwegian oil and gas industry [32] reports that low availability of instructors is one of the main factors that restrict simulator use in the industry, thus indicated by 36 % of the survey's respondents.

Further, the delivery of effective simulator training involves an investment on significant resources; this is especially true in the case of the industry where substantial

costs must be covered such as the time required by the trainees and the instructors to undertake the training, in addition to travel and accommodation costs for both [3]. Also, the cost was indicated as one of the restrictive factors for training simulators by 19 % of the respondents of the survey in the Norwegian oil and gas industry [32].

Therefore, a proper scientific study is needed to evaluate how to cope with the low availability of instructors and the high cost related to the mobility of the trainees to undertake simulator training.

1.3 Aim of the Project

The main objective of this investigation is to contribute to a solution to the low availability of qualified instructors for simulator training. Therefore, the primary hypothesis evaluated in this research is the following:

- H1: Automatic feedback allows trainees to be more independent during simulator training.

The following hypotheses will also be tested to reach the specific objectives that will lead to the primary goal:

- H2: Process status can be summarized using relevant performance indicators.
- H3: Relevant performance indicators help trainees solve process upsets independently.
- H4: Prompt feedback messages can be developed based on performance indicators.
- H5: Prompt feedback messages help trainees understand and solve abnormal process situations independently.
- H6: Trainees' preparation before the simulator training session allows them to be more independent during the session.
- H7: The way feedback is presented to trainees affects its efficiency.
- H8: Data mining leads to the development of non-deterministic feedback methods.

1.4 Outline of the Thesis

This thesis is divided into five main chapters. In Chapter 2 a brief literature review is presented, together with an overview of the most relevant theoretical background implemented in this work. The research methods and materials used are described in Chapter 3. Chapter 4 explains the contribution of this work, a summary of the results obtained, and the discussion of the results. Finally, the conclusions and future work are discussed in Chapter 5 and Chapter 6, respectively.

Figure 1.3 shows a diagram of the sequence of the articles on which this thesis is based. Each quadrant represents one article and shows the main topic developed in it and the hypothesis addresses by it. It can be seen that Article 1 (A1) is a literature review. Article 2 (A2) deals with the development of an automatic feedback method based on OPIs; this article addresses hypothesis two (H2). Article 3 (A3) has to do with the implementation of the automatic feedback method developed in A2; it addresses hypothesis one (H1) and three (H3). Article 4 (A4) presents a comparison of the implementation of different automatic feedback methods; it addresses hypothesis one to seven (H1-H7). Article 5 (A5) presents the development of an automatic feedback method based on data mining (one of the methods implemented in A4), it addresses hypothesis eight (H8). Finally, Article 6 (A6) is a further development of A5, hence it also addresses H8.

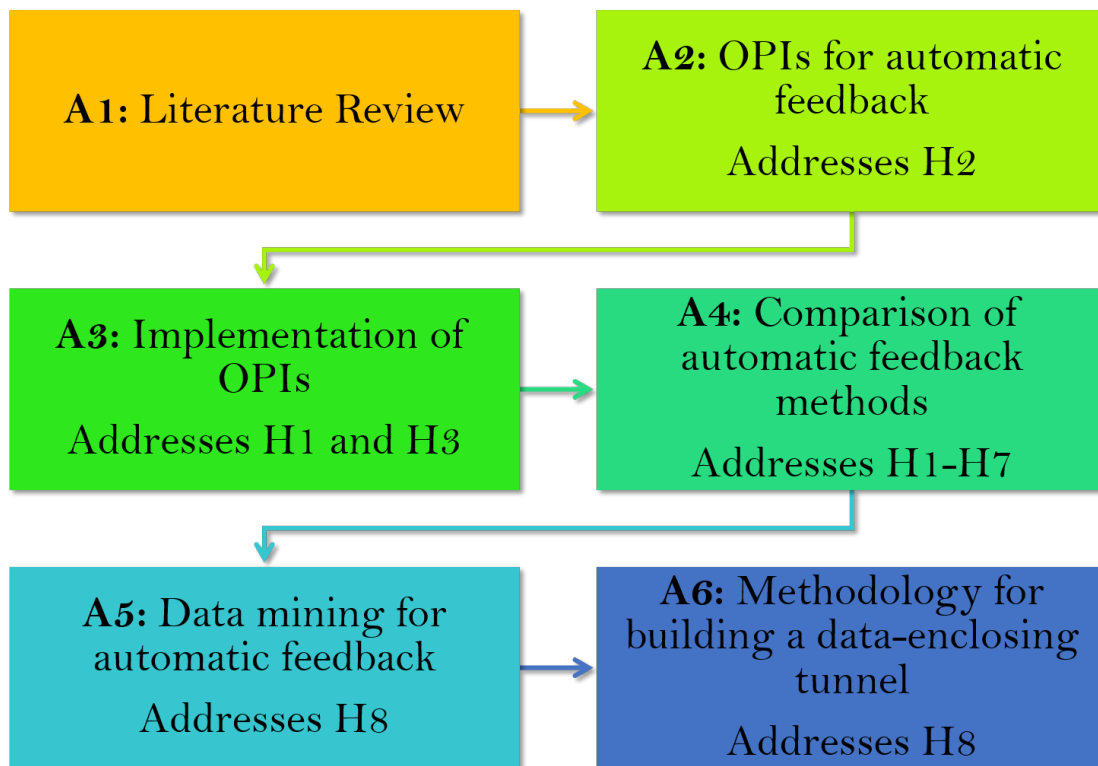


Figure 1.3: Sequence of the articles on which this thesis is based.

2 Literature Review and Relevant Theoretical Background

The aim of this chapter is to give a background overview of the work carried out in this research project. First, a summary of the literature review on simulator training practices and methodologies is presented. Next, a brief theoretical background is provided. The theoretical background is divided into two sections. The first section corresponds to the pedagogical models and concepts implemented in this research work, and the second section corresponds to the technical and numerical concepts.

2.1 Literature Review

One of the contributions of this PhD thesis is a thorough literature review on simulator training and how individual simulator training can be enabled (Article 1). Therefore, this section only presents a brief summary of what was reported there.

One common factor that can be found throughout the literature is the general agreement that there is a wide range of benefits in simulator training. Some of the benefits more often mentioned in the literature are that simulator training offers a realistic virtual environment, training flexibility, higher process understanding, the possibility of training under emergency or rare situations, and continuous practice [11], [29], [33].

The main findings of the literature review were presented into three specific topics in the article; these are summarized below:

Supplement to on-site training: Results from the literature review showed the following issues with the traditional simulator training practices on-site:

- at the training center there is low frequency of training (usually once a year, for three to five days) [4], [32],
- the number of operators that can train at the same time is limited (usually two to six operators) [7], [11], [34],
- knowledge is lost with the retirement of expert operators/instructors [7], [27], and
- pre-training is not implemented regularly.

2 Literature Review and Relevant Theoretical Background

Therefore, individual simulator training could help to cope with these issues. With individual simulator training, trainees can train more often because they wouldn't need to be at the training center to do so. More operators could be trained at the same time to develop individual technical skills. Tools for individual simulator training should record and save operators' performance data. In this way, examples of different performances will not be lost by the moment operators retire and can be used to help future generations of operators. Finally, individual simulator training could be established as pre-training of individual technical skills so when trainees are at the training center, the focus can be on team training.

Feedback and assessment: Feedback and assessment are widely mentioned in the literature, these are critical parameters of effective training [2]. To give relevant feedback and to develop useful assessment methods, it is necessary to establish the goal trainees are supposed to reach. In this way, feedback can be based on indicating the trainee whether they are approaching or deviating from the goal. The same reasoning concerns the assessment; a final evaluation should be based on how close or far the trainee was from reaching the expected goal. Furthermore, sound and clear learning objectives lead to successful simulator-training because objectives help trainees be aware of what they are supposed to achieve, which helps to keep them motivated because they will have a purpose, and they can orient their efforts towards achieving it [1], [7], [35], [36].

To quantify or determine whether the training objectives are being fulfilled or not there exist special parameters. These parameters are commonly known as performances indicators. There are different types of indicators depending on what needs to be evaluated. Some indicators are mainly related to process and plant performance; these are known as Key Performance Indicators (KPIs) [14]. Other indicators are closely related to trainees development and characteristics; these are known in the literature as Operator Performance Indicators (OPIs) [33]. The implementation of well-defined performance indicators helps to develop objective and repeatable assessment, i.e., unbiased assessment [14]. Furthermore, adequate and relevant feedback can also be based on performance indicator values.

The implementation of performance indicators can be the basis for automatic feedback and assessment, which are both topics frequently mentioned in the literature. It is suggested, for example, that effective feedback methodologies embedded in simulator-based training can enhance learning outcomes [1]. Regarding assessment, it is indicated that to deliver an unbiased evaluation of the operators' performance; this must be based on objective and measurable parameters [14].

Therefore, to develop effective individual simulator training, sound learning objectives must be established, and sound and clear automatic feedback and assessment must be guaranteed.

Human-centric perspective: A human-centric perspective refers to actions that focus on the user's needs or opinions when developing and improving technologies or training methodologies. It can be found in the literature a common concern about how simulators are designed without taking into account individual training needs; they are usually technology-centered [1], [35]. As a consequence, only some of the users benefit from simulator-based training. Research suggests that there are great

benefits in implementing human-centric perspectives when developing training systems, involving users from different fields results in an exhaustive evaluation of the models from different points of views [37]. Moreover, the literature suggests that the quality of training does not depend only on the technology used. Successful training also depends on the development of simulation designs and training exercises based on trainees' needs, user-friendly technologies that can be used by a broader range of trainees, and human factor considerations. Therefore, different learning strategies must be evaluated, and of course, the motivation of the trainees towards the training must be taken into account as well. Consequently, these are points that must also be considered to develop effective individual simulator training.

2.2 Theoretical Background

This research is based on three different simulator training modules. The planning and execution of these simulator training modules required the implementation of pedagogical knowledge. The activities prepared and the tools used in each module required the application of technical and numerical knowledge. In this section is explained what pedagogical and technical insights were implemented in this study.

2.2.1 Pedagogical Background

The Didactic Relation Model was implemented to plan and organize the simulator training modules carried out in this PhD work. The type of feedback given by two of the feedback methods developed was reflective, to help trainees meditate on their actions. Both of these pedagogical methods are described in this section.

The Didactic Relation Model

The Didactic Relation Model is an educational tool for planning and reflection. It helps educators analyzing their planning, teaching, and evaluating activities [38]. The model was initially developed by Bjørndal and Lieberg [39] in 1978. Given that the model is the basis for designing the simulator training courses at the training centers [8], [32], [23], it was used in this investigation to organize and plan each of the Simulator Training Modules. In 1998 Hiim and Hippe [40] built upon the original model and identified six categories: learning objectives, learners' prerequisites, content, teaching-learning methods, resources, and evaluation. Figure 2.1 shows how all the categories are interrelated, it can be seen that changes in one category can influence the other categories.

Below a brief description of each of the categories of the model is presented. The descriptions presented are based on what is explained by Tobiassen [41].

- *Learning objectives* refer to what is expected the trainees to achieve. In simulator training, the learning objectives are established according to the aim of the simulation tasks, and the knowledge that can be obtained from these tasks.

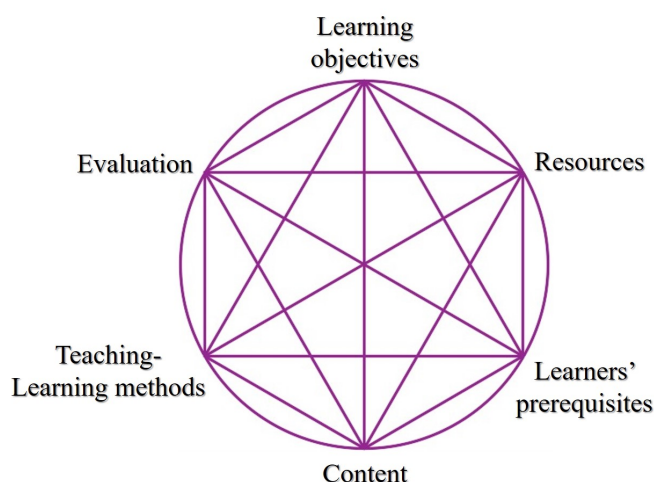


Figure 2.1: The Didactic Relation Model.

- *Resources* are the external conditions for learning and teaching. It refers to taking into consideration matters such as the room, the time disposition, learning materials, equipment, and the like. In the case of the simulator training modules some examples of the resources implemented are the room where the sessions were carried out, the time allocated for the sessions, the training material, and the software used.
- *Learner's prerequisites* refer to the trainees' knowledge, motivation, skills, and attitudes. It also relates to the trainees' social qualities, such as their ability to cooperate and work in groups. For the simulator training modules, one of the requirement was that trainees should understand basic process control terms. Also, they should know the functionality of some of the most relevant process equipment.
- *Content* refer to the main topics that are covered with the learning activity. It must be chosen in relation to the learning objectives. One of the main topics addressed in the simulator training modules was the analysis of the dynamic responses of the process, due to changes in the system.
- *Teaching-Learning methods* include trainees' actions and instructors' actions. It refers to the processes that lead to learning. Some of the methods implemented in the simulator training modules include pre- and post-tests, briefing and debriefing, automated and instructor feedback, hands-on experience in the simulator.
- *Evaluation* refers to control or measure the learning and the teaching as well. It includes the assessment of the trainees' progress and the teaching methods. In the case of the simulator training module, the evaluation of the trainees was made with pre- and post-tests and the trainees gave their opinions on their experience answering questionnaires.

Reflective Feedback

Hattie and Timperley [42] define feedback as information provided by an agent regarding aspects of someone's performance or understanding. This agent can refer to anyone or anything able to deliver the information, e.g., teacher, peer, book, parent, experience, simulator.

For feedback to be considered effective, it should help trainees improve in knowledge, skill, or self-reflective behavior [43]. Also, research indicates the feedback must be timely; it should come as close to the instructional event as possible so that there is still time for the trainees to act on it [43], [44]. In the literature different types of feedback can be found, below we describe the four main categories defined by Hall and Simeral [43] based on a simulator training perspective:

- *Positive comments:* It refers to positive, affirming feedback, it can be expressed in different forms, including specific praise.
- *General or specific observations:* This type of feedback is meant to report only what was observed, without including the observer's opinion about it. These observations can be used later during the debriefing, after the simulator training session, as an entry point for a reflective discussion with the trainee.
- *General or specific suggestions:* It refers to more direct feedback, which can include either affirmation of right actions or recommendations about possible mistakes.
- *Reflective prompts:* This type of feedback refers to the use of questions designed to create a reflective thought on the part of the trainee. These questions are intended to urge the trainee to think critically about their actions during the simulator training task.

2.2.2 Technical Background

Three feedback methods were tested in this research, each in one of the simulator training modules. The first two feedback methods are based on the same principle, using OPI values to give information to the trainees about process status. The last feedback method developed is based on a data mining approach; different techniques were implemented. Hierarchical clustering was used to classify generated training data into good and bad execution paths. PCA was used to reduce the dimension of the data. The Minimum Enclosing Circle (MEC) problem was implemented to find the MEC of the reduced data projected on a 2D plane. The sliding window algorithm was applied to take averages of the reduced data along the time length of the scenario. Finally, the confusion matrix was used to determine the performance of the feedback method developed based on data mining, and to compare its performance with that of other approaches. Below an overall description of how to use OPIs to give process information and each of the data mining techniques mentioned above is presented.

Operator Performance Indicators as the Base for Automatic Feedback

Different OPIs can be selected to create one main performance indicator (MPI) that can give a general assessment of the status of the process. The individual OPIs chosen to form the main performance indicator must be relevant enough so that altogether represent valuable information about the process. Figure 2.2 shows a representation of this.

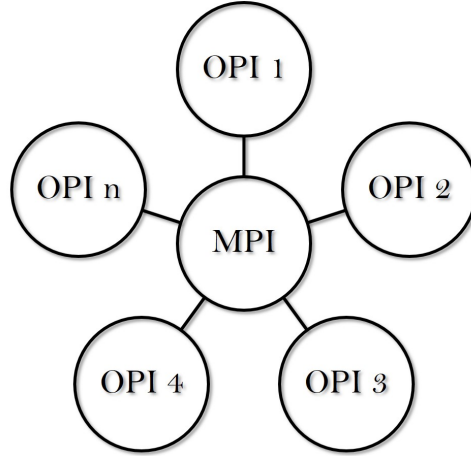


Figure 2.2: Main performance indicator and complementary OPIs.

Once the most suitable OPIs are selected, it is necessary to assign different weights to each of them, given that not all OPIs have the same relevancy. The contribution of each OPI can be determined using the Analytic Hierarchy Process (AHP) [45]. The AHP consists of creating a square matrix based on a pairwise comparison of the factors. The values that indicate how many times one factor is more relevant than another are according to Saaty's scale, that Saaty [45] defines as the fundamental scale of absolute numbers, where 1 indicates equal importance, and from there up, the higher the number, the higher the importance of one factor with respect to another. Finally, the matrix entries satisfy the condition $a_{i,j} = 1/a_{j,i}$. Then, the contribution of each OPI can be found calculating the priority vector of the pairwise comparison matrix, which correspond the normalized principal eigenvector of the matrix [46].

Brunelli [46] explains the calculation of the priority vector of the pairwise comparison matrix as follows. Taking a matrix \mathbf{A} whose entries are ratios between weights and multiplying it by \mathbf{w} , the following is obtained:

$$\mathbf{A}\mathbf{w} = \begin{pmatrix} w_1/w_1 & w_1/w_2 & \dots & w_1/w_n \\ w_2/w_1 & w_2/w_2 & \dots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \dots & w_n/w_n \end{pmatrix} \begin{pmatrix} w_1 \\ \vdots \\ w_n \end{pmatrix} = \begin{pmatrix} nw_1 \\ \vdots \\ nw_n \end{pmatrix} = n\mathbf{w}$$

$\mathbf{A}\mathbf{w} = n\mathbf{w}$ indicates that n and \mathbf{w} are an eigenvalue and an eigenvector of \mathbf{A} , respectively. Brunelli [46] indicated that knowing that the other eigenvalue of \mathbf{A} is 0, and has multiplicity $(n - 1)$, then n is the largest eigenvalue of \mathbf{A} . If the entries of \mathbf{A} are ratios between weights, then the weight vector is the eigenvector of \mathbf{A}

associated with the eigenvalue n . According to [46], Satty proposed to extend this result to all pairwise comparison matrices by replacing n with the more generic maximum eigenvalue of \mathbf{A} . Then, vector \mathbf{w} can be obtained from Equation 2.1, for any pair comparison matrix \mathbf{A} :

$$\begin{cases} \mathbf{A}\mathbf{w} = \lambda_{max}\mathbf{w} \\ \mathbf{w}^T\mathbf{1} = 1 \end{cases} \quad (2.1)$$

where λ_{max} is the maximum eigenvalue of \mathbf{A} , and $\mathbf{1} = (1, \dots, 1)^T$.

Having the the priority vector \mathbf{w} , the main performance indicator can be calculated with Equation 2.2:

$$\text{MPI} = \sum_i R_i \cdot w_i \quad (2.2)$$

Where w_i is the weight of the i^{th} OPI. The term R_i can be calculated in two ways depending on the type of OPI and the type of simulation scenario:

- *OPI max*: If an OPI is supposed to be maintained to its initial value during the simulation scenario, or if it should reach a maximum, then Equation 2.3 should be used:

$$R_i = \frac{r_i}{r_{i,max}} \quad (2.3)$$

Where r_i corresponds to the actual measured value of the i th OPI, and $r_{i,max}$ is the maximum value required.

- *OPI min*: If an OPI must be kept at a minimum value, and below a maximum, then R_i is calculated with Equation 2.4:

$$R_i = \frac{r_{i,max} - r_i}{r_{i,max} - r_{i,min}} \quad (2.4)$$

Data Mining as the Base for Automatic Feedback

Han et al. [47] defines data mining as the process of discovering interesting patterns and knowledge from large amounts of data. There are different data mining techniques; below are described the ones that were implemented in this work.

Hierarchical Clustering: A hierarchical clustering model is a multilevel hierarchy of clusters, where each internal node represents a cluster that is divided into subclusters [48]. It groups data over a variety of scales by creating a cluster tree or dendrogram [49]. Figure 2.3 shows an example of a dendrogram; the figure was taken from Cichosz [48] (Figure 13.1, p. 354). Hierarchical clustering can be especially helpful when used as a form of preparation for other data mining tasks,

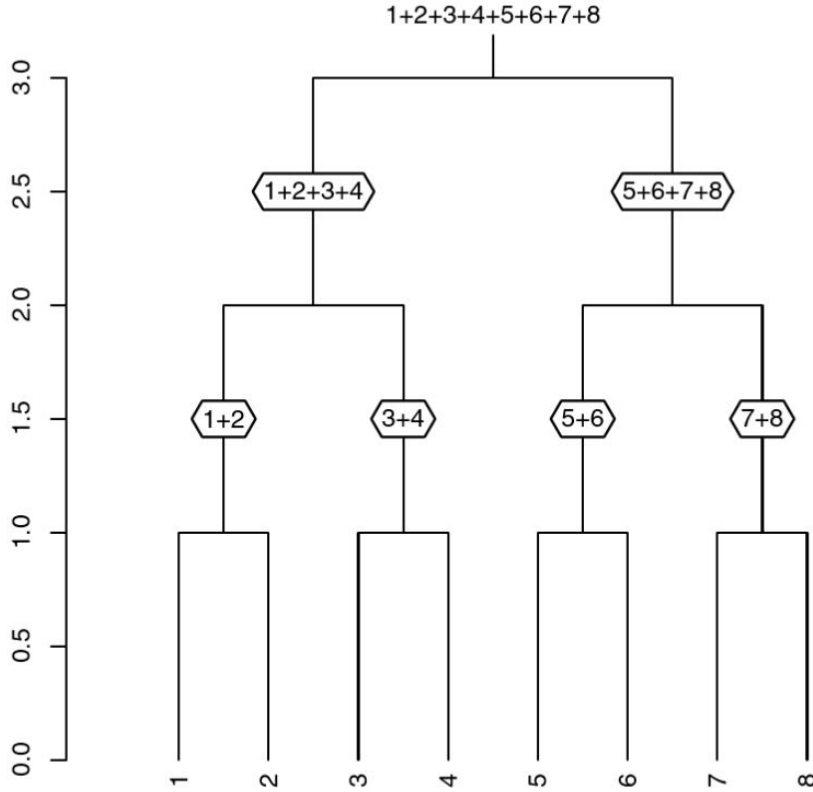


Figure 2.3: Illustrative dendrogram plot [48].

to decompose the domain [48]. Usually, hierarchical clustering algorithms can be implemented using arbitrary dissimilarity or similarity measures [48].

One similarity measure are distances, in this thesis, three methods for distance calculation were implemented:

- *Euclidean distance*: The Euclidean distance between two time series, X and Y , of the same length N , is defined as Equation 2.5. Figure 2.4a shows an intuitive representation of the Euclidean distance, the figure was taken from Lin et al. [50] (Figure 6, p.6).

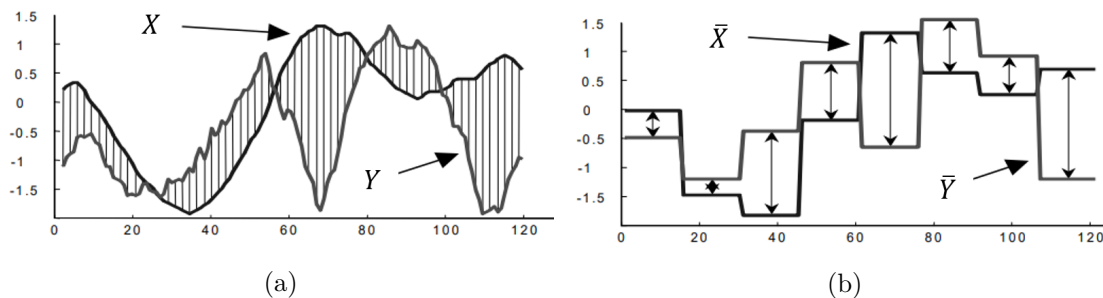
$$D(X, Y) \equiv \sqrt{\sum_{i=1}^N (x_i - y_i)^2} \quad (2.5)$$

- *Dynamic Time Warping (DTW)*: DTW is a method for measuring similarities between two time series; it finds the optimal alignment between two given sequences X of length N and Y of length M [51], where

$$X = x_1, x_2, \dots, x_n$$

$$Y = y_1, y_2, \dots, y_m$$

To align the sequences X and Y implementing DTW, an n -by- m matrix must be constructed. The (i^{th}, j^{th}) element of the matrix corresponds to



$$\begin{aligned} \hat{X} &= \mathbf{baabcbbc} \\ &\quad \updownarrow \updownarrow \updownarrow \updownarrow \updownarrow \updownarrow \updownarrow \updownarrow \\ \hat{Y} &= \mathbf{babcacca} \end{aligned}$$

(c)

Figure 2.4: Intuitive representation of the Euclidean, PAA, and SAX methods [50].

the squared distance $D(x_i, y_j) = (x_i - y_j)^2$, i.e., the alignment between the points x_i and y_j . To find the best match between the two time series, a path that minimizes the total cumulative distance must be retrieved through the matrix. The optimal path is the one that minimizes the warping cost [52], as shown in Equation 2.6:

$$DTW(X, Y) = \min \left\{ \sqrt{\sum_{k=1}^K q_k} \right. \quad (2.6)$$

Where q_k is the matrix element $(i, j)_k$ that also belongs to the k_{th} element of a warping path Q , which corresponds to a contiguous set of matrix elements that form a mapping between X and Y [52].

- *Symbolic Aggregate Approximation (SAX)*: The SAX algorithm finds similarities between series by transforming them into strings. The method reduces a time series of arbitrary length N to a string of arbitrary length w , ($w < N$, typically $w \ll N$). The alphabet used to transform the time series into strings also has an arbitrary length a , where $a > 2$. Before the raw time series is transformed into strings, there is an intermediate representation. First, the data is converted to Piecewise Aggregate Approximation (PAA), and then the PAA representation is changed into a discrete string [50].

To reduce the dimension of a time series X of length N via PAA, X is represented in a w -dimensional space by a vector $\bar{X} = \bar{x}_1, \dots, \bar{x}_w$. The i^{th} element of \bar{X} is calculated with Equation 2.7 [50]:

$$\bar{x}_i = \frac{w}{N} \sum_{j=\frac{N}{w}(i-1)+1}^{\frac{N}{w}i} x_j \quad (2.7)$$

Once the time series X has been changed into PAA, it can be transformed into a discrete representation. SAX uses a discretization technique that produces symbols with equiprobability [50]. The original time series (X and Y), used in the Euclidean distance, can be transformed into PAA representations, \bar{X} and \bar{Y} , using Equation 2.7. Next, a lower bounding approximation of the Euclidean distance between the original X and Y is obtained with Equation 2.8, this is illustrated in Figure 2.4b [50].

$$DR(\bar{X}, \bar{Y}) \equiv \sqrt{\frac{N}{w}} \sqrt{\sum_{i=1}^w (\bar{x}_i - \bar{y}_i)^2} \quad (2.8)$$

Finally, the data is transformed into the symbolic representation with Equation 2.9, where the MINDIST function returns the minimum distance between the original time series of two words, as illustrated in Figure 2.4c [50].

$$\text{MINDIST}(\hat{X}, \hat{Y}) \equiv \sqrt{\frac{N}{w}} \sqrt{\sum_{i=1}^w (\text{dist}(\hat{x}_i, \hat{y}_i))^2} \quad (2.9)$$

The $\text{dist}()$ function can be implemented using a table lookup (Table 2.1). Table 2.1 is for an alphabet of cardinality 4, the table was taken from Lin et al. [50] (Table 4, p. 6). The distance between two symbols can be read off by checking the corresponding row and column. For example, $\text{dist}(\text{a}, \text{c}) = 0.67$ [50].

Table 2.1: A lookup table used by the MINDIST function [50].

	a	b	c	d
a	0	0	0.67	1.34
b	0	0	0	0.67
c	0.67	0	0	0
d	1.34	0.67	0	0

Principal Component Analysis (PCA): PCA is a method of dimensionality reduction. The data that needs to be reduced may consist of several data vectors described by n dimensions. PCA searches for k n -dimensional orthogonal vectors that represent better the original data, where $k \leq n$. Thus, the original data is projected onto a smaller space. PCA combines the essence of the attributes creating a smaller set of variables, which usually leads to new interpretations of the data that were originally unnoticed [47].

Han et al. [47] presents the following basic procedure for PCA:

1. The input data are normalized. This step ensures that variables with large domains will not dominate those with smaller domains.
2. PCA determines k orthonormal vectors, these provides the basis for the normalized input data. These vector are known as principal components.

3. The principal components serve as a new set of axes for the data, and they are sorted in order of decreasing significance, which means that the first axis shows the most variance among the data, the second axis shows the next highest variance, and so on.
4. The data size can be reduced by eliminating the weaker components, i.e., those with low variance.

Minimum Enclosing Circle (MEC): The minimum enclosing circle problem, also known as Smallest Enclosing Circle (SEC), is defined as the circle with minimum radius that encloses a set of points in a plane [53]. Banik et al. [54] present the following definition of the MEC problem:

When the distance between a pair of points is measured in the L_2 metric (Euclidean metric), this gives rise to the notion of the Euclidean 1-center and the minimum enclosing circle (MEC) of a set of points. The Euclidean 1-center of a set of fixed points S is the center of the smallest circle that encloses all the points of S . More formally, if the Euclidean distance between any two points a and b in \mathbb{R}^2 is denoted by $d(a,b)$, then for a finite set S in \mathbb{R}^2 , the Euclidean 1-center of S is the point $\mathcal{E}(S)$ in \mathbb{R}^2 that minimizes the function $\lambda(q) = \max_{p_i \in S} d(q, p_i)$ over all the points $q \in \mathbb{R}^2$. The value of $\lambda(\mathcal{E}(S))$ is the radius of the MEC of S and is denoted by $r(S)$ [54].

Sliding Window Algorithm: Fumarola et al. [55] defines the sliding window algorithm as follows. Given a time point p , the set of elements arriving in the time period $[t-p+1, t]$ represent a slide B . Being B_i the i^{th} slide, the sliding window W_i associated with B_i is the set of w consecutive slides from B_{i-w+1} to B_i . The window moves forward by adding the new slide (B_i) and dropping the old one (B_{i-w+1}). The number of units of analysis that are added to (and removed from) each window is $|B_i|$ [55].

Confusion Matrix: A confusion matrix is a practical tool for analyzing the performance of a classification method [47]. The confusion matrix presents the results based on the following terms:

- **True Positives (TP):** These correspond to positive elements that were classified correctly.
- **True Negatives (TN):** These refer to negative elements that were classified correctly.

		Actual class		
		Yes	No	Total
Predicted class	Yes	TP	FP	P'
	No	FN	TN	N'
	Total	P	N	P+N

Figure 2.5: Confusion Matrix.

2 Literature Review and Relevant Theoretical Background

- **False Positives (FP):** These are negative elements that were incorrectly classified as positive.
- **False Negatives (FN):** These refer to positive elements that were incorrectly classified as negative.

TP and TN indicate that the classification method is doing things correctly, while FP and FN suggest that the classification method is doing something wrong [47]. Figure 2.5 shows a general structure of a confusion matrix. In the figure, P' corresponds to the total number of elements that were classified as positives, and N' to the total number of elements that were classified as positive.

3 Materials and Methods

3.1 Materials

3.1.1 SPSS

SPSS is a computer-based data management and inferential statistical analysis program. It means “Statistical Package for the Social Sciences” and was first launched in 1968, in 2009 SPSS was acquired by IBM. Since then it is officially known as IBM SPSS Statistics. It is widely used in many fields, such as psychology, sociology, market research, business, and government [56], [57].

Bronstad and Hemmesch [56] indicate that SPSS can accommodate large data sets with many thousands of variables and cases. Researchers can enter the data manually, or they can import them from other database or statistical programs, such as Microsoft Access, SQL Server, SAS, and Microsoft Excel. The software incorporates many analytic methods such as basic descriptive statistics, which is supported by the base package, nonparametric tests, and different parametric analyses. Simple analyses like the t test, one-way analysis of variance (ANOVA), correlation, and linear regression are included with the base system. SPSS supports most data visualization methods that are typically used in the social sciences, such as histograms, scatterplots, and bar or line graphs [56].

3.1.2 MATLAB

MATLAB is a mathematical and graphical software package with numerical, graphical, and programming capabilities; it also allows for data analysis and visualization. The software includes an integrated development environment, along with procedural and object-oriented programming constructs. MATLAB has built-in functions and Toolboxes that can be added to expand these functions [58], [59].

App Designer

App Designer is an app development environment in MATLAB that provides layout and code views. It has a drag and drop visual component to lay out the design of the graphical user interface (GUI) and uses the integrated editor to program its behavior [60].

3.1.3 K-Spice

K-Spice is a dynamic process simulation tool developed by Kongsberg Digital. It includes different features for system management, thermodynamics, and solvers. K-Spice enables detailed dynamic simulation of oil and gas processes and control systems. It is a Windows-based tool with a flexible GUI, designed for different engineering applications, such as [61]:

- project feasibility and concept selection,
- pre-engineering and detailed engineering,
- commissioning and production start-up,
- operator training, and
- online operations, maintenance, support, and process optimization.

Oil and gas production model

The oil and gas production model consists of a three-stage, three-phase separation train. A detailed description of the process can be found in [23]. Komulainen and Løvmo [23] explain, the flow from the wells is sent to the High Pressure (HP) Separator or Test Separator, where the initial separation into water, gas and hydrocarbon liquids occurs. The hydrocarbon liquids are further degassed in the Medium Pressure (MP) Separator and the Low Pressure (LP) Separator. The crude from the LP separator moves to an Electrostatic Coalescer for final dewatering before it is exported. The water removed in the Coalescer is pumped back to the inlet of the HP Separator.

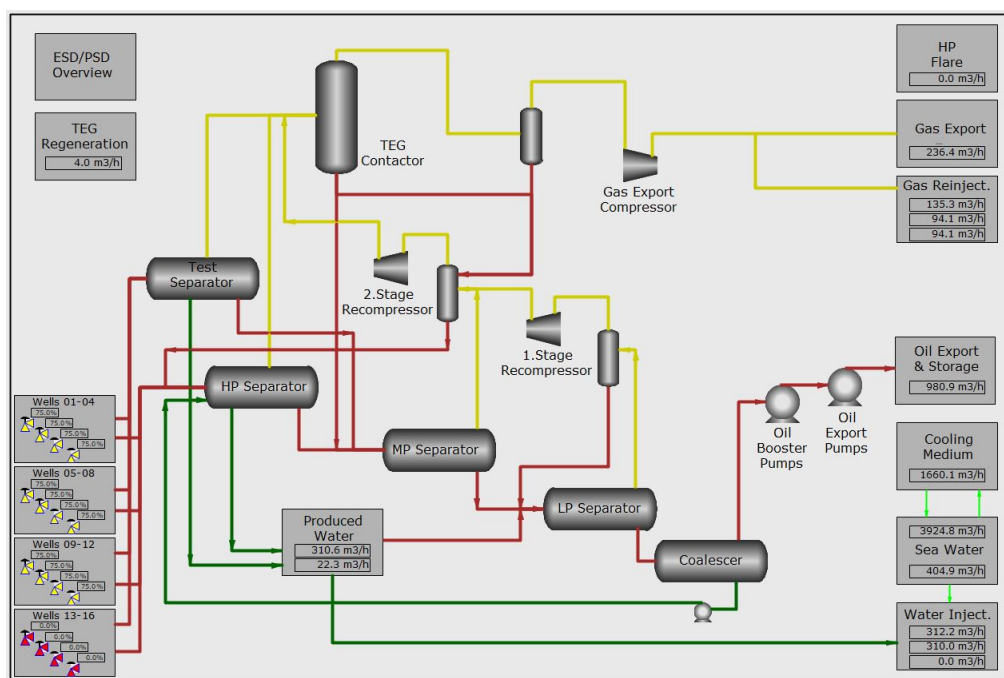


Figure 3.1: Overview of the K-Spice oil and gas production model.

Komulainen and Løvmo [23] continue explaining, the gas separated at the MP and LP stages is re-compressed to HP stage, and mixed with the gas from the HP and Test separators. Next, the total gas stream is cooled to remove heavy hydrocarbons and then dehydrated in a Contactor with lean Tri Ethylene Glycol (TEG); this is done to meet export specifications. The dried gas is compressed and then cooled for delivery into the Gas Export Pipeline, and the rich TEG is returned to the Regeneration System. The water produced in the HP Separator and Test Separator is sent to their respective Hydrocyclones to remove any oil left, and then it is sent to the Degassing Drum to remove any gas left. Finally, the clean water is pumped to the Water Injection System or disposal to sea [23]. An overview of the oil and gas production process is shown in Figure 3.1. The process also has several utility systems and emulated control and safety systems.

Exercise Manager

Exercise Manager is an extra tool for K-Spice mainly used by the instructors; it works to set malfunctions based on time or to trigger events (e.g., leak, failure, etc.) defined in the training scenario. It also functions as an assessment tool and enables the instructor to grade the operators based on their performance [62]. Figure 3.2 shows the Exercise Manager window in which it is established the trigger that will activate a specific message for the user.

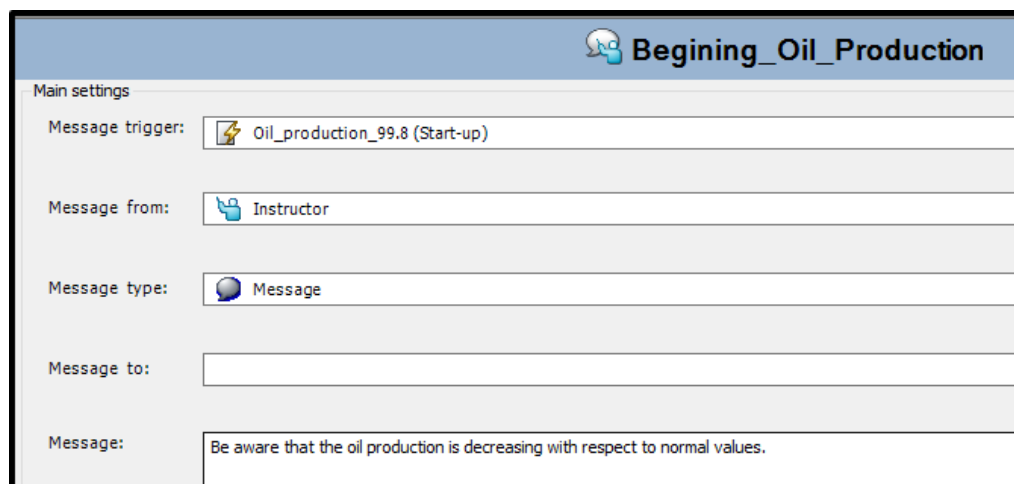


Figure 3.2: Exercise Manager view.

3.2 Quantitative Methods

3.2.1 Descriptive Statistics

Descriptive statistics involve describing, organizing, and summarizing research data so they can be easily understood. Data are presented in graphs, tables or as numerical indices [63]. The central goal of descriptive statistics is to display large data in a more manageable form so that the information they hold can be communicated effectively [63].

There exist three main types of descriptive statistics: measures of central tendency, measures of variability, and measures of distribution shape, these are summarized in Table 3.1.

Table 3.1: Types of descriptive statistics.

Measures of central tendency	Measures of variability	Measures of distribution shape
-Mean	-Range	-Skewness
-Median	-Variance	-Kurtosis
-Mode	-Standard deviation	
	-Coefficient of variation	

In this thesis, the descriptive statistic methods used were the mean and standard deviation. Hence, these are further described below.

- *Mean:* The mean or average is a central tendency of the data. It refers to a number around which the entire data are spread out. The mean corresponds to the summations of all the data values divided by the number of observations. Due to this, it can be significantly affected by isolated values that are either too large or too small [63].

The arithmetic mean of a sample of n numbers y_1, y_2, \dots, y_n can be defined with Equation 3.1 [64]:

$$\bar{y} = \frac{\sum_i y_i}{n} \quad (3.1)$$

- *Standard deviation:* The standard deviation is the most common variability measure. In general, a low standard deviation indicates that the data points tend to be close to the mean of the data set (low variability), while a high standard deviation indicates that the data points are spread out over a broader range of values (high variability) [63]. The standard deviation can be expressed as shown in Equation 3.2 [64]:

$$s = \sqrt{\frac{\sum_i (y_i - \bar{y})^2}{n - 1}} \quad (3.2)$$

3.2.2 Inferential Statistics

According to Jawlik [65] in inferential statistics, a numerical property of a sample of data, for instance, the sample mean, is calculated and used to estimate the value of that selected property for the entire population or process from which the sample was taken [65]. Usually, it is impossible to find out the exact value of a population or process parameter, i.e., a 100 % accuracy cannot be reached. However, with

inferential statistics is possible to specify the level of confidence needed. The level of confidence is one minus the level of significance, Alpha (α). The most common level of confidence is 95 % [65].

Inferential statistics is involved in different kinds of analysis, such as ANOVA, regression, z-tests, and t-test. Given that the t-test was employed in this thesis work, it is briefly described in the following.

t-test

Burrell and Gross [66] explain that a t-test is a statistical analysis of the differences between sample populations; it evaluates how the sample population differs from the actual population. A t-test indicates at what level of confidence the null hypothesis can be rejected [66]. The null hypothesis is a statement that there is no statistically significant difference, change or effect [65]. Hence, if it is rejected, there is a statistical significance in the results. Nonetheless, there is always a difference between what is observed from the sample and what occurs in the actual population, which generates a standard error. The probabilities of error increase with small sample size [66].

There are three types of t-tests; the difference between them is based on the types of means that they described. Table 3.2 shows a summary of the different versions of t-tests and their formulas [65]. In this thesis work, the 2-sample and the paired t-tests were employed.

Table 3.2: Types of t-tests.

t-test	Means being compared	t	Degrees of freedom (df)
1-Sample	Sample mean to a specified mean	$\frac{\bar{y} - \mu}{s/\sqrt{n}}$	$n - 1$
2-Sample	Means of samples from two different populations or processes	$\frac{\bar{y}_1 - \bar{y}_2}{s_p/\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$	$n_1 + n_2 - 1$
Paired	Mean of the differences in pairs of measurements to a mean of zero	$\frac{\bar{d} - 0}{s_d/\sqrt{n}}$	$n - 1$ (n is the number of pairs)

\bar{y} , \bar{y}_1 , and \bar{y}_2 are sample means.

μ is a specified mean.

\bar{d} is the mean of the differences in the two values comprising each pair.

s_p is called the ‘‘pooled standard deviation’’; it has its own multi-term formula.

s_d is the standard deviation of the differences.

3.3 Qualitative Methods

3.3.1 Observations

According to Rosen and Underwood [67], observations refer to watching and recording the occurrence of specific behaviors during an episode of interest. Observational research is a systematic method, this means that it is based on an structure plan and specific techniques, so that it can be reproduced by others [68].

Types of Observational Design

Rosen and Underwood [67] indicate that there are two types of observational design: naturalistic and laboratory observations.

- *Naturalistic observations* are those that take place in everyday environments, such as classrooms, playgrounds, animal colonies, and retail settings. According to [67], the main advantage of this observational design is that researchers have the great benefit of studying people or animals in their natural surroundings. On the other hand, a disadvantage associated with naturalistic observations is that there is no control over the settings, which can lead to confounding factors [67].
- *Laboratory observations* are those that occur under laboratory settings. Rosen and Underwood [67] indicate that the benefit of this type of observational design is that the researcher can structure the observations, and can trigger certain behaviors by communicating with the participants. Nonetheless, a significant disadvantage of laboratory observations is that participants may behave unnaturally, given that they are aware of being observed [67].

Relationship Between Observer and Observed

The researcher can assume one of several roles when carrying out observations; these roles range from being a full participant to being only a spectator [68]. The four types of observational roles discuss below correspond to the classic typology introduce by the sociologist Raymond Gold in 1958 [69]:

- *Complete participant*: The researcher is fully embedded in the group that is being studied, and the participants are not aware that they are part of an observational study, even though they fully interact with the researcher [68], [70].
- *Participant as observer*: The researcher is completely engaged with the participants who are aware of the researcher's role. In this case, the researcher is more like a friend or colleague than a neutral third party [70].

- *Observer as participant:* The participants know the researcher's activities, and the researcher participation in the group is limited, their goal is to play a neutral role as much as possible. The execution of this method may lead to access to many people and a wide range of information. However, the participants being investigated control the amount of information revealed [68], [70].
- *Observer as participant:* This is a detached observer, which means that the researcher is either hidden from the group or not noticed, like in the case of public spaces such as an airport, library, coffee shops, subway stations, etc. In these settings, participants are more likely to act natural since they are not aware of being observed [68], [70].

In the case of this PhD work, we made naturalistic observations. The STM was an activity part of the course that each group of participants was taking at the moment. The students were observed in a computer classroom while developing the training tasks designed for the corresponding STM. Naturalistic observations were chosen so that the participants would feel comfortable, and they wouldn't be distracted by the fact they were participating in a research test. Regarding the relationship between the observer and the observed, the type implemented was *participant as observer*, although, the way the observer participated in the experiment was by being the instructor, giving verbal feedback to the trainees. This type of observation was implemented because it was desired to get a close look at the participants' reactions towards the tools evaluated.

Being an observer is an engaging experience. It makes you more attentive to what trainees do and able to perceive when they are only guessing, which is noticed from their erratic impulse for clicking everywhere with no apparent order. Also, it can be seen when they are entirely concentrated and trying to reflect on what they are doing. Being a participant observer is beneficial since the observer gets a very close look of each participant behavior and reaction to the stimuli coming from the simulator. However, a participant observer can also miss many of what is happening with the participants of the experiment because of being too close, thus not having the complete view of what is happening with all participants.

3.3.2 Questionnaires

Questionnaires are a data gathering technique. Chasteauneuf [71] explains that questionnaires allow researchers to collect quantitative or qualitative information through written self-reports from an individual unit, such as a student, group, university or community. The data collected is regarding the unit's knowledge, beliefs, opinions, or attitudes about or toward a phenomenon under investigation. Questionnaires can be used as the primary strategy for data collection, or they can be combined with other techniques, like participant observation, interviews or document analyses [71].

Usually, a questionnaire consists of a series of scaled affirmations that the participants of the study must respond by indicating where in the scaled is their per-

ception of such affirmations. The Likert scale is one of the most widely employed methods of attitude measurement in survey research [72].

Likert Scale

The Likert scale is a psychometric scale measure, it is named after its inventor, psychologist Rensis Likert. The Likert scale is constructed from multiple ordered-category rating items. The response sets may include four or more points, though five categories are traditional [72]. Brill [72] indicates that the main characteristics of this methods are as follows:

- Each item has a set of response categories representing different levels of agreement or disagreement with an incentive statement expressing an attitude or opinion (e.g., The simulation exercises were useful for learning).
- Each level in the response category receives its own label (e.g., Strongly Agree, Agree, Disagree, Strongly Disagree).
- The names of a consecutive pair of labels are assigned in such a way they seem similar so that there is a gradual change along the scale.

Questionnaires were implemented in this PhD work to gather trainees' opinion on the automatic feedback tools they used. We applied a 5-point Likert scale, given that it is one of the most commonly implemented. Further, it was planned to combine the results from the questionnaires with those obtained with the observations.

It was noticed that the use of questionnaires brings useful results. It was possible to obtain different opinion trends when all the data were analyzed. It was also possible to notice some contradictions among the participants; structuring the same question in different ways in the same questionnaire allowed seeing this. Further, most of the results from the questionnaires were a reflection of what was observed, which strengthened the general conclusions made.

Nonetheless, the implementation of questionnaires also had some drawbacks; it is a method very much dependent of the sample size, the bigger the sample size, the more information is possible to extract from the questionnaire results. Moreover, when implementing questionnaires the research is exposed to trainees that might not be honest when answering the questions, it is a method that can be affected by biased opinions, which is something that can also be mitigated with bigger sample size. In the case of this PhD work, we consider that a favorable sample size must be more than 30 participants.

3.3.3 Pretest-Posttest Designs

Pretest-posttest designs are commonly implemented in behavioral research. The main goal of this design is to compare groups and measure changes that result after an experimental treatment [73]. Bell [74] explains that a pretest measure of the relevant objectives is obtained before implementing a treatment, and then, a post-test on the same measure is obtained after the treatment occurs. Pretest-posttest

designs can be applied either in experimental or quasi-experimental research. Quasi-experimental pretest-posttest designs are not bound to include control groups. On the other hand, experimental pretest-posttest designs must have control groups [74].

Even though pretest-posttest designs is a popular assessment tool, it still has some limitations, including threats to internal validity, due to this, there are some criticisms against its implementation. Therefore, it is important to evaluate carefully when a pretest-posttest design is an appropriate choice [74], [75].

One-Group Pretest-Posttest Design

One-group pretest-posttest is the simplest design. Data about certain outcomes is gathered through the pretest. Then a treatment is implemented, and finally, data from the posttests is collected based on the same measures [74]. Figure 3.3 shows an illustration of the one-group pretest-posttest design.



Figure 3.3: One-group pretest-posttest design [76].

Two-Group Pretest-Posttest Design

In a two-group pretest-posttest design, there is one group, which will go through treatment, and a nontreated control group. Researchers gather data related to specific outcomes through the pretest, implement the treatment to the corresponding group, and then gather data with the posttest on the same measure [74]. Figure 3.4 shows an illustration of the two-group pretest-posttest design.

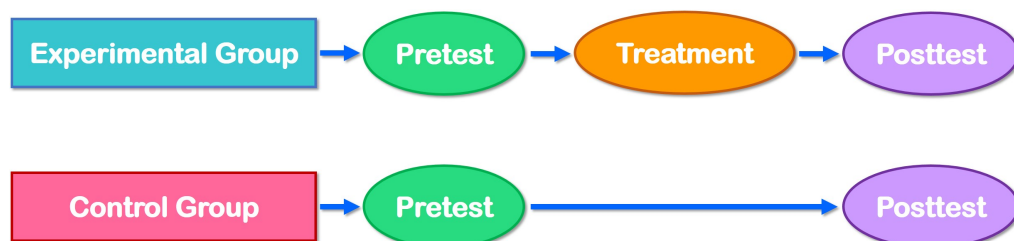


Figure 3.4: Two-group pretest-posttest design [76].

A pretest-posttest design was implemented in all the STMs carried out in this PhD work. This design was chosen to be able to confirm at least that the participants learning-progress was not affected by the experiments. The pretest-posttest design resulted in being an advantageous method that allows comparing the performance of the trainees based on different factors, such as trainees that used the tool vs.

trainees that did not, master's students vs. bachelor students, chemistry students vs. computer science students, and so forth. However, it was noticed a weakness in the design. Even though it helped to compare performances between different groups, it is not enough for claiming that the learning-progress observed is due to the tools that were tested. It remains only as a fact, there was a learning improvement, but the tests are not enough to determine the exact reason that promoted it.

3.4 Experimental Design

There are two basic categories of research design, quasi-experimental and true experimental designs, both of which were employed in this thesis work.

3.4.1 Quasi-Experimental Design

Quasi-experiments are those in which study units are not randomly assigned to observational conditions because of ethical or practical constraints [77]. In this thesis work, the implementation of a quasi-experimental design was due to practical constraints, there were not enough participant in the studies to create a control group. Therefore, during the Simulator Training Module 1 (STM1), all participants went through the treatment, which was Feedback Method 1 (FM1), the graphic with performance indicators. The design implemented was the one-group pretest–posttest, explained in the Subsection 3.3.3. The design can be depicted as:

$$O_1 \quad X_A \quad O_2$$

Where O_1 is the pretest measure before the manipulation X_A (FM1), and O_2 corresponds to posttest measure.

3.4.2 True Experimental Design

The term true experiment is used in some cases to refer to any randomized experiment. In other cases, it is used to refer to all studies with an independent variable that can be manipulated and a dependent variable that will be studied [78]. In any case, the main characteristic of a true experimental design is that the units of study are randomly selected for different treatment conditions [79].

A randomized experiment requires a minimum of two conditions, the experimental units must be assigned randomly to these treatment conditions, and a final post-test assessment of the units must be done. In the following R indicates random assignment of a group, X is the treatment and O is the observation [79]. Below are described the randomized experimental designs that were implemented in this work.

The Basic Randomized Design Comparing Two Treatments

During Simulator Training Module 2 (STM2), two treatments were compared, the use of Feedback Method 2 (FM2), the pop-up windows, and the instructional videos. In the following we refer to FM2 as treatment X_B and to the instructional videos as X_D , then the design can be depicted as:

R	X_B	X_D	O
R	X_B		O
R	X_D		O

As it can be seen, both treatments were implemented at the same time, and also separately.

The Pretest-Posttest Control Group Design

During Simulator Training Module 3 (STM3), one treatment was assessed, the use of Feedback Method 3 (FM3), the online automatic feedback tool. In the following we refer to FM3 as treatment X_C , then the design can be depicted as:

O	R	X_C	O
O	R		O

It can be noticed that the random assignment of the groups occurred after the pretest.

Figure 3.3 presents a detailed summary of all the experimental designs described above. The participants were master's students from the University of South-Eastern Norway (USN) and bachelor students from OsloMet – Oslo Metropolitan University.

Table 3.3: Experimental Design

Experiment	STM1	STM2	STM3
Research design	Quasi-experimental design: One-group pretest-posttest design	True experimental design: Randomized design comparing two treatments	True experimental design: Pretest-posttest control group design
Treatment	FM1: Graphic with performance indicators	Before session: Instructional videos & FM2: Pop-up windows	Before session: Instructional videos
Participants description	USN Master Process Control	OsloMet Bachelor Control Eng.	OsloMet Bachelor Control Eng.
N of participants	9	6	11
			9
			9
			10
			8
			40
			13
			6

4 Contribution by this Work

This thesis builds on and contributes to the field of simulator training. Although studies in this field have examined different simulator training practices, there has not been much research on how to enable more independent training. In this study different methodologies and technologies were implemented to evaluate their effect on trainees independence during simulator training. Below, the articles that support the argument of this thesis are described.

4.1 How Can Individual Simulator Training be Enabled?

Article 1: Review of Simulator Training Practices for Industrial Operators: How Can Individual Simulator Training be Enabled?

Article 1 is a literature review that answers to the research question “How can individual simulator training be enabled?”. This article begins with an explanation of what is meant by individual simulator training. Individual simulator training is the use of appropriate technology and learning methods that allow trainees to develop individual technical skills. Further, it allows training with the simulator remotely and as long as needed. The article also presents a brief study of different individual training technologies such as, *e-learning*, *Learning Management Systems (LMS)*, *Intelligent Tutoring Systems (ITS)*, and *Instructional Videos*. A pedagogical analysis of these technologies based on Bloom’s taxonomy is presented. The analysis aimed to demonstrate how individual training technologies can be used to enable individual simulator training.

The literature review was made to identify gaps in traditional practices of simulator training that could be filled by the implementation of individual simulator training. Also, it aimed to identify appropriate methodologies, features, and conditions that could facilitate individual simulator training. It was developed using a thematic analysis, the final themes found are shown in Figure 4.1. Based on the results from the thematic analysis, the final conclusions from Article 1 indicate:

- Individual simulator training can be a supplement to on-site training. It can be implemented as a pre-training. It can help to cope with the loss of process knowledge due to the retirement of experts instructors by keeping individual training records. Further, individual simulator training allows for more operators training simultaneously and more frequently.
- The literature shows that two key features of adequate simulator training are effective feedback and assessment. Therefore, for individual simulator training to be a successful practice, it must also be based on these two features, and

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in the case of individual training, feedback and assessment must be provided automatically by the simulator. Performance indicators are well-known measures in the simulator training field; they can be implemented as the basis for developing objective automatic assessment and feedback. Also, well-defined learning objectives can allow the development of practical automatic feedback tools and unbiased automatic assessment methods.

- Finally, the literature review findings indicate that the development of technology should be based on human-centric perspectives, i.e., users' needs and opinions should be considered when developing new tools. When evaluating the efficacy of new tools, it is essential to take into consideration trainees motivation when practicing with the simulator, given that it has been proven that this has a significant impact on their performance. Moreover, the benefits of simulator training can be further improved with the implementation of appropriate learning strategies; these can be selected depending on the characteristics of the training group and topic to be learned.

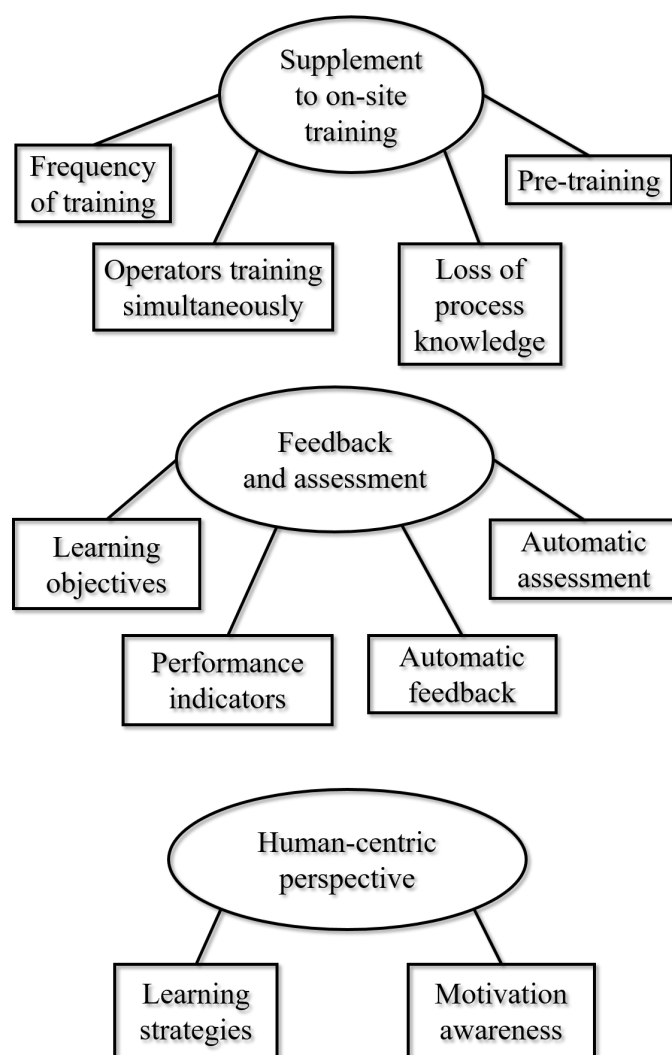


Figure 4.1: Themes found by means of thematic analysis.

4.2 OPIs as the Basis for Automatic Feedback

Article 2: Constructive Assessment Method for Simulator Training

Article 2 presents a discussion of the performance assessment challenges in both industrial and academic simulator training. Usually, the evaluation of trainees' performance is based on the instructor verbal feedback during the scenario and the instructor's verbal assessment after the scenario. There exist some automatic feedback tools available, but they require the implementation of specific sequences, which makes them too deterministic, i.e., they do not give room for any other possible good alternatives. Also, it is discussed that in academia, more specifically, the experience at HiOA (Now called OsloMet), shows that simulator training provides proper practice for many students. However, they do not receive appropriate individual assessment based on their performance. It is of great importance developing appropriate assessment methods to ensure that trainees are acquiring the necessary competencies. Based on these concerns, Article 2 presents the development of a tool that shows the status of an oil and gas production process based on OPI values.

The article offers an approach based on one of the findings from Article 1, OPIs can be used as the basis for automatic assessment and feedback. It gives a detailed description of different OPIs, and proceeds to explain how they can be used to develop a performance assessment tool that can help trainees be aware of the process status. It is explained how to define an MPI based on different OPIs, having each OPI a distinct contribution to the MPI depending on the relevance it has for the process. The different weights of each OPI were determined using AHP (See Section 2.2.2). The article shows a practical example of how to determine the MPI for a specific case.

Article 2 addresses hypothesis two (H2) - process status can be summarized using relevant performance indicators - and confirms it. It was demonstrated that it is possible to provide an overview of the process status based on relevant OPIs. The tool developed gives numeric feedback about the process status while executing the scenario.

4.3 Implementation of OPIs for Automatic Feedback

Article 3: Implementation of Performance Indicators for Automatic Assessment

The implementation of the tool introduced in Article 2, is presented in Article 3. This article summarizes the first STM experiment, STM1. Two groups used the tool: master's students from USN, who were taking the course Process Control, and bachelor students from HiOA (now called OsloMet) who were taking the course Dynamic Systems. In this first experiment, there were few participants, nine students from USN and six from HiOA. Therefore, there was no control group (See Section 3.4.1). Observations notes and questionnaires answered by the students were gathered, in addition to pretest and posttest evaluations.

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The results from the questionnaires related to the tool indicate that trainees considered that the numeric feedback given by the automatic assessment tool helped them understand the status of the process. However, trainees opinion is less firm in what it refers to the tool being useful to solve the scenario task. The questionnaire results are a reflection of what was observed. It was noticed that the students were able to understand with the tool that something was not working correctly in the process, but it was not enough for them to locate the source of the problem. Regarding, the pre- and post-test, the results show there was a learning improvement in both groups, especially in the case of the bachelor group.

Article 3 is based on three research questions, the first of which was 1) How can an automatic assessment tool help the students achieving the learning goals of a simulator training session? Our results show that the numeric feedback provided by the automatic assessment tool increases the students' awareness of the process state. The implemented performance indicators in the automatic assessment tool helped the trainees understand the status of the process. The second research question was 2) What role does the instructor play when the automatic assessment tool is used? Testing with the two groups shows that the instructor still plays a significant role in the simulator training session and only a numeric assessment tool is not enough to "replace" the instructor's guidance. Finally, the third question was 3) How should the automatic assessment tool be developed further? Based on the results from this first experience, we considered that the assessment tool could be a standalone tool if it is improved further with the design of an online feedback function, based on natural language, given that it was noticed that only numeric values are not sufficient to guide the trainees solve the scenario task. In this way, the simulation session could even be carried out without the instructor having to be around during the entire session, which can help trainees to become more independent in their learning processes.

This article addresses hypothesis one (H1) - automatic feedback allows trainees to be more independent during simulator training, and hypothesis three (H3) - relevant performance indicators help trainees solve process upsets independently. H1 is confirmed to a certain extent. Trainees did manage to understand the process status with the numeric feedback given by the automatic assessment tool. Nonetheless, this numeric feedback was not enough to solve the scenario task independently; they still needed to ask for the instructor's help. In this sense, H3 must be rejected, since the process indicator values were not sufficient for the trainees to solve independently the process upset triggered in the scenario.

4.4 Comparison of Different Automatic Feedback Methods

Article 4: Effect of Automatic Feedback on Large-Scale Simulator Training

Article 4 summarizes the main experiments of this PhD work. There were three STM periods, fall 2016, fall 2017, and fall 2018 - spring 2019. The results from STM1 that were first discussed in Article 3 are further analyzed and explained in

Article 4. The article presents a detailed description of each of the STMs and the feedback methods tested in each of them; this is summarized in Table 4.1.

Table 4.1: Simulator training modules and corresponding feedback methods

	Tasks	Feedback Method
STM1	Part 1 - Familiarization	FM1 - Numeric feedback: Performance assessment tool based on OPI values
	Part 2 - Scenario 1: increase oil production	
	Part 3 - Scenario 2: create a failure in the level controller	
	Part 4 - Scenario 3: blind scenario, fix a malfunction (avoid process shutdown)	
STM2	Same tasks as in STM1	FM1 - Improved GUI FM2 - Prompt feedback: pop-up windows, activation of messages based on OPI values
STM3	Part 1 - Familiarization	FM1 - Improved GUI FM3 - Online automatic feedback tool: an app that informs about the process status and gives suggestions if requested
	Part 2 - Scenario 1: increase oil production	
	Part 3 - Scenario 2: blind scenario, fix a malfunction (avoid process shutdown)	
	Part 4 - Scenario 3: blind scenario, fix a malfunction (avoid flare activation)	

Article 4 was based on five research questions:

- *RQ1*: Were the feedback methods useful for solving the simulation tasks?
- *RQ2*: Were the trainees who used the feedback methods more independent than those who did not?
- *RQ3*: Was the learning outcome of the trainees affected by using the feedback methods?
- *RQ4*: Does preparation before attending the simulator training session has any effect on the trainees' performance?
- *RQ5*: What are the trainees' perceptions towards the simulator training modules?

The design and planning of each STM were carried out using the Didactic Relation Model (See Section 2.2.1). In all the STMs observations, questionnaires, and pre- and post-test were made. Also, from STM2, the implementation of instructional videos was introduced, and its effect on trainees performance was studied. The participants of all the STMs were either master's students from USN or bachelor students from OsloMet. Article 4 presents a detailed description of each of the simulator training sessions developed, and further explanation of the experimental design is introduced in Section 3.4. Based on the observations made, the questionnaires and pre- and post-test results, we have developed a summary table that shows the pros and cons of each of the feedback methods tested, Table 4.2.

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Table 4.2: Pros and cons of the feedback methods tested

Feedback Method	Pros	Cons
FM1 - Numeric feedback	- System state awareness.	- Not enough to be independent.
FM2 - Pop-up windows	- Guided reflection on actions. - Can lead to be more independent.	- Imposed feedback, can be overwhelming. - Negative effect on independence.
FM3 - Online automatic feedback tool	- Control over the feedback tool. - Offers further suggestions. - Can lead to be more independent.	- Not always in sight. - Can be forgotten by the user.

When analyzing each of the research questions established for Article 4, the results indicated the following. Regarding RQ1, results suggest that overall trainees considered that the three methods tested were useful, some to a greater extent than the others. However, the participants' opinions show that overall, they did not consider any of the feedback methods were enough to solve the scenario tasks independently. Respecting RQ2, participants who used the pop-up windows (FM2) believed that they needed to ask for the instructor's help more often than those who did not use the tool. On the other hand, in the case of the online automatic feedback tool (FM3), results show that the participants that use it were less affected by the instructor not being available at all times than the participants who did not use FM3.

Further, trainees who use FM3 had greater improvement in the posttest than the trainees who did not use the tool. RQ3 refers to the learning outcome and whether or not it was affected by the use of the feedback methods tested. All results from the pre- and post-tests show that this was not the case. There was always an improvement in the participants' performance. Regarding RQ4, results show that preparation before attending the simulator training does affect trainees performance. Trainees who indicated that they either watched the videos or read the instructions manual before attending the session had a better performance in the pretest, and they asked for the instructor's help less often than the trainees who did not prepare themselves for the training session. Finally, in the case of RQ5, the observations, questionnaire results, and comments from the trainees show that they considered the simulator training modules were useful for learning and in some cases even an enjoyable experience.

Article 4 addresses hypothesis one (H1) to seven (H7) (See Section 1.3). Since H1 is the most relevant, we will discuss it last. H2 and H3 were already addressed in Article 2 and Article 3, respectively. H4 - prompt feedback messages can be developed based on process indicators. It was demonstrated that it is possible to design a tool that gives instant feedback messages based on performance indicators; therefore, H4 can be accepted. H5 - prompt feedback messages help trainees under-

stand and solve abnormal process situations independently. H5 was not confirmed entirely, trainees were able to realize there was a process upset with the help of the prompt feedback, but overall, they did not consider it was enough to solve a malfunction in the process independently.

H6 - trainees' preparation before the simulator training session allows them to be more independent during the session. H6 was confirmed, it was discussed above by answering to RQ4. H7 - the way feedback is presented to trainees affects its efficiency. H7 was also confirmed, in the experiments described in Article 4, automatic feedback is presented in three different ways. FM1 gave only numeric feedback, and it was not enough for the trainees to be more independent. Feedback presented only with numeric values turned out to be too compressed, hence not a very efficient tool. FM2, helped trainees reflect more, but it was not welcome by all trainees since they did not have the option to decide whether they want it the help or not, it was an imposed feedback, which represented a significant deficiency of the tool. Finally, FM3 was the most accepted among the tools tested; results show that trainees considered it useful, clear, and understandable. However, one drawback of FM3 is that contrary to FM2, it is not always in sight. Trainees had to remember to maximize the tool's window, and very often, they did not remember to do so, which turned into the trainees under-utilizing the tool.

H1 - automatic feedback allows trainees to be more independent during simulator training. Article 4 presents the comparison of three different automatic feedback methods. Overall, the results show that automatic feedback can be useful for trainees. In general, all the methods tested were considered helpful. Hence we can say that automatic feedback does have a positive impact on simulator training. However, it was not possible to confirm that trainees who used the feedback methods were more independent than those who did not. As mentioned above, the general opinion among the participants of the study is that none the automatic feedback methods were enough to solve the training scenarios independently. It is a great challenge to try to match the instructor's feedback. This research confirms that it is possible to help trainees be more independent with the support of automatic feedback. Nevertheless, the results also show that not any type of automatic feedback method is suitable; some can be more useful than others. Therefore, it is necessary to point out that trainees may be completely independent during simulator training with effective automatic feedback, meaning a type of automatic feedback that is close to giving inputs similar to those an instructor would provide.

4.5 Data Mining as the Basis for Automatic Feedback

Article 5: Using the Concept of Data Enclosing Tunnel as an Online Feedback Tool for Simulator Training

Article 5 is a detailed study of how FM3 (introduced in Article 4) was created. In this article is demonstrated how records of previous trainees' performances can be of great use to develop a tool able to identify good or bad execution paths. In the article, it is shown how the data enclosing tunnel was created for a training scenario in which trainees are asked to increase the oil production of the process.

4 Contribution by this Work

The first step is to select the most suitable variables to study the process. Then, it is necessary to collect data based on the variables of interest. In this research, there were no actual data from trainees available. Therefore, the data were generated; for that, an algorithm was created. The algorithm has a repository of different possible actions that trainees could execute intending to achieve the goal of increasing the oil production; it randomly selects one, two, or maximum three of these options to create an execution path that would correspond to one trainee. In this way, 75 different execution paths were designed.

Later it was necessary to determine which of the execution paths were good and which ones were bad, this, to create balanced groups for training and validation. Each of the execution paths corresponds to a time-series. To classify different time-series is fundamental to have a notion of similarity. In this case, the similarity concept used was the distance between the time-series. Article 5 introduces three different methods for calculating distances: Euclidean, DTW, and SAX, Section 2.2.2 presents a detailed explanation of each of the methods. Once the similarities between the time-series are defined, they can be classified. To do so, the hierarchical clustering was the method implemented, further explained in Section 2.2.2. Sorting the data is very important to separate good performances from bad performances and to be able to promote learning from the good paths.

Once the data is classified and separated into training and validation, the variables of the good execution paths in the training data are reduced using PCA. The data projected in a new plane is used to build a data enclosing tunnel. Using only the scores from PC1 and PC2, different MEC were defined, for different time sections of the good training data. Then, these circles are used to create a surface around them, thus building a tunnel of changing radiuses. This tunnel represents the limits in which execution paths are considered good. Then, to test the accuracy of the tunnel, the validation data was projected on the PCA plane and surrounded by the tunnel. It was established a tolerance for the bad execution paths inside the tunnel. If an execution path was less than 20 % of the total simulation time inside the tunnel, it was classified as bad. If an execution path was 80 % or more of the total simulation time inside the tunnel, it was classified as good. Based on these conditions, the accuracy of the tunnel was 68 %. A more flexible condition to classified the bad ones was also tested, keeping the same terms for classifying the good ones, but if an execution path was less than 35 % of the total simulation time inside the tunnel, it was classified as bad. Based on the last classification conditions, the accuracy of the tunnel was 84 %.

Article 5 addresses hypothesis eight (H8) - data mining leads to the development of non-deterministic feedback methods - and confirms it. It was demonstrated that it is possible to create a feedback method that does not force trainees to follow deterministic procedures to solve a training scenario successfully. That is the idea behind building a data enclosing tunnel based on different examples of good execution paths, to expand the limits of what is considered correct so that trainees are able to use their knowledge in creative ways, and not be bound to solve scenarios only in one manner when there exist different procedures that can be correct.

4.6 Methodology for Building a Data-Enclosing Tunnel for Automatic Feedback

Article 6: Methodology for Building a Data-Enclosing Tunnel for Automated Online-Feedback in Simulator Training

Article 6 presents a general methodology for building a data-enclosing tunnel for any training scenario. The procedure introduced in the article is summarized in Table 4.3.

Table 4.3: Methodology for building a data-enclosing tunnel

Step	Description
1. Selection of a simulation tool	<ul style="list-style-type: none"> - Dynamic model of the process - Able to save and export historical data - Able to connect with external programs
2. Definition of the training scenario	<ul style="list-style-type: none"> - Selected from the simulator options or created from scratch - Establish clear operational goals and learning objectives
3. Selection of the study variables	<ul style="list-style-type: none"> - Depends on the case study - Variables should be related to the operational goal and learning objectives - Variables combinations as KPIs and OPIs
4. Data collection	<ul style="list-style-type: none"> - Records of the performance of actual trainees - Generated data created with an algorithm
5. Data classification	<ul style="list-style-type: none"> - Label data beforehand if possible - Clustering methods
6. Data processing and dimensionality reduction	<ul style="list-style-type: none"> - PCA analysis for the different time slots - Sliding window algorithm
7. Design of the data-enclosing tunnel	<ul style="list-style-type: none"> - Minimum enclosing circle (MEC)
8. Validation of the tunnel	<ul style="list-style-type: none"> - Validation data projected on the previously defined PCA plane - Validation data must be plotted together with the tunnel - Metric 1: outside tunnel >35 % total time = bad - Metric 2: outside tunnel >50 % total time = bad

Article 6 also presents two case studies to demonstrate the viability of the methodology. The first case study (SC1) presented in the article corresponds to the one already described in Article 5. The second case study (SC2) is a new example; this was also based on generated data, the goal of this second training scenario was to decrease 10 % of the gas production compared to the initial conditions. The data

4 Contribution by this Work

was labeled while generated, so it was not necessary to use a clustering technique to make balanced groups for training and validation. In Article 6, three simpler methods were introduced to compare the classification accuracy of the tunnel with other approaches. The three simpler methods were enclosing bands. Instead of all variables being studied at once, like with the tunnel, each variable is analyzed separately. In the following, it is described how each enclosing band was created:

1. *Defining a reference path:* The first step is to establish a reference path. For the first approach (AP1) the reference path is defined by making a curve fitting for each of the study variables. For the second (AP2)) and third (AP3) approach the reference path was chosen from the good execution paths.
2. *Data scaling:* Data were scaled in AP1 and AP2 using the mean values and standard deviation for each group of variables. In the case of AP3, the data was not scaled.
3. *Enclosing band:* For AP1 and AP2 the band was created by summing up and subtracting from the scaled reference path the radiuses of the tunnel. For AP3, a generic factor of 15 % was used. The enclosing band was created by summing up and subtracting from the reference path the generic factor.

A comparison of the classification accuracy of each of the methods, based on the metrics presented in Table 4.3, is shown in Table 4.4. The table shows the result for SC2, and it can be seen that the data-enclosing tunnel is the most accurate of all the methods evaluated.

Table 4.4: Comparison of the accuracy of the methods for Scenario 2

Method	Metric 1: 35%	Metric 1: 35%
	outside is "bad"	outside is "bad"
	Accuracy (%)	Accuracy (%)
SC2 Tunnel	94.3	85.7
SC2 AP1	81.4	74.3
SC2 AP2	62.9	78.6
SC2 AP3	70.0	70.0

Article 6, as Article 5, addresses hypothesis eight (H8) - data mining leads to the development of non-deterministic feedback methods - and confirms it. The purpose of Article 6 was to organized the steps for creating a data-enclosing tunnel in a generic and practical way so that it can be implemented by anyone interested in it. Also, the article aims to make a more thorough validation of the data-enclosing tunnel method.

5 Conclusions

The research conducted within the scope of this PhD project comprises six articles related to simulator training in the industry and academia. The thesis introduces the problem that currently exists in the simulator training field regarding the deficit of expert instructors. In this PhD project, different strategies that can help to cope with the instructors' problematic are studied. The first conclusions gathered correspond to the findings of a literature review. The literature review answered to the question: how can individual simulator training be enabled? The results indicate that individual simulator training can be a supplement to on-site training, that effective feedback and assessment are necessary to develop successful individual training, and that the training should be based on a human-centric perspective. The findings from the literature review allowed to define eight hypotheses on which this PhD thesis was founded, in the following the conclusions related to the drawn hypotheses are discussed.

It was demonstrated that it is possible to describe a process status based on performance indicators, thus confirming H2. The implementation of KPIs and OPIs is of great significance in the simulator training field, given that these metrics allow creating numeric objective values that provide useful information about a process in a compressed manner. Further, given that they are defined by following clear numerical steps, methods based on them are unbiased. In what it refers to the utility of these values when presented to the trainees, they resulted to be too limited information. Performance indicators help to give trainees a notion of the process status, hence increasing their awareness about the process situation. However, they do not offer enough information to allow trainees to work independently, i.e., without the instructor's help. Thus, H3 was rejected.

Given that only numeric feedback resulted in being too limited, it was intended to develop a more elaborate method, also based on performance indicators. According to the values of the performance indicators, prompt feedback in the form of pop-up windows was given to the trainees. Depending on the type of performance indicator and its value, a different guidance message would appear on the screen of the trainees while working in a training scenario. The method was successfully developed, confirming H4. Regarding the implementation, it was positively received by some of the trainees who indicated that the messages in the pop-up windows helped them reflect on their actions and guided them towards solving the training scenario. On the other hand, there were also several trainees who did not appreciate the prompt feedback because it was imposed, they did not like not being able to avoid the messages from suddenly appearing on the screen. Nonetheless, the results indicated that in general, the trainees who used this method considered it was helpful, but they did not consider the prompt feedback was enough to solve the training scenario independently. Therefore, H5 was rejected.

5 Conclusions

The effect of preparation before attending the simulation session was also evaluated. An instructions manual and instructional videos were developed. The results from the study show that trainees who prepared themselves before attending the simulator training session found the simulator easy to use, they felt more confident and considered they needed the instructor's help less often than those who did not prepare. Further, the trainees who read the manual or watch the videos before the session did better in the pretest than those who did not. Thus, H6 was confirmed. Preparation is a very significant factor for trainees to be more independent during simulator training sessions.

The last automatic feedback method developed was based on a different approach from performance indicators. In this case, the data mining theory was implemented. There are many operators in the industry and students in academia using simulators often. The information that these trainees produce while training should be recorded and studied since it contains extensive information on how training scenarios can be solved correctly in many different ways. These data can be of great help to improve simulator training practices. Given that the amount of data that can be gathered by recording trainees performances is substantial, and the data can be very diverse, it is crucial to count on suitable classification methods. Proper classification methods allow sorting the data according to their more relevant characteristics, including data that represent bad examples of how to execute a training scenario are essential since the information they hold can be of advantage to recognize the type of mistakes the trainees are making. All this was demonstrated with the development of the online automatic feedback tool, thus, confirming H8.

After developing three different automatic feedback methods, with three different presentations and testing them with trainees, H7 was confirmed, the way feedback is presented to trainees affects its efficiency. Every method had a different effect and reception from the trainees. The first automatic feedback method, based only on numeric information, resulted in being a very passive method. The second method, the pop-up windows, some considered them helpful and reflective, but others found them invasive and overwhelming. The third method, the online automatic feedback tool, was the one that was better welcomed by the trainees. However, this last tool was not always in sight. Consequently, trainees sometimes forgot that it was there for them to use it and ask for suggestion if they wanted more information. These results lead to an important conclusion, automatic feedback methods must always be visible so that trainees are aware that the tool is there to help them at all times, but without being invasive, without blocking the simulator view, so they are free to decide whether to use it or not.

The central hypothesis of the thesis, H1, argues automatic feedback allows trainees to be more independent during simulator training. The development of this project has proven that the use of automatic feedback in simulator training has a positive effect on trainees development during the training session. Overall, trainees considered helpful all the automatic feedback methods, ones to a greater extent than the others. A consensus is that the methods developed were useful to understand or analyzed what was happening in the process. Nonetheless, in general, trainees did not consider any of the methods to be enough to solve the training scenario independently, without the instructor's feedback. However, it is worth mentioning

that, in the case of the online automatic feedback tool, trainees who used the tool felt more confident with the instructor not being available at all times than the trainees who did not use the tool. Further, trainees who used the online automatic feedback tool had a better performance in the posttest than the trainees who did not use the tool.

Nevertheless, even though results that prove a positive effect of the feedback methods were gathered, there are not sound results that demonstrate that trainees were, in fact, more independent with the help of the automatic feedback tools developed. Therefore, H1 was not confirmed neither rejected, which leads to the conclusion that experiments must be developed in a way that tangible prove is gathered about trainees independence, this is discussed further in the following section.

6 Future Work

6.1 Future Work Built on this PhD Thesis

In this section, suggestions for the development of future work based on the research introduced in this PhD thesis are presented.

First of all, it is necessary to measure in an assertive way the effect of the automatic feedback method on the independence of the students. For that, we present the following suggestions:

- If possible, record the simulator training session to be able later to re-watch the session and count how many times help from the instructor was requested when using the tool.
- If the possibility of recording is not available, then a counting system should be designed. It could be, to make a mark on the trainee's questionnaire sheet every time they require the instructor's help.

In this way, it can be compared how many times the instructor's help is requested in the group that uses the automatic feedback tool, from how many times help is requested in the control group.

It can be a great benefit to record trainees' actions in the simulator when trying to solve the training scenarios so that the performance of the trainees using the tool can be compared to that of the control group. This information will show whether the trainees that use the tool manage to solve the scenario faster and less erratically than the control group, thus having more solid proof of the tool efficiency.

The size of the sample is also critical to be able to extract more in-depth statistical information from the analysis of the results. Therefore, having at least one hundred participants that can be separated into a control group and experimental group is highly recommended.

It is crucial to keep track of each trainee's contribution to the research so that the individual progress and opinion from every single participant can be studied. It is recommended to develop a smart and practical identification system so that the researcher can follow each trainee anonymously. It could be a pseudonym repository to which participants can log in and fetch a unique pseudonym that will be assigned, for example, to their email address. They should always be able to go back to the repository and recover the same pseudonym they got the first time, in case they lose it or forget it.

Regarding the automatic feedback tool, further development is needed:

- First, it is essential to guarantee that the tool is always visible for trainees so that they do not forget that it is there to help them, but taking into consideration that it should not disturb the trainee's visibility of the simulation.
- Currently, the online automatic feedback tool runs properly for 30 min. However, trainees may take longer than that to solve a training scenario, they stop, think, reload the scenario, and start over. The tool needs to be improved and made more robust so that these disturbances do not affect its performance.
- The functionality of the tool should be extended. Currently, it is designed to help to solve the first scenario studied, which is to increase the oil production of the process. The necessary data to help to solve the second scenario should be integrated into the tool as well. Also, an option in the GUI should be added so that the user can indicate which scenario they are going to be solving.

6.2 Future Work in the Simulator Training Field

To what it refers to the forthcoming of the simulator training field, it will have eventually to get more involved in the great revolution of data analysis. Data hold so much information that it is imperative to learn about the many different analysis methods that exist to be able to decode them and get the advantages of all that can be gained from them. This project presents a simple example of the benefits that can be obtained by analyzing data, and it is only based on one case. Further development should include advanced data analysis techniques and machine learning methods. These techniques should be used to build a smart system able to learn from trainees performances, able to differentiate and classify correct and incorrect actions, an autonomous system capable of growing in knowledge so that it can provide better and personalized feedback. It has to be taken into consideration that such a system should count on a sound database to save the vast amount of information that will be produced. Further, in this era of development of the Internet of Things (IoT), different systems could be connected to benefit from a larger pool of data.

What makes instructors' feedback so valuable is that they can give personalized comments, based on the specific execution of each trainee. That is the reason why it is imperative to develop a system capable of learning from data analysis of previous performances so that it can give adaptive feedback according to every trainee's needs. In this way, trainees can be more independent and able to train for developing or refreshing individual skills whenever needed. Consequently, the industry will always have operators with sharp knowledge and well prepared, and this can result in safer industrial operations and less human errors.

The great benefits that can be obtained from data analysis can be beneficial not only for the trainees but also for the instructors. Instructors could also receive feedback that can guide them to identify trainees errors, when and where they made a mistake, and even give suggestions on how the scenario could have been solved better. Thus increasing the instructors' confidence and allowing for more in-depth discussions and reflections with the trainees. To guarantee this kind of

support for the instructors could also be a means to motivate trainees to become instructors since they will be more confident when giving feedback if they have such a tool.

Finally, data analysis can also be a great advantage at the plant level. IoT is already helping different companies to gather valuable plant information and make more informed business decisions. The used of embedded sensors can help to collect a significant amount of data from different areas of an industrial plant. The analysis of big data from plant operations can lead to a better understanding of the process, which makes it easier to optimize it and develop new control strategies. Further, the implementation of IoT can lessen industrial risks given that a well-built industrial IoT platform could identify potential issues before they turn into real safety hazards.

Knowledge is power. In the case of the industry, if operators are well-trained, the instructors are well-prepared, and there is a sound understanding of the plant operations, these can lead to improved process monitoring with fewer errors and high process efficiency, which results into cleaner operations with a smaller environmental footprint. In the case of academia, if students are appropriately educated, the instructors are well-prepared, and there is a solid understanding of the process studied, academia will prepare better professionals for doing an excellent job in the industry, thus creating a virtuous cycle.

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Appendices

A Review of Simulator Training Practices for Industrial Operators: How Can Individual Simulator Training be Enabled?

L. Marcano, F. A. Haugen, R. Sannerud, and T. Komulainen, “Review of simulator training practices for industrial operators: How can individual simulator training be enabled?,” *Safety Science*, vol. 115, pp. 414-424, 2019. doi: <https://doi.org/10.1016/j.ssci.2019.02.019>

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Review

Review of simulator training practices for industrial operators: How can individual simulator training be enabled?



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Individual simulator training
Off-site training

ABSTRACT

The aim of simulator training is to improve the safety and integrity of operations. Effective simulator training involves relevant feedback and sound assessment of the operator's performance. Operators need proper feedback to be able to identify and fill gaps in their competency or learn new practices. Appropriate feedback and assessment are of great importance to ensure that process operators have the competences required to ensure smooth and safe plant operation. Consequently, delivering effective training and evaluation represents a very significant challenge for the process industry. Further, the availability of on-site simulator training is often very limited and the costs related to it are high. Therefore, individual simulator training, in addition to team training, can be a practical option to be considered. This article presents a thematic analysis of simulator training practices in different industries. The findings suggest that individual training can be implemented as a supplement to on-site training, that effective feedback and assessment are necessary, and that the training should be based on a human-centric perspective.

1. Introduction

Simulator training consists of learning and developing different skills by using computerized models that can emulate a variety of real phenomena and processes. As a learning strategy, simulator training promotes transfer, which, according to Perkins and Salomon (1992), “occurs when learning in one context or with one set of materials impacts on performance in another context or with other related materials.” Research by Spetalen and Sannerud (2015) indicates that simulation can be a suitable strategy for achieving close transfer, given context similarity and a connection between tasks in the simulation and the application context. Simulator training has many benefits, and it has been widely implemented among industrial operators since the 1990s. Simulators for training industrial operators are known as Operator Training Simulators (OTSs) (Patle et al., 2014). OTSs are based on dynamic simulations of industrial processes. The simulation software available in the market includes Aspen Dynamics & HYSYS Dynamics from Aspen technologies; ASSETT and K-Spice from Kongsberg Oil & Gas Technologies; TSC Sim from TSC Simulation, UniSim from Honeywell, and OLGA from SPT Group (Patle et al., 2014).

References to simulator training for industrial operators mainly

concern on-site training. This means that the operators have to travel to the training facilities, where training takes place in a room that replicates the actual control room with all the necessary equipment (hardware and software) (Kluge et al., 2014). It also includes a user interface that shows a distributed control system (DCS) resembling the real process. This allows the operator to learn and understand the process by practicing different scenarios (Kluge et al., 2014; Nazir et al., 2015b). Usually, this is the only place where a simulator is available to the operators; all training they do is carried out at the designated location, where they are guided by and receive feedback from an expert instructor. During simulator training, the operators can practice handling different scenarios, such as malfunctions, troubleshooting, abnormal or emergency conditions (Komulainen et al., 2012; Kluge et al., 2014; Patle et al., 2014). In many cases, the scenarios have to be solved in groups, with the aim of improving team skills. During the training, each operator has her/his own computer that interfaces the same process model, as in the actual plant where each operator has her/his workstation that interfaces the same DCS. This is the traditional way in which simulator training is carried out. However, even though extensive research exists that discusses the benefits of this type of simulator training approach (Asbjörnsson et al., 2013; Kluge et al., 2014;

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Patle et al., 2014; Salas et al., 2012), several factors suggest that operator-training methodologies need to be improved. For instance, throughout the training, operators have to adapt to the rhythm decided by the instructor or to the flow of the training session that arises together with their colleagues. In the case of team training, it is difficult to award individual scores to the operators. Further, the time the process industry allocates per year to simulator training sessions is very limited (Komulainen and Sannerud, 2014). In the case of Statoil ASA in Norway, the training time allocated for expert operators is two days a year; for novice operators, it can be five days a year (Nordsteien, 2015). The availability of expert instructors is limited as well, and one instructor can only train four or six operators at the same time. Therefore, some of the training tasks may not be completed, and the quality of the training may be affected. Moreover, in the last decade, there have been major developments in advanced process control technologies, which means that operators at industrial plants encounter strong challenges due to the complexity of the highly interconnected processes, the high information load of the control and safety systems, and other related technologies (Nazir et al., 2014; Zou et al., 2015). Limited training time, together with technological challenges, increases the probability of human errors, which, in turn, can lead to industrial accidents (Nazir et al., 2012), many of which occur every year (Koteswara and Yarrakula, 2016; Bureau of Labor Statistics, 2016; Eurostat, 2017). It seems that the solution to this industrial vulnerability does not rely entirely on the implementation of advanced automation; it is also related to learning methodologies and training time. Technological development aimed at achieving automated control of industrial operations leads to an increased need for new and improved methods for training operators – to ensure that they are competent and skillful enough to properly meet the high requirements of automated systems. In order to identify how to enable individual simulator training practices that could reinforce the traditional training methods for operators, a review was carried out of various articles relating to industrial simulator training.

The rest of the paper is organized as follows: the second section presents contextual information, being this: what is meant by individual simulator training and which technologies already exist that offer individual training. These technologies will be analyzed from a pedagogical perspective to identify how they can be implemented to support individual simulator training. The next section describes the methodology followed for the literature review. Findings are presented in Section 4, and the analysis of the findings is presented in Section 5. Finally, some conclusions are drawn in Section 6.

2. Contextual information

2.1. Individual simulator training

Before proceeding, it is necessary to explain what is meant by individual simulator training. As the name implies, individual simulator training is not focused on teams, but rather on the individual. Team training is already taken care of during on-site training at the training facilities. Individual simulator training refers to the implementation of suitable technology and learning strategies that enable operators to:

- develop individual technical skills,
- have access to off-site simulator training whenever they feel they need it,
- train on the simulator until they have completed all the recommended training tasks,
- refresh previous knowledge they may be in doubt about due to infrequent use.

2.2. Individual training technologies

There exist different technologies that allow individual training; a

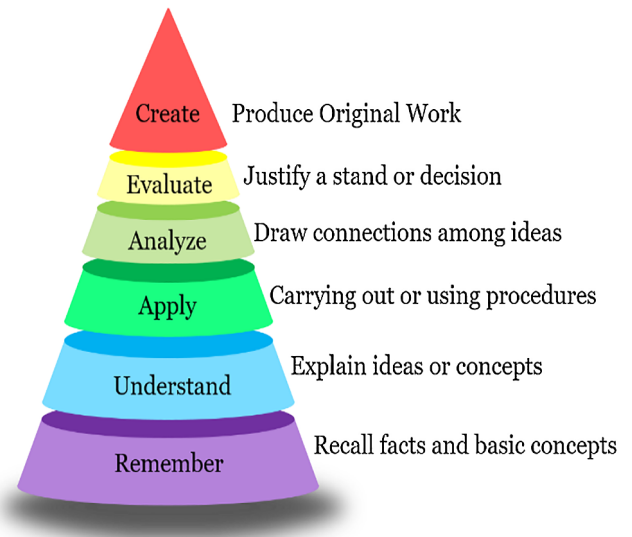


Fig. 1. Revised Bloom's taxonomy (Krathwohl, 2002, Vanderbilt University Center for Teaching, 2016).

pedagogical analysis of these technologies can show how they can be implemented to enable individual simulator training. The pedagogical analysis was done using Bloom's taxonomy, which is a suitable classification system to categorize cognitive skills. It was introduced in 1956 by Benjamin Bloom and colleagues as the Taxonomy of Educational Objectives (Bloom, 1956). In 2001, a revised version of the taxonomy was presented by Krathwohl (2002). Bloom's taxonomy is a model for classifying statements about what students are expected or intended to learn from specific training (Krathwohl, 2002). It consists of six main categories in the cognitive domain, which, in the revised version, are: remember, understand, apply, analyze, evaluate, and create. A pyramid illustrating the categories is shown in Fig. 1. The categories are organized hierarchically from simple at the bottom of the pyramid to complex at the top. In connection with the present rapid technological evolution, the name Bloom's digital technology has been introduced (Common Sense Education, 2016, Churches, 2008). The term has been coined from the perspective of how technology affects the model; in this sense, the focus should not be on the technological tools themselves, but rather on how the tools can help to foster each of the cognitive levels in Bloom's taxonomy (Common Sense Education, 2016). Given that Bloom's taxonomy is a very well known model, and one of the most used tools in the pedagogical field, it was selected as the basis for the analysis of the individual training technologies.

Which technologies can promote individual training, then? Some of the most relevant examples are mentioned below. In addition, Table 1 shows which cognitive levels of Bloom's taxonomy are supported by these technologies.

In general, *e-learning* refers to learning via electronic information frameworks that allow the user to access information that is available without limitations of time or space (Aparicio et al., 2016). Alexander and Cosgrove (1995) defined a four-level model of e-learning, Chang (2016) explains each level as follows:

- First level: online presentation and publishing
- Second level: online quizzes and assessment
- Third level: online forums, opportunity to give and receive feedback and participate in open discussions.
- Fourth level: role-play, face-to-face presentations, discussions, and online debates.

Based on this four-level model, e-learning can support several categories in Bloom's taxonomy (Table 1). The first e-learning level is

Table 1
Cognitive levels supported by individual training technologies.

Category	Individual training technology
Create	<ul style="list-style-type: none"> ● e-learning (4th level)
Evaluate	<ul style="list-style-type: none"> ● e-learning (3rd level) ● ITS
Analyze	<ul style="list-style-type: none"> ● Simulator training ● e-learning (3rd level) ● LMS ● ITS
Apply	<ul style="list-style-type: none"> ● Simulator training ● ITS ● LMS
Understand	<ul style="list-style-type: none"> ● Simulator training ● e-learning (2nd level) ● LMS
Remember	<ul style="list-style-type: none"> ● Instructional videos ● e-learning (1st level) ● Instructional videos

where learning material and information are found. This level, therefore, supports the lowest category of Bloom's taxonomy, *remember*. The next e-learning level is associated with quizzes and assessment; here, students should explain what they have understood from the information acquired, thus supporting the second category of Bloom's taxonomy, *understand*. In the third level of e-learning, students need to *analyze* what they have learned in order to be able to participate in open discussions. They should also be capable of criticizing and *evaluating* what others say in order to be able to give them feedback, thus supporting the fourth and fifth categories of Bloom's taxonomy, respectively. Finally, the last level of e-learning supports the highest category of Bloom's taxonomy, *create*, since role-play, presentations and online-debates require the production of new and original work (Table 1).

E-learning is implemented in many different fields, such as lower and higher education, the corporate sector, industry, and health care (Cheng et al., 2014).

In the case of individual simulator training for industrial operators, e-learning could be very useful, especially for novice operators, since they are learning new concepts and how to understand the plant. Using e-learning, operators could have access to the necessary information at all times; they could consult the material whenever need to, no matter where they are. Moreover, they could participate in forums where they can discuss the process with their peers or with instructors when available.

Learning Management Systems (LMSs) provide the virtual platform for e-learning. Among other features, they enable management, monitoring of students, tracking of learning, testing, communication, and scheduling. They offer many time-saving utilities that are very useful for instructors (Cavus, 2015), who, as a result, are satisfied with the implementation of this technology (Almarashdeh, 2016). Moreover, LMSs enable students to organize their training time and to adapt the training to their personal requirements (Ramírez-Correa et al., 2017). LMS implementations can be found in small businesses and even the health care sector. However, they are most commonly implemented in higher education; examples include Edmodo, Moodle, and Blackboard.

LMSs support the second cognitive level of Bloom's taxonomy (*understand*) through testing and communication. Further, the opportunity they give students to organize and schedule their own learning also situates LMSs in the third and fourth categories of Bloom's taxonomy, *apply* and *analyze* (Table 1).

LMSs can be a great help in the training of individual operators because they make it possible to remotely keep track of each trainee. The instructor can monitor the operators' performance and progress at all times, and the operators can be informed about their development, and keep track of which scenarios they need further practice in. LMSs could be very useful for novice and even expert operators. In the case of

novice operators, they need constant monitoring and to practice more often, both of which can be achieved with an LMS. In the case of expert operators, LMSs can include tasks they could practice on and thereby refresh procedural scenarios; an instructor can remotely monitor that the operators have carried out the required activities and give them feedback when possible. This idea is presented by Bessiris et al. (2011), who propose an LMS for long-distance operator training.

Intelligent Tutoring Systems (ITS) refers to a type of computer tutoring in which the learner is given feedback and hints. This is done via a user interface that allows the learner to enter the steps required to solve a certain task (VanLehn, 2011). Polson and Richardson (2013, p.1) explain that an ITS must pass three tests of intelligence. First, it must have sufficient information, "knowledge", about the subject matter to be able to draw inferences or solve problems in the domain. Second, the system must be able to determine the learner's absorption of that knowledge. Third, the tutoring strategies or pedagogy embedded in the system must function in such a way that the ITS implements these strategies to improve the learners' performance. ITSs are mainly implemented for academic purposes; in elementary and secondary education (Huang et al., 2016; Wijekumar et al., 2013), and in higher education, such as engineering (Hooshyar et al., 2016; Huertas and Juárez-Ramírez, 2013; Khalfallah and Slama, 2015; Ramírez-Noriega et al., 2017), and medicine (Sehrawat et al., 2013; Wolfe et al., 2016).

ITSs support the third, fourth and fifth cognitive levels of Bloom's taxonomy, which correspond to *apply*, *analyze*, and *evaluate* (Table 1). Using ITSs, students have to execute procedures and implement what they know to solve tangible problems. Furthermore, high analytical and decision-making skills are required to perform the different tasks that can be practiced on an ITS.

An ITS would be the most appropriate tool for individual simulator training because it offers automated feedback. In the case of the other learning technologies mentioned (e-learning and LMS), even though they offer the possibility of feedback, they still depend on an instructor being available, which is not the case with ITSs. ITSs could be especially useful in the training and guidance of novice operators, but they could also guide expert instructors through complex tasks by giving them automated intelligent suggestions.

Instructional videos, also called educational videos, are becoming a very common learning tool. Wang and Antonenko (2017) indicate that this is due to the continuous growth of online learning. Consequently, it is imperative for educational/training institutions to support users in online learning environments. Instructional videos are an example of the current tools that help to reach online learners. Instructional videos are used in medical education in particular (Kon et al., 2015; Phillips et al., 2016; Rapp et al., 2016). Nevertheless, instructional videos are now also available about a great number of topics in a wide range of fields. Massive open online courses (MOOCs), such as Khan Academy, edX, and coursera, are good examples. YouTube is an even simpler and more accessible example. Instructional videos aim to teach and help students to understand concepts and procedures. Hence this technology is situated on the first and second cognitive levels of Bloom's taxonomy, which are *remember* and *understand* (Table 1).

Instructional videos are a smart way of explaining new concepts and demonstrating how to perform different activities; they could also be a good help in individual training. For example, well-produced videos could teach novice operators about the functions of the simulator, and they could show trainees how to perform different training scenarios. The operators could practice remotely on the simulator while following the instructions given in the video.

These four technologies are an example of the variety of existing tools that support individual training, and any or all of these tools, combined with simulator training, could result in a sound and effective individual simulator training system that enables trainees to reach the highest cognitive levels explained by Bloom's taxonomy.

3. Methodology

A literature review and a thematic analysis were carried out of 32 articles published during the period 2007 and 2017. The aim was to identify gaps in simulator training within traditional practices that could be filled by individual simulator training. Another aim was to identify relevant methodologies, features, and conditions that could facilitate individual simulator training. The literature studied was gathered from the following electronic databases: Science Direct, EBSCOhost, Scopus, and Taylor & Francis. The search strings used were: simulator training, process industry, training methods, and control room operators. The literature was supplemented by relevant publications found in the reference lists of the selected articles.

This paper explores the methodologies used for the implementation of simulators as training tools and how traditional practices could be improved by including individual training. A total of 65 articles were extracted from the literature search. All the publications that addressed the topics of simulator training implementation and methodologies, training strategies within the process industry, and evaluation of training performance were selected for the study. Of the 65 articles, 32 had the required characteristics.

Of the 65 articles extracted from the literature search, 33 were removed for the following reasons. A significant number of the articles are related to the design and development of operator training simulators (OTs) (Ahmad et al., 2016; Gerlach et al., 2015; Duca and Tamas, 2012; Pereira et al., 2009; Balaton et al., 2013). Many of them were not included because they mainly focus on mathematical modeling and the technical development of OTs, which is not the focus of this study. Rather than how OTs are designed, we wish to focus on whether effective use is made of them based on relevant learning methodologies. In other cases, the articles focused on the study of teamwork training (Gao et al., 2015; Kim and Byun, 2011; Yim and Seong, 2016), which is not the main interest in this article; this study focuses on determining the path to enabling individual training when necessary. Articles were also found that focused on finding the cause of risk or emergency situations in industrial processes, based either on the analysis of human factors or on the design of the simulators (Li and Harris, 2013; Brambilla and Manca, 2011; Ikuma et al., 2014; Kim et al., 2016). Articles of this type were also excluded because they were outside the scope of this paper.

The method used to analyze the selected literature was thematic analysis, which is a method that consists of identifying and analyzing patterns or themes within data (Braun and Clarke, 2006). This method was chosen due to its flexibility and usefulness for summarizing key features across a data set (Braun and Clarke, 2006). Further, it is a multidisciplinary method (Milch and Laumann, 2016; Salleh et al., 2017; Teruel et al., 2016), an indication of its soundness and reliability. The selected literature was imported into NVivo 11 and it was coded following the steps indicated in Braun and Clarke (2006). The first stage of the analysis of the publications consisted of reading the articles and getting to know the themes addressed. A number of themes within the material were coded, the result of which is very broad. Later, the codes were refined and grouped into more specific themes and sub-themes.

4. Results

The reviewed literature shows a wide range of themes. The most common one in the majority of the literature studied is the benefits of simulators. Advantages of simulators include realistic virtual environments, training flexibility, process understanding, training in emergency or rare situations, practice in standard operating procedures, etc. (Alamo and Ross, 2017; Gerlach et al., 2014; Kluge et al., 2014; Manca et al., 2012b). However, even though they are relevant, the benefits of simulator training were not the main concern of this paper, given that this is an already well-known subject. The focus was on finding how to enable individual simulator training. This section presents the results

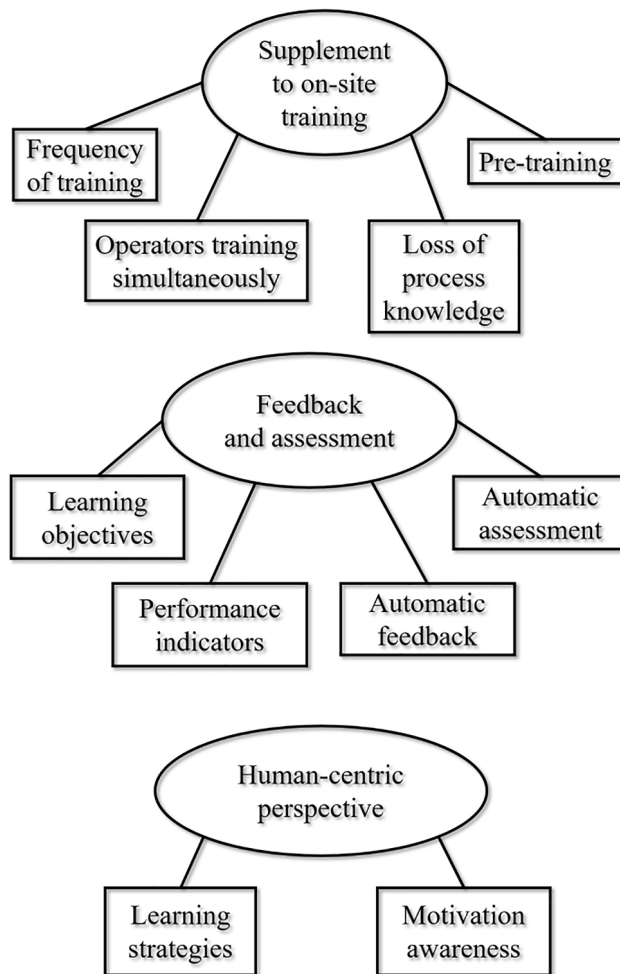


Fig. 2. Themes found by means of thematic analysis.

from the thematic analysis of the literature. The thematic analysis resulted in three themes, each containing several sub-themes: *supplement to on-site training*, *feedback and assessment*, and *human-centric perspective*. An overview of the themes is shown in Fig. 2.

4.1. Supplement to on-site training

The literature indicates areas in which individual simulator training can be integrated in order to supplement traditional practices for simulator training: *frequency of training*, *operators training simultaneously*, *loss of knowledge*, and *pre-training*. They are addressed in the following.

4.1.1. Frequency of training

The frequency of training is not a very common subject in the literature. It is not usually stated how often the operators train on the simulator or for how long. Nevertheless, it was possible to draw a conclusion from the material. The literature suggests that the frequency of on-site simulator training is very low. Normally, simulator training takes place once a year (Idrees and Aslam, 2010; Kluge et al., 2009; Ritz et al., 2015; Komulainen and Sannerud, 2014) and it can last for from three to five days (Bronzini et al., 2010; Håvold et al., 2015; Kluge et al., 2009).

4.1.2. Operators training simultaneously

During on-site simulator training, the number of operators that can be trained at the same time is contingent on the architecture of the training room, which is usually as similar as possible to an actual control room (Kluge et al., 2014; Manca et al., 2014; Nazir and Manca,

2015; Patle et al., 2014). This means that, depending on the process, the number of operators who can use the simulator simultaneously varies between two and six. Bessiris et al. (2011) point this out as one of the disadvantages of traditional simulator training sessions, given that, for large-scale processes, there can be high demand for operator training. In this article, they proposed a “Corporate OTS” approach that would enable remote training and the possibility of training a high number of operators at the same time. Concern about the number of operators that can train simultaneously on the simulator is also found in Vellaithurai et al. (2013), who suggest implementing a remote simulator tool that enables several operators to be trained at the same time.

4.1.3. Loss of process knowledge

Simulator-training instructors are typically expert operators, who are usually senior workers who have been controlling and learning about the process for many years. Their long careers and vast experience are the main reasons why they are experts. Therefore, it is of great concern in many industries that all of the knowledge acquired by experienced operators will be lost when they retire, without this knowledge being passed on to new operators (Dozortsev, 2013; Patle et al., 2014; Worm et al., 2012).

The loss of process knowledge in the industry due to generational transitions is one of the key motivations for research and development work on better and improved operator-training methodologies. Alamo and Ross (2017) argue that it is critical to ensure swift and adequate training for the remaining employees who will take over once the experienced operators retire, if the success of operating companies is to be maintained. Bronzini et al. (2010) also mention in their research that there is a great need for training of junior operators who have less on-the-job experience and must cover the positions previously held by experienced senior operators.

One approach to dealing with the loss of process knowledge caused by the retirement of expert operators is suggested by Manca et al. (2012a) and Nazir and Manca (2015). They suggest that it is necessary to develop an assessment tool that is reliable and repeatable. An assessment tool with these features must consist of standardized methods for operator training, and it must be based on certified and validated procedures, thereby ensuring that process knowledge is retained inside the plant. Vellaithurai et al. (2013) present an example of such a tool. They propose a system that learns by analyzing the corrective control actions taken by expert operators when using the simulator. Later, the system aligns the control actions calculated automatically with the data saved during the operators’ interaction. Based on this, the system can present the experts’ knowledge with precision.

4.1.4. Pre-training

Gerlach et al. (2014) carried out a research experiment where the performances of two groups of operators, one with pre-training and one without, were compared. The pre-trained group showed a better performance when following the SOP protocol than the group without pre-training. The authors concluded that pre-training on an OTS prior to the practical training in the plant enhanced the entire training process. Another example of the use of pre-training is found in Asbjörnsson et al. (2013). They developed an online training simulator for a crushing plant that was not yet built; they suggest that this would enable the operators to start training and be prepared for the ongoing training and actual management of the plant when it is operational. Dozortsev (2013) explains that operators carry out tasks that consist of multistage operations (e.g., detection of deviations from the norm, diagnosis of their causes, and planning and implementation of compensatory actions). He suggests that operators need to develop specialized skills for the different stages and argues that these skills should be developed during pre-training. The author also mentions Honeywell’s Russian branch as an example of a simulator vendor that has developed a range of pre-training products in response to user requests.

Even though some examples of pre-training are found in the

literature, it is not implemented regularly in traditional simulator training. However, in several of the articles, the authors suggest that the basic knowledge that each operator has of the process is a relevant factor that influences their learning and performance development when using the simulator (Asbjörnsson et al., 2013; Dozortsev, 2013; Gerlach et al., 2014). Therefore, it is critical to ensure that operators have the necessary basic knowledge before training how to handle complex processes and abnormal situations in the simulator. Prior knowledge of the process can reduce the cognitive load during ongoing training and thus lead to effective learning of new concepts and better performance (Bell et al., 2008). In conclusion, although not always explicitly, the literature reflects that it is essential to ensure that the operator has the necessary basic knowledge before starting formal simulator training.

4.2. Feedback and assessment

Feedback and assessment are key parameters of effective training (Salas et al., 2012). They are widely mentioned in the literature. According to Salas et al. (2012), timely, constructive, and diagnostic feedback makes the training more useful. Through clear feedback, the learning experience can be more effective; trainees can be guided to learn properly what is required, they can be guided to learn about the consequences of actions taken, and they can be guided to learn from errors (Håvold et al., 2015; Kluge et al., 2009; Tichon and Diver, 2010).

Training systems and methodologies are developed with the aim of improving operators’ skills. Thus, it is only reasonable that evaluation methods are implemented to determine whether the training results are successful or not, i.e., to determine whether the operator has achieved the training goals (Darken, 2009; Idrees and Aslam, 2010; Nazir and Manca, 2015). A thorough assessment procedure must be developed, and, to ensure the validity of the assessment, it must be capable of accurately determining and quantifying the skills operators have gained, their performance rate, and improvement (Bronzini et al., 2010; Dorey and Knights, 2015; Tichon and Diver, 2010). Further, assessment results mean that it can be determined whether or not an operator is well-prepared to work on the actual process (Vellaithurai et al., 2013), and they can be used to identify training needs and support the development of “tailor-made” training exercises (Håvold et al., 2015).

Nevertheless, although the importance of assessment is well reflected in the literature, several articles point out that there is a need for further research on the development of effective assessment methods for simulator training (Darken, 2009; Nazir and Manca, 2015; Nazir et al., 2015a). It is also mentioned that the assessment methods currently implemented in simulator training need to be improved. Bell et al. (2008) report that simulator trainees do not have an accurate assessment of their knowledge. This makes them overconfident about their skills, and, as a consequence, they underestimate the importance of training, which results in poor performance. Bessiris et al. (2011) mention that conventional simulators’ poor ability to track and assess operators’ performance is a weakness. Moreover, Nazir et al. (2015b) argue that another limitation of current training methods is the lack of objective performance assessment. Operator training does not usually involve systematic assessment methodologies; the evaluation of the operators is strongly influenced by the trainer’s experience and perception of what is correct. Therefore, the evaluation is subjective and non-repeatable, and hence not very effective (Manca et al., 2012a, Darken, 2009).

As a supplement to the theme of feedback and assessment, three sub-themes linked to the subject were identified in the literature: *learning objectives*, *performance indicators*, *automatic feedback*, and *automatic assessment*.

4.2.1. Learning objectives

The idea behind training is to develop or reinforce specific skills and acquire specific knowledge. Therefore, simulator-training

methodologies should be structured in such a way that the trainees are motivated to achieve the primary goals of the training process (Bell et al., 2008; Blake and Scanlon, 2007; Darken, 2009; Patle et al., 2014). Trainees need to be aware of the purpose of their training, so that they can orient their efforts towards achieving the learning objectives. Consequently, a logical assessment method must be centered on the learning objectives for the exercise, and it should be based on collecting relevant data that show whether or not the trainee has achieved the required goals (Salas et al., 2012).

Structured and clear learning objectives for training tasks form the basis for a comprehensive assessment, which, accordingly, leads to improvement and more effective simulator training.

4.2.2. Performance indicators

To be able to quantify or determine compliance with training objectives, special parameters that can express performance numerically must be defined. In the literature, these parameters are generally called performance indicators. However, in some research, the authors also refer to them as indexes or factors. Bronzini et al. (2010) define a Simulation Performance Index (SPI). They link a specific SPI to each training module and each index is determined using a reference value, which corresponds to the performance of senior operators. Park et al. (2017) use Performance Shaping Factors (PSFs) to determine Human Error Probabilities (HEPs). The authors state that each of these factors represents a particular aspect that may affect the operator's performance. On the other hand, indexes established to assess different trainees' characteristics are defined by Manca et al. (2012b) as Operator Performance Indicators (OPIs). They explain that the intrinsic human attribute in OPIs hinders evaluation of this type of indicator. Manca et al. (2012b) also state that the selection of OPIs depends on the training stage; some OPIs can be related to normal operating conditions and others to abnormal plant conditions. Therefore, OPIs must be defined according to the training circumstances. There are also Key Performance Indicators (KPIs), which are well-known industrial indicators, mainly associated with the process and plant performance (Manca et al., 2012a). The study and evaluation of well-defined KPIs leads to more readable and understandable performance analyses (Nazir et al., 2013). Another type of performance indicator is found in Nazir et al. (2015a), who define Distributed Situation Awareness Indicators (DSAs), which are used to describe and measure the distributed situation awareness (DSA) of the operators during training. Based on these indicators, it is possible to study whether the operators are focusing their attention on the most relevant aspects of the training.

There are a great variety of performance indicators; they have to be defined thoroughly and within the training context. Well-defined performance indicators form the basis for a repeatable and objective assessment that enables the training level of the operators to be described in quantitative terms (Manca et al., 2012a). Furthermore, adequate and relevant feedback can also be based on performance indicator values.

4.2.3. Automatic feedback

There are many suggestions in the literature concerning automatic feedback in simulations. Several articles point out that prompt guidance should be given during execution of the simulation tasks, and not only after the simulation is completed (Bell et al., 2008, Malakis and Kontogiannis, 2012). Bell et al. (2008) suggest that adaptive guidance and support throughout the simulation can enhance learning outcomes. Hence, it is essential to develop effective feedback methodologies that can be embedded in simulator-based training (Bell et al., 2008). Similarly, Malakis and Kontogiannis (2012) conclude that integrating instructional guidance into simulators leads to more successful training. Moreover, Manca et al. (2014) suggest that the results obtained from automatic assessment procedures could be used to produce robust automated feedback, which may increase operators' motivation to train more frequently with the simulator.

4.2.4. Automatic assessment

With respect to automatic assessment procedures, the literature suggests that they must be based on objective and measurable parameters (Manca et al., 2012a) and they must be consistent and repeatable (Manca et al., 2012b). This guarantees that the evaluation of operator performance is objective. Automatic assessment allows the operators' performance results to be stored in a database, to which the instructors must have access, so that they can retrieve and analyze the results, and observe and compare the operators' improvement and needs. In this manner, automatic assessment can be beneficial for instructors as well (Manca et al., 2014, 2012b).

4.3. Human-centric perspective

In the context of this research, a human-centric perspective refers to actions that focus on users' needs or opinions when developing and improving technologies or training methodologies. In the case of simulator training, human-centric refers to the design and development of the necessary tools based on operators' needs and suggestions.

Bell et al. (2008) present their concern about how simulations are designed; they point out that most simulation products do not take account of the individual learning differences between trainees, and, as a consequence, only some of the users benefit from simulator-based training. Therefore, they argue that future research on simulation development must pay close attention to the learner-centered perspective. Darken (2009) discusses the same topic, reporting that many training systems are technology-centered. The author argues that training technologies change rapidly with time, so it is not convenient to base the design of training systems on them; he suggests that the development of training systems should be based on human performance instead. Moreover, Darken (2009) states that some desirable characteristics of training systems are that assessment is focused on the trainee, and that they are developed using a common language, so that others can build new systems on top. More recent research also mentions human-centric considerations, thus recognizing their importance (Bronzini et al., 2010; Dozortsev, 2013; Håvold et al., 2015; Patle et al., 2014).

Velez et al. (2013) present an example of the advantage of implementing a human-centric perspective in the development of training systems. They developed a training simulator using a user-centered methodology, and they concluded that involving users in the development process led to satisfactory results. Given that the users were experts from different fields, this resulted in an exhaustive evaluation of the model from different points of view.

The literature suggests that the quality of training depends on much more than just the technology that is used. Successful training also depends on the development of simulation designs and training exercises based on trainees' needs, user-friendly technologies that can be used by a broader range of trainees, and human factor considerations.

On the other hand, two additional sub-themes that are also based on human-centric perspectives were identified: *learning strategies* and *motivation awareness*.

4.3.1. Learning strategies

Research indicates that simulators are valuable and useful tools. Nonetheless, to exploit their full potential, simulator training should be combined with a structured and well-planned training program based on a reasonable combination of theory and practice and users' needs (Alamo and Ross, 2017; Blake and Scanlon, 2007). Unfortunately, these last components are often overlooked. Learning strategies, feedback mechanisms, and analysis of training needs are not sufficiently prioritized in the development of training programs (Darken, 2009; Malakis and Kontogiannis, 2012). The importance of learning strategies is that they are developed based on a human-centric perspective; they involve structured thinking about the best methods for trainees to learn and retain new skills. Learning strategies allow trainees to get a better sense

Table 2
Learning strategies.

Learning strategies	Characteristics
Drill and practice (D&P)	<ul style="list-style-type: none"> • Continuous practice. • Procedural skills and instances. • Novices training. • Experienced operators case (further research needed).
Emphasis shift training combined with situation awareness training (EST/SA)	<ul style="list-style-type: none"> • Management of several tasks simultaneously. • Voluntary attention control. • Decision-making skills. • Events anticipation.
Transfer appropriate processing	<ul style="list-style-type: none"> • Increasingly difficult. • Less instructor support. • Novices training.
Error training	<ul style="list-style-type: none"> • Learning from errors. • Encourage effort to learn. • Freedom to experience. • Practice of complex cognitive tasks.
Self-regulation	<ul style="list-style-type: none"> • Self-monitoring of performance. • Comparison of progress. • Adaptability to the task demands.
Guided discovery	<ul style="list-style-type: none"> • System discovery on their own. • Basic training courses. • Generic simulators.
Knowledge-based training	<ul style="list-style-type: none"> • Deep understanding of the system. • Fault detection and correction. • Procedural skills.
Visual instruction	<ul style="list-style-type: none"> • Videos/visual presentations. • Visual demonstrations. • Guided reflection.

of the simulator and improve their use of it. Well-established learning strategies enable better understanding and longer retention of the information gained during training.

The literature presents many different learning strategies. However, only those found relevant to individual simulator training were selected for discussion in this paper. Table 2 presents a summary of the selected learning strategies.

Drill and practice (D&P) consists of practicing a task continuously with the aim of gradually improving performance (Burkolver et al., 2010). In D&P, trainees are systematically guided through the correct execution of the tasks. This thereby promotes the acquisition of procedural skills (Burkolver et al., 2010; Kluge et al., 2009). Further, the research of Burkolver et al. (2010) revealed that D&P is an effective method for developing the skill of diagnosing common fault states, and is thus especially favorable for the training of novice operators.

Kluge et al. (2014) indicate that learning to handle complex systems takes place through the accumulation of instances, which can only happen through experience or practice-based training. Practice-based training enables operators to acquire the necessary instances and mental models that build their knowledge of the process.

Emphasis shift training combined with situation awareness training (EST/SA). This method consists of combining two learning methodologies, EST and SA training. In EST, the priorities of the elements of a task change often, which requires voluntary control of attention. It mainly consists of learning to handle several tasks simultaneously (Burkolver et al., 2010, Gopher et al., 1989) (Kluge, 2014, pp. 127–129). SA refers to the perception and understanding of the components of the environment and estimation of how the situation will develop in the short term. Mechanisms for redirecting attention to what is of interest can support the development of SA. SA training leads to the improvement of decision-making skills and event prediction (Burkolver et al., 2010).

Transfer appropriate processing refers to the idea that the difficulty of training conditions should increase as the trainees begin to master the

required skills. The trainees should receive less support from the instructors and the tasks practiced should resemble the actual work more (Salas et al., 2012) (Kluge, 2014, p. 125).

Error training consists of exposing the trainees to making errors, so that they can learn from the consequences of their actions. Error training encourages trainees to make a greater effort to learn and enable a deeper understanding of the training tasks (Kluge et al., 2009, Salas et al., 2012).

This kind of training gives trainees freedom to test and experience actions that might be too risky to try in the actual plant. Trainees can examine the effect that their decisions have on the process, and, in the case of possible errors, they can correct them and learn from them. Salas et al. (2006) suggest that there are two sub-components of error correction: self-correction and supported correction. In the case of self-correction, trainees study the errors by themselves without any guidance from the instructor or any other aids (Salas et al., 2006), thus developing their own strategies and increasing their resilience. With supported correction, on the other hand, trainees can receive directions and feedback to help them (Salas et al., 2006). Lorenz et al. (2005) indicate that guided error training combined with supported correction may be the best combination for improving skills development. Salas et al. (2012) recommend the implementation of error training, especially when practicing complex cognitive tasks.

Self-regulation. Salas et al. (2012) explain that self-regulation refers to trainees' knowledge which enables them to maintain their attention on learning by self-monitoring performance, comparing their progress to the final objective, and adjusting their learning effort and methods, as required. They state that self-regulation is a way to structure training to improve learning.

Guided discovery. In this method, trainees are supposed to discover the relevant characteristics of the training task by themselves. The instructor selects the learning tasks, but the trainees have to be active and find system relationships and connections between variables and interpret them on their own (Kluge et al., 2009). It is suggested that guided discovery could be implemented in basic training courses in which generic or basic-principles simulators are used. The method is expected to help to improve the knowledge and rule acquisition of the trainees (Kluge et al., 2009).

Knowledge-based training aims to help the trainees to develop a deep understanding of the system, so that they can find and fix faults. This type of training involves learning about the interdependencies of system parameters and system boundaries (Kluge et al., 2009). The method contributes to the acquisition of procedural skills through simulator training, and it also helps the operators to sharpen their strategies and response capacity (Kluge et al., 2009).

Visual instruction refers to the use of videos or visual presentations instead of verbal instruction, which leads to observational learning (Kluge et al., 2009; Ritz et al., 2015). The method can be used to demonstrate good performance and to enable guided reflection (Ritz et al., 2015).

Refresher interventions (RI). In addition to the learning strategies mentioned above, Kluge and Frank (2014) and Salas et al. (2012) discuss the importance of refresher intervention, which aims to avoid skill decay due to long periods of non-use (Kluge and Frank, 2014). Refresher intervention involves scheduling training sessions close in time so that trainees can implement what they have learned and not lose their knowledge (Salas et al., 2012). The results of the research of Kluge and Frank (2014) show that trainees who receive refresher intervention can perform better than those who do not. They conclude that refresher intervention supports skill and knowledge retention and that it is a useful tool for mitigating skill decay (Kluge and Frank, 2014).

4.3.2. Motivation awareness

Operator simulator training is a subject that must necessarily have a human-centric perspective, given that the training is directed at people. It is therefore reasonable that a human-centric perspective takes into

consideration the influence of emotions. Dorey and Knights (2015) explain that several external factors can affect the probability of trainees benefiting from simulator training. They argue that “pre-training motivation” is one of those factors, because it can influence trainees’ performance and the extent to which they learn. Trainees with high motivation can benefit more from practicing on the simulator, and the higher the motivation before training the more significant the learning will be (Bell et al., 2008; Salas et al., 2012). Tichon and Diver (2010) conducted a training session where trainees operated a simulated plant while their peers watched. The final performance results were shown on a screen that the peers could also see. The authors explain that the trainees wanted to do well and to be seen to do well; they report that use of the simulator created a degree of competition among the trainees, which could be a way of motivating trainees to learn and perform better. Salas et al. (2012) claim that motivation to learn can be enhanced by giving the trainees a clear explanation of how the training content relates to learning needs, and by providing relevant training support.

5. Discussion

This literature review aimed to identify how to enable individual simulator training. To do so, a thematic analysis of the literature selected was carried out. Fig. 2 shows a summary of the three central themes that were found. The results indicate that individual simulator training can be used as a supplement to on-site training. Further, prompt and real-time feedback, and end-performance assessment are necessary to enable effective individual simulator training. Finally, the development of an efficient individual simulator training setup must have a human-centric perspective. In the following, each theme will be discussed separately.

5.1. Supplement to on-site training

On-site simulator training has excellent benefits, it offers an environment that closely resembles the actual work conditions, and it allows for team training. However, the results of the literature review show that traditional on-site training practices have certain limitations. Individual simulator training can be implemented to supplement the conventional training practices and offset their weaknesses.

Training time is a significant constraint on traditional simulator training. The frequency of on-site training is once a year on average. Enabling individual simulator training would make it possible for operators to train as often as they consider necessary. They could practice specific scenarios and be able to complete all the necessary individual tasks. With individual simulator training, the frequency of training could be increased.

The number of operators who can be trained at the same time is another aspect that can be improved by individual simulator training. With individual simulator training, the number of operators who can train simultaneously will not depend on the room layout or the instructor’s capabilities. This could be a significant advantage, especially in the training of novice operators, who are usually more numerous than expert operators. In fact a technical solution to this problem already exists. It has been implemented in Statoil ASA in Norway. They have a virtual simulator to which the operators have access off-site, and several operators can be connected at the same time (Nordsteien, 2015). It is not a widely used solution, however.

Further, the implementation of individual simulator training could help to assuage the great concern that currently exists in different industries about loss of knowledge due to experts’ retirement. Individual simulator tools must be developed in such a way that all operators’ performances are recorded and saved. This will enable a database to be created. The data should be classified so that it is possible to identify the best performances, which could be used as benchmarks for feedback and the assessment of other operators. Expert operators should mainly

be encouraged to perform the most relevant training tasks, so that their knowledge is saved as examples of correct performance. Their expertise and experience will thereby not be lost when they retire.

Lastly, the results of the literature review also show that individual simulator training given as pre-training could supplement the traditional simulator training practices. Individual training could be an excellent tool for developing novice operators’ basic knowledge. The novice operators could train individually on general simulations to learn the basic concepts associated with specific processes and equipment. Regular operators could also use individual simulator training as a pre-training tool. They could practice tasks that help them keep their awareness of the process sharp, and refresh procedures before taking the on-site training, making the latter even more useful. Monitoring complex systems entails extensive mental demands. It can be overwhelming for operators to handle the vast amount of information that is displayed to them, especially, during abnormal or emergency situations, when they have to be more concentrated and attentive to changes in the process, and to active alarms. Hence, continuous practice is necessary to ensure that operators keep their knowledge fresh.

5.2. Feedback and assessment

The results from the literature review do not just show that individual simulator training could be a supplement to traditional training practices. They also reveal essential characteristics of simulator training that should be considered if individual simulator training is to be successful. In general, feedback and assessment are critical parameters of adequate training. Hence, both must be included in order to develop sound individual training strategies.

The literature review shows that training programs must be based on structured learning objectives. Trainees must be aware of these objectives, so that they know where special effort and attention are required during a training task. Consequently, individual simulator training must include a reasonable explanation of well-defined learning objectives. Given that trainees are on their own during individual simulator training, relevant information must be provided. This is a good example of how individual training technologies could be implemented to increase the value of individual simulator training. E-learning, LMSs, or instructional videos could be practical tools for providing a clear explanation of learning objectives.

Further, the results of the literature review indicate that a proper assessment method must be objective and repeatable; several studies suggest that the implementation of performance indicators can ensure this. Performance indicators are quantitative values that help to measure operators’ performance, study the process status, and determine whether the learning objectives have been achieved. Hence, the assessment of individual simulator training must be based on appropriate performance indicators. The most representative performance indicators for the training tasks must be defined. This is especially relevant to the development of automatic feedback and automatic assessment. The automatic assessment should be presented to the operators once they have concluded the training task. The operators can thereby receive a final analysis of their performance. They can take note of their mistakes, reflect on, and learn from them. Further, an automatic assessment also enables the operators to see their improvement and their training progress.

As regards automatic, real-time feedback, this is the main characteristic required of individual simulator training. Fruitful individual training must guarantee that trainees can succeed in learning by themselves. Automatic feedback can be based on different performance indicators and other relevant process values, such as flows, temperatures, pressure, etc. Real-time monitoring of these indicators will enable prompt feedback to be given to the trainees and inform them in time about possible abnormalities in the system. The experimental results presented in Bell and Kozlowski (2002) show that adaptive guidance during simulator-based training leads to greater comprehension of the

learning content. Real-time feedback can be achieved by using an ITS. Mitrovic et al. (2013) suggest that ITSs that mainly address errors could be more efficient if they are combined with positive feedback features. Using ITSs for operator training was formally proposed several years ago (Frasson and Aimeur, 1998; Gutierrez et al., 1998; Shin and Venkatasubramanian, 1996). The current progress in technology suggests that now is an excellent moment to proceed with its implementation in practice.

In addition, automatic feedback could also be a beneficial solution for new instructors, who may feel insecure about giving feedback to their peers. If they have a tool that can help them to decide in real time what kind of feedback to offer, they may feel more confident. Moreover, this could also motivate other expert operators to become instructors. In this way, the benefits of individual simulator training are broadened, since they are also an asset for instructors.

5.3. Human-centric perspective

It is crucial to keep in mind that training technologies and methodologies are designed to be used or implemented by people. The literature review shows that simulator training can be more efficient when it takes into account the trainees' needs, such as individual learning differences or user-friendly options. Therefore, for individual simulator training to be successful, both the technical aspect and the learning aspect must be based on human-centric strategies.

Shorter non-training periods are one of the trainees' needs that must be addressed. As mentioned above, one of the main weaknesses of traditional simulator training practices is the limited time set aside for training. Therefore, trainees forget essential knowledge due to long periods of non-use. Individual simulator training is a practical solution to this issue. It can enable regular refresher exercises that can be useful for both novice and experienced operators. A common strategy for refresher interventions (RI) is Drill and Practice. Repeatedly performing a task helps to develop attention allocation and correct timing (Kluge and Frank, 2014). Kluge and Frank (2014) claim that "the effects of the Practice-RI can be attributed to a higher skill automatization, which results in a lower mental workload." Individual simulator training can be used as a refresher intervention based on drill and practice. Moreover, it can be based on any of the different learning strategies found in the literature review. Motivation is another relevant consideration in a human-centric perspective. The results from the literature review indicate that trainees' motivation is a critical issue that should be taken into account when evaluating performance. Therefore, individual simulator training must also consider trainees' motivation as an integral and effective element. Trainees' motivation to learn should be assessed before the training session, and these data should later be compared with her/his performance results. This will make it possible to study how motivation affects trainees' performance, and what kind of strategies to implement to keep them motivated.

Assessing trainees' motivation can be a complex task. There are several studies within the field of psychology and education dedicated to this issue (NOE and Schmitt, 1986; Pintrich and De Groot, 1990; Midgley et al., 2000). In the studies by NOE and Schmitt (1986), Pintrich and De Groot (1990), and Midgley et al. (2000), the authors developed self-report questionnaires that include specific items to assess trainees' motivation to learn. Trainees have to respond to these items on a Likert scale. Even though these studies are not specific to the field of simulator training, they can be used as a basis for developing a motivation assessment questionnaire that is adapted to the needs of the simulator-training field.

6. Conclusion

The aim of this article was to study how to enable individual simulator training as a supplement to traditional on-site training practices; to do so, a literature review was carried out based on a thematic

analysis of literature related to the topics of simulator training, operator training, and training methodologies. Three key themes were identified: *supplement to on-site training, feedback and assessment, and human-centric perspective.*

The findings indicate that individual simulator training can supplement traditional simulator training practices. Individual simulator training can be used to address the weaknesses of the conventional methods, such as limited training time, the limited number of operators who can train simultaneously, or the limited availability of instructors. Further, the results also show which primary requirements individual simulator training should fulfill to be a successful practice. These primary requirements are effective automatic, real-time feedback, and automatic assessment. Moreover, individual simulator training should be based on proper learning strategies, and it should take into account operators' training motivation. Individual simulator training aims to make the operator independent of on-site training and the instructors. Thus, effective real-time feedback is one of the most critical conditions for individual simulator training being a sound and useful strategy. The conclusion is that individual simulator training should include an embedded intelligent tutoring system, which is a current, particular training solution that gives prompt and effective real-time feedback.

At the general level, individual simulator training can be seen as an always-available refresher intervention tool. Operators can at all times practice and thereby remember specific procedures. In the case of novice operators, they can rely on learning new concepts through hands-on experience of different scenarios. This research shows that there is room to integrate individual simulator training into traditional training practices. Furthermore, we conclude that individual simulator training could even help to offset the weaknesses of conventional practices.

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Declarations of interest

None.

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B Constructive Assessment Method for Simulator Training

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Constructive Assessment Method for Simulator Training

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Abstract

Industrial operator assessment is a very controversial subject in the scientific community, as determining the most suitable, objective and effective means of giving feedback on an operator's performance is a great challenge. This paper presents a proposal on assessment methods for simulation training. The development is based on the results from simulator training courses held at Oslo and Akershus University College of Applied Sciences (HiOA) from 2010 to 2014. The results and course evaluation were analyzed to identify where new methods could be applied that would lead to improvement. The method proposed consists of an automatic assessment procedure, which will give feedback to the simulator course participants during the simulator session and help the students to achieve the learning outcomes. The proposed method will be tested in the simulator training courses at HiOA in spring 2017 and the results will be presented in a later paper.

Keywords: assessment, performance, operator, feedback, students, learning outcome

1 Introduction

1.1 Simulator training and performance assessment challenges

The evaluation of operators' performance represents a significant challenge for the process industry, as the appropriate assessment of operators' performance is of great importance to ensuring the right competencies and safe plant operations.

A recent study in the Norwegian oil and gas industry (Komulainen and Sannerud, 2014) reveals that only 30% of the respondents take exams after the simulation courses. The evaluation of the simulator trainee performance is based on the instructor's verbal feedback during the scenario and the instructor's verbal assessment after the scenario.

The automatic assessment tools available require the implementation of a specific sequence of actions for each scenario. The main criticism of automatic assessment is the high implementation and maintenance workload of the scenarios, the difficulty of implementing just one optimal sequence for complex scenarios, i.e. there can be many good alternative

solutions, and the interpretation of operators' learning outcomes, competencies and skills from the figures generated by the automatic assessment system. Thus, the use of automatic assessment tools is not widespread in the Norwegian oil and gas industry.

Virtual laboratories i.e. complex process simulators, are important learning tools in modern engineering education; they are relevant to industrial practice, they facilitate collaborative, active learning among the students, and they are time and cost effective (Coble et al., 2010; Corter et al., 2011; Edgar et al., 2006; Komulainen and Løvmo, 2014; Martin-Villalba et al., 2008; Rasteiro et al., 2009; Rutten et al., 2012; Wankat, 2002).

Dynamic process simulators have been used as an additional learning tool at HiOA since 2010 (Komulainen and Løvmo, 2014). Our experience shows that simulator training provides industrially relevant practice for large student groups. However, in order to provide prompt assessment of learning outcomes at an individual level, an effective personal feedback and assessment tool is required.

Both industrial and academic experience on simulator training indicate a need for effective automatic assessment measures. The challenge in developing such a tool is to avoid too deterministic measures (i.e. scenario-specific sequences), and to ensure the clarity and measurability of the learning outcomes.

1.2 Introduction to the proposed work

The simulation module is built up using the six categories of the didactic relation model: learning goals, content, learning process, learning conditions, settings, and assessment. These categories are relative to each other i.e. if changes are made in one of the categories this will lead to changes in the other categories (Bjørndal and Lieberg, 1978; Hiim and Hippe, 1998).

Thus, the assessment of the simulation module has to be directly related to the learning goals of the simulation module. In the following, we suggest measuring the theoretical knowledge using key performance indicators (KPI) and to measure practical competencies using operator performance indicators (OPI).

1) Key performance indicators (KPI): The evaluation of the performance of any process is a matter of high

priority, as it is necessary to determine how efficient the process is and whether it is being executed as optimally as possible. In the research of Manca et al. (2012), it is indicated that from the 1980s, the scientific community became aware of the industry's need for performance assessment. Therefore, it was necessary to establish quantitative indicators that could help to measure the production efficiency of a process; these indicators are known as Key Performance Indicators (KPIs).

Key Performance Indicators express the performance of a whole process; they measure the performance of all types of equipment that form a plant and of the entire plant itself (Lindberg et al., 2015). In the industry sector, performance indicators based on human factors are called operator performance indicators (Manca et al., 2012), which, conversely to KPIs require a more complex evaluation due to their implicit human attributes.

2) Operator performance indicators (OPI): Kluge et al. (2009) carried out extensive research on different training methods used for process control simulators. They explain several of the goals of simulator training, some of which are summarized below:

- Lead the trainees to an understanding of physical processes, the overall operation of the plant, and system functionality.
- Start-up and shut-down procedures.
- Procedural knowledge for normal plant operation and the use of checklists.
- Operators should be able to improvise and adapt to the contingencies of abnormal events.

The goals of simulator training are thereby to meet an overall main objective: efficient operator performance. From the research of (Nazir et al., 2015), several relevant factors can be recognized that can be considered as operator performance indicators. In the process industry, there are two kinds of operators, Control Room Operators (CROPs) and Field Operators (FOPs). One of the most important features of the teamwork between these two kinds of operators is communication. Effective collaboration between CROPs and FOPs leads to the necessary actions to avoid accidents. Therefore, one important OPI is effective communication. Another OPI that can be associated with the teamwork between CROPs and FOPs is the accomplishment of tasks. Process safety is determined by different capabilities that must be associated with operators. Hence, these capabilities are related to OPIs as well: the ability to interpret the available information; ability to identify abnormalities; understanding the process in terms of operation, equipment, and instruments; being able to interact with different teams and deal with abnormal and escalating situations. Another specific characteristic of great importance, which is also related to OPIs, is time. The time taken to execute certain tasks and more specifically, the time

taken to deal with abnormal or emergency scenarios, as this is a direct reflection of the responsiveness and attention skills of the operator (Nazir et al., 2015).

Similarly, based on the research conducted by (Nazir et al., 2012) on situation awareness in industrial plants, Manca et al. (2012) identified some characteristics that are related to the concept of OPI. These characteristics are:

- level of knowledge of the fundamentals of the process;
- the role played by the streams involved in the process;
- the ability to run the process under new conditions;
- the ability to deal with abnormal situations;
- the ability to establish a safety culture and
- the ability to coordinate actions.

There is a common factor in the last four studies referred to above, namely the understanding of the process; this can be considered as one of the most important OPIs, as good performance is based on good knowledge of what is done. Kluge et al. (2009) suggested that "knowledge of how to operate the plant to achieve certain goals can lead to good performance". Nevertheless, it is becoming a challenge for operators to obtain good and sufficient knowledge of the processes they operate due to the great advancements in automation, which are more and more complex and lead to information overload and difficulties related to human machine interface (Nazir et al., 2014; Zou et al., 2015).

Nazir et al. (2013) mention the relevant role played by the execution of an appropriate performance evaluation of the operators. The authors suggest that a correct assessment of the operators is also part of a well-designed training method, in order to reduce the number of accidents occurring in the industrial sector and their impact. It is indicated in the study, that the assessment procedure should be completely objective, in order to guarantee consistency, quantitative assessment, repeatability, and neutrality. Therefore, the assessment process must be automatic. In order to do so, the specific characteristics that the system will evaluate must be identified. These are: OPIs, KPIs and help requirement analysis. In their article, they present an example of the methodology of performance assessment for a catalytic inject process and a C3/C4 splitter. The operator performance indicators evaluated in this case were: Reaction time, Identification ability, Self-dependence, Attentiveness, Multitask handling, Voice communication, Identification ability, Recalling ability, and Situation handling.

Within the same context, Manca et al. (2012) conducted research where they indicate the importance of the assessment of the training performance of CROPs. The authors indicate that developing these evaluations represents a challenge, because the assessment is based on performance indicators related to

human beings and therefore on their intrinsic complexity, which leads to subjective evaluations by the instructors. Because of this, it is very important to develop assessment methods based on quantitative values and not just qualitative appreciation, so the assessment can be as unbiased as possible. In the research, they present a hierarchy scheme with different categories and classifications that form the overall CROP mark. The structure is used as a basis for determining the importance and the weighting of each OPI for the operator assessment. Each OPI is assigned a different value according to its place in the hierarchy using the Analytic Hierarchy Process (AHP). The authors suggested this method in order to overcome the drawbacks related to the subjectivity of the trainers.

Characteristics of the OPIs: One of the main features of OPIs is that they are intrinsically related to human factors as they are linked with the assessment of human beings; this is precisely what makes their evaluation so complex. However, Manca et al. (2012) explain that OPIs are not only based on human factors, there are other parameters that also contribute to the OPIs' definition, such as consistency and association.

2 Materials and Methods

2.1 Software tools for simulator training

The dynamic simulation software used is K-Spice® by (Kongsberg, 2016). K-Spice® is a modular simulation tool for oil and gas unit operations based on first principles physics, chemistry, and engineering.

Exercise Manager is an automatic assessment software product for the K-Spice tool. The simulation model used for the study is a generic oil and gas production simulator model that consists of a three-stage, three-phase oil and gas separation train, the utility systems, and emulated control and safety systems. An overview of the plant is given in Figure 1. More details on the model and the assessment tool are given by (Komulainen and Løvmo, 2014).

2.2 Software tools for simulator training

1) Sample selection: All the participating students attend two different courses at HiOA.

2) Data collection: The anonymous data collected included a multiple-choice questionnaire and the numerical results of the final exam. The questionnaire included several questions about simulators as an additional learning tool, and was evaluated on a 5-point scale. The questionnaire was given to the students at the end of the simulation module. The exam results were obtained from the teacher, who prepares and grades the final exam.

3) Data analysis: Questions on whether simulation enhanced the students' learning outcomes were evaluated on a 5-point scale, the percentages for "agree" and "highly agree" are presented in the following. The

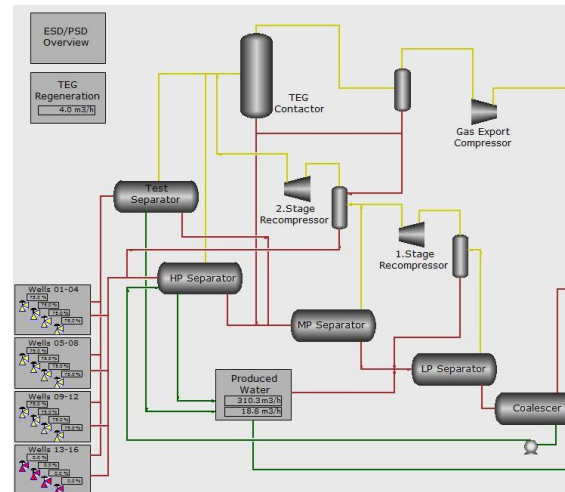


Figure 1. Overview of the large-scale oil and gas production plant model.

marks of the simulation task(s) in the final exam were compared to the average marks in the final exam.

3 Teaching and Learning in Simulator Training

3.1 Teaching and learning in simulator training at HiOA

The simulator training at HiOA follows the industrial briefing – simulation – debriefing structure. During the two-hour briefing session, the teacher presents the simulator, the dynamic trends, and the tasks in a classroom for all the students. For the four-hour simulation sessions, the students are divided into larger groups. Typically, the students work on familiarization tasks (60-75min) before the simulation scenarios (2-3h). The students start writing a preliminary simulation report during the simulation session, and spend approximately two hours afterwards to finish the report before the debriefing workshop. In the two-hour debriefing workshop, the students compare and discuss the simulation results in new groups of four students. At the end of the workshop, the teacher facilitates the summarization of the simulation results and of the overall experience on a whiteboard. The total time spent on one simulation training module is 7-10 hours.

The teacher explains the basics of the simulation tasks and gives a simulation demonstration during the introduction lecture. During the simulation sessions, the teacher has an instructor role, only providing help if the student group cannot find the solution themselves. In the workshop, the teacher is a facilitator, setting a framework for the group discussions on the simulation results and guiding the final plenary presentation of the results. The teacher gives the students feedback during the simulation sessions and the workshop, and grades the simulation reports.

The simulation tasks aim to enhance social interaction in small groups while the main focus is for each student to learn by doing the simulation tasks and reporting at their own pace. Discussions on the simulation results are encouraged during the simulation sessions and during the debriefing workshop, i.e. learning from peers and through reflection.

3.2 Current feedback and evaluation methods for simulator training

There is no feedback during the simulation scenarios if the students do not ask the instructor questions. During the debriefing workshop, students get feedback from their peers.

The learning outcomes of the simulation module are measured using the results of the formal final exam.

The students evaluate the simulation module as part of the compulsory report using a multiple-choice questionnaire.

3.3 Experience with simulator modules at HiOA

In the following, the results of two different simulation modules, namely laboratory distillation system and industrial large-scale oil production facility, are presented. The simulation modules were taught to two groups of chemistry students and two groups of electrical engineering students over a period of four years.

The simulation modules were taught in three sessions using briefing–simulation–debriefing (i.e. lecture–computer exercise–workshop) structure, which is typical for industrial simulator training. At the end of the simulation module, the students deliver their simulation reports in groups and present their results in groups at the workshop. The instructor for all simulator modules was the main teacher of the course.

The undergraduate chemical engineering course (fall 2010–spring 2011, 20 chemistry students) where mandatory dynamic distillation simulator exercises were given prior to laboratory experiments: 95% of the chemistry students agreed that simulation enhanced their learning. The average final exam result was 56%, whereas the simulation tasks received an average mark of 70% (Komulainen et al., 2012).

The results for the undergraduate chemical engineering course (fall 2011–spring 2012, 20 chemistry students) were similar, 90% of the students agreed that simulation enhanced their learning. The average final exam result was 43%, whereas the four simulation tasks received an average mark of 47%. The reason for the generally lower exam scores in 2012 was the change of exam type from written to multiple-choice with similar calculation task (Komulainen, 2013).

The undergraduate course in dynamic systems (fall 2013, 60 electrical engineering students) resulted in 97% of students agreeing that simulation exercises increase their understanding of process dynamics in

fluid systems. The average final exam result was 59%, whereas the simulation tasks received an average of 48%. One possible explanation for the low score of the simulation tasks was an unclear simulation chart (Komulainen and Løvmo, 2014).

The following year (fall 2014, 60 electrical engineering students) in the exam, the simulation chart was prepared with better resolution and clearer marking of the axes. The final exam result was 58% on average and the simulation task received an average mark of 54%.

In the final exam, the students scored higher than average when the simulation exercise was related to a practical laboratory experiment, and lower than average when the simulation results were not applied afterwards. One possible explanation is that group work without direct feedback might lead to misconceptions.

The students' evaluation of the simulation module and the students' evaluation of their own learning from simulation were very positive for all the groups. The students learn to use industrially relevant tools and their understanding of industrial processes increases.

3.4 Conclusions based on previous experiences

Utilization of industrial large-scale simulators enables students to gain additional skills: industrially relevant process knowledge, and teamwork skills. However, the feedback and assessment system needs to be developed further in order to clearly indicate whether the students have reached the learning goals.

4 Suggested Practices

4.1 Suggested effective assessment method for simulator learning

The main goal of the simulation module is to help the students obtain a better understanding of complex processes and to see the application of theoretical equations and concepts by means of realistic examples and methods. Therefore, there is always an academic commitment to develop revised strategies and procedures that can lead to improvement of the learning outcome.

The aim of this project is to improve the learning outcome of the practices that apply to the simulation module at HiOA. Hence, it is important to be able to measure the knowledge of the students before and after taking the simulation module. This will enable us to make a more formal and reliable evaluation of the benefits of using simulators as a learning tool. In order to achieve this, a diagnostic test based on the required conceptual knowledge about the subject in question should be applied.

The tasks connected to the simulation course have, until now, been based on the students making certain changes to the system and then analyzing the results.

The proposed idea is to add a new section to the simulation module, where the changes in the system will be pre-established, and the students should be able to recognize the abnormal situation and fix it.

The abnormal situation scenarios will be developed using a simulation program associated with the subject or topic of interest. In the case of the present project, which is based on industrial process control, the K-Spice Exercise Manager will be used. The students will have to run different simulation scenarios and observe the possible deviations from normal operations. They will see on the screen the corresponding alarm(s) that will lead them to the source(s) of the abnormal situation. Once the students recognize the problem, they should correct it based on their knowledge of the process. Once the scenario task is completed, a short assessment report will be delivered. The assessment report will be based on strategic performance indicators so that the evaluation is objective and unbiased. The total assessment will correspond to a main performance indicator, which is the Abnormal Situation Management (ASM). This main indicator at the same time may depend on different complementary factors as can be seen from Figure 2.

In Figure 2, the effectivity of the trainee refers to the total time required by the student to fully complete the task. The oil production must be monitored since this is the main goal of the industrial process related to the simulation module, and abnormal situations must be solved as soon as possible and efficiently, in order to avoid major oil production losses. It is also very important to monitor the environmental indicators, such as the flare flow rate or the produced water composition, since abnormal situations can also have serious repercussions for the environment. Another significant

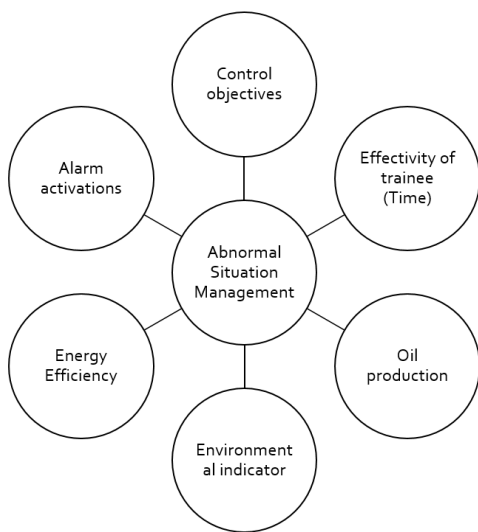


Figure 2. Main performance indicator and complementary factors.

factor is the energy efficiency of the process, which is analyzed through the total power consumption of the plant.

Every abnormal situation in industrial processes is reported by an alarm. The scenarios will be designed such that the problem presented in each task will constantly activate an alarm until the student solves the problem. A record of how long the alarm is active before the problem is solved is indicative of the performance of the student. Finally, the control objectives will be evaluated by the calculation of the integral of the squared error for the controller XC, which indicates how well the problematic controller was tuned, if this is the case. The following equation will be used to determine the total evaluation of the main performance indicator ASM.

$$ASM = \frac{r_{OP} \cdot w_{OP}}{r_{OP,max}} + \sum_i \left(\frac{r_{i,max} - r_i}{r_{i,max} - r_{i,min}} \right) \cdot w_i \quad (1)$$

Where the first term of the equation is related to the oil production (OP), r_{OP} , w_{OP} and $r_{OP,max}$ correspond to the performance measure, the weight of the OP factor and the maximum value of oil production, respectively.

In the second term of the equation, the rest of the factors are evaluated, r_i corresponds to the performance measure of the i_{th} factor, w_i is the weight of the i_{th} factor and $r_{i,max}$ and $r_{i,min}$ are the maximum and minimum value of r_i , respectively.

Each factor makes a different contribution to the total evaluation of the main performance indicator ASM. The Analytic Hierarchy Process (AHP) (Saaty, 2008), was used to calculate the corresponding weight of each factor. This method consists of creating a square matrix based on a pairwise comparison of the factors. The values that indicate how many times one factor is more relevant than the other are according to Saaty’s scale. Finally, the matrix entries satisfy the condition $a_{i,j}=1/a_{j,i}$.

Table 1 shows the pairwise comparison matrix for the factors that constitute the main performance indicator. The final priorities associated with each factor (Table 1) correspond to the priority vector of the pairwise comparison matrix, which is the normalized principal eigenvector of the matrix (Brunelli, 2015).

4.2 Specific example of effective evaluation methods for simulator learning

The scenarios must be related to the tasks that the students are going to develop during the first part of the simulation module. The goal is to gradually increase the difficulty of the tasks within the same contexts. In the first part of the module, the students make changes in the system themselves and evaluate the results. In the second part, they are not going to make the changes but to recognize them and solve them.

Table 1. Pairwise comparison matrix for weighing the factors that constitute the main performance indicator.

Pairwise Assessment	ET	OP	EI	EE	AA	CO	Priorities
Effectivity of Trainee (ET)	1	1/4	1/3	1/3	1/2	1/2	0.063
Oil Production (OP)	4	1	1	1	3	3	0.262
Environmental Indicator (EI)	3	1	1	1	3	3	0.251
Energy Efficiency (EE)	3	1	1	1	2	2	0.218
Alarm Activations (AA)	2	1/3	1/3	1/2	1	1/2	0.091
Control Objectives (CO)	2	1/3	1/3	1/2	2	1	0.115

For example, one of the tasks of the first part of the module consists of producing a failure in the level controller of the HP separator by changing the controller to manual mode and decreasing the controller output. As a result, the level in the separator increases and reaches the High-High level, which activates the security alarm, and a partial shutdown occurs. The corresponding assessment scenario will also be based on a controller failure, but the students will not know this in advance. The student will have to run the simulation and observe the system behavior, identify the alarm and solve the problem.

In this particular case, the level will reach the High limit, and it will then stabilize for a moment before reaching the High level again. These kinds of scenarios are also devised with the aim of developing the students' situation awareness, since they must be attentive to recognize the changes in the system.

An example is presented below to demonstrate how to apply the Analytic Hierarchy Process together with (1) to calculate the result of the main performance indicator. The results presented below correspond to a trial test executed by the authors.

As mentioned before, the scenario consists of a failure in the level controller of the HP separator. When the scenario starts, the controller mode switches from auto to manual and the controller output is decreased until the level in the separator reaches the High Level Alarm, then the controller output increases again until the level inside the tank reaches a safe value. This sequence is constantly repeated until the problem is solved, as shown in Figure 3. The solution is simply to switch the controller back to auto. Since no controller tuning is required in this scenario, and the abnormal situation does not affect any environmental aspects of the process, these two factors are not considered in the pairwise comparison matrix developed for the example, which is shown in Table 2.

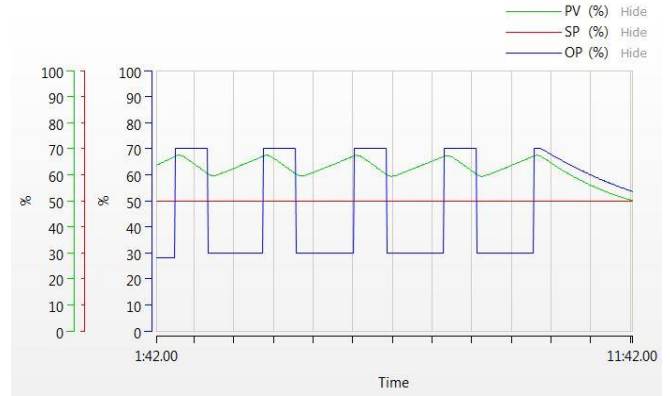


Figure 3. Level controller behavior during the simulation scenario.

Table 2. Pairwise comparison matrix for the example of the level controller failure.

Pairwise Assessment	ET	OP	AA	Priorities
ET	1	1/4	1/2	0.137
OP	4	1	3	0.625
AA	2	1/3	1	0.239

Table 3 shows the values needed for the calculation of each term of (1), and the final calculation of the main performance indicator that correspond to this example. Table 3 also shows the contribution made by each factor to the final value of the Main Performance Indicator. The example was solved in 11.7 min. The minimum time was 5 min and the maximum time was 20 min. There were five alarm activations. In this case, the minimum alarm activations was 2 and the maximum was 10. Finally, the average oil production during the total running period of the example was 908.3 m³/h and the maximum production under normal circumstances is approximately 980.0 m³/h. The sum of the values obtained for each factor multiplied correspondingly by their individual contribution gives a final performance of 80%.

Table 3. Calculation of the final value of the main performance indicator.

	r_i	$r_{i,min}$	$r_{i,max}$	W_i	Equation Term
ET [min]	11.7	5.0	20.0	0.137	0.076
AA [-]	5	2	10	0.239	0.149
OP [m ³ /h]	908.3	-	980.0	0.625	0.579
Main Performance Indicator					0.804

5 Conclusions

The simulator training at HiOA currently lacks quick, individual feedback for the participants, and the learning outcomes of the simulator training are not properly assessed after the simulator course. The formal final exam results from HiOA reveal that in spite of the debriefing-workshop after simulator training sessions, some misconceptions remain.

An automatic assessment method is proposed that gives immediate feedback to the students after a scenario is run. The method is based on the evaluation of a main performance indicator that consists of different factors related to the functioning of the process. This main indicator comprises an overall evaluation of the students' progress while dealing with an abnormal situation in the process. The students will receive early and individual feedback on their performance before the workshop, which means they will be able to recognize where there is room for improvement and have the opportunity to work on this before the final exam. Since the instructor will have access to the scenario results of each student, this will also provide the instructor with a clearer picture of how effective the simulator training has been.

The proposed assessment method will be tested at HiOA during the spring and fall semesters of 2017, for the undergraduate courses on chemical engineering and dynamic systems.

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C Implementation of Performance Indicators for Automatic Assessment

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Implementation of performance indicators for automatic assessment

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Abstract

Simulator training is widely used in different industries and in academia as a teaching tool. An expert instructor, who guides the users through the learning process with the simulator by giving verbal feedback, pausing the scenarios if necessary, and sometimes by developing certain evaluations, leads the simulation sessions. However, the availability of instructors is not always enough for the training demand, which can slow down the training process, as the trainees often need to wait for the instructor's feedback before they can proceed with their tasks. This research evaluates the feasibility of combining the guidance of the instructor with an automatic live assessment tool, based on performance indicators, to improve simulator training. Two simulator training sessions were evaluated. The strategy used for the simulation sessions consists of three stages: briefing, simulation and debriefing. During both sessions, it was observed that the assessment tool makes the users aware of the state of the process and in most of the cases helps them to find faster the source of an abnormality in the system. However, further development of the automatic assessment tool is needed in order to require less instructor guidance during the simulator training.

Keywords: simulator training; automatic assessment; performance indicators.

1. Introduction

Currently, simulator training implies the presence of an expert instructor that guides the trainees through the learning process mainly through verbal feedback (Komulainen and Sannerud, 2014, Nazir et al., 2015, Patle et al., 2014). This strategy brings many benefits since the trainees get comments and directions from someone who has good experience in the subject matter. However, often there are not enough instructors for the training demand. There is a need for more independent training sessions, where the trainee do not require urgently the guidance of an instructor. This research studies the option of offering trainees more independence prior and during the simulator training sessions, by implementing an automatic assessment tool. There exist different research on intelligent tutoring systems, which aim to become an intelligent and economical alternative to expert human tutors, tutoring systems have been implemented in different educational fields and it has also been considered as a possible strategy for simulator training (Gonzalez-Sanchez et al., 2014, Goldberg and Cannon-Bowers, 2015, Speshilov and Khabarov, 2017). This study is based on the implementation of the assessment method described in Marcano and Komulainen (2016), which was firstly introduced in Manca et al. (2014).

The automatic assessment tool was applied in two simulation sessions organized for the courses Process Control at USN and Dynamic Systems at HiOA. The Process Control course is an introductory course for master students. Dynamic Systems is one of the compulsory courses for bachelor students of Electronic Engineering. The implementation of simulators for teaching can be a very beneficial approach; it supports general pedagogical principles such as motivation, activation, concretization, collaboration, and individualization. Noticeable benefits of using simulators in a process control course are:

- Students get experiences with processes and their dynamics, which resembles practical experiences, without the possibility of injuries or damages, and at a convenient time scale – up scaled for slow processes and downscaled for fast processes.
- Students develop an understanding of relations between theoretical (mathematical) models of dynamic systems and the behaviour and characteristics of the systems.
- Students learn that using simulators may be a valuable engineering tool, e.g. for design of processes and their control systems, for example controller tuning, for system analysis, and for testing.
- From the instructor's point of view, using simulators may increase the effectivity of the teaching as several students may run simulators concurrently (in parallel). Furthermore, using simulators increases flexibility of the teaching as students may run the simulators at different scheduled times.

The aim of this study is to test how an automatic assessment tool can benefit simulator training session. The research questions are: How can an automatic assessment tool help the students achieving the learning goals of a simulator training session? What role does the instructor play when the automatic assessment tool is used? How should the automatic assessment tool be developed further?

2. Materials and Methods

2.1. Training Strategy

The simulation session was planned to last three hours, the training strategy implemented consisted of three different stages, which are commonly used in the industry (Argyris and Schön, 1978, Komulainen and Løvmo, 2014): 1) The briefing stage is an introductory presentation where the trainees receive an overview of what they are going to do. Later, during the 2) simulation stage, the trainees interact with the simulator, they get familiar with the process and solve certain tasks. Finally, 3) the debriefing is an open discussion between trainees and instructor where they analyzed and reflect on what they have done.

2.2. Research Methods and Sample Selection

A qualitative approach, based on observation notes was carried out. For the quantitative approach, a questionnaire was handed to the participants, in order to get feedback about automatic assessment tool. Further, with the aim to evaluate if the learning outcomes of the simulation sessions were reached, a theoretical test was imparted before and after the sessions in order to compare the results and observed if there was any improvement.

- Sample selection: There were two simulation sessions, one with a group of nine students from the master level course Process Control at USN, and a second session with six students from the bachelor level course Dynamic System at HiOA.

- Data collection: A 5-point scale questionnaire, based on statements related to the automatic assessment tool was delivered in order to get feedback from the students. Further, since the groups were small, it was easy to observe each student and gather notes about their responses and development during the simulation tasks. Additionally, a theoretical test was imparted at the beginning and at the end of the simulation session.

2.3. Simulation Software

The simulation software is K-Spice®, from Kongsberg Oil and Gas Technologies. It is a dynamic process simulation tool (Kongsberg, 2016). The generic oil and gas production model, included in K-Spice was used; it consists of a three-stage, three-phase oil and gas separation train, the utility systems, and emulated control and safety systems. Finally, the Exercise Manager, which is an extra tool for K-Spice, was used to trigger an abnormal event in the oil and gas model (Komulainen and Løvmo, 2014).

2.4. Simulation Scenarios

There were three different scenarios. During the first two scenarios, the trainees made changes in the system and studied the effects. In the third scenario they had to study the effects in order to find out the change that was made in the system, here the trainees were supposed to work independently, rely on what they learned with the first two scenarios and use the automatic assessment tool to solve the problem.

- First Scenario: the trainees had to increase the oil production with respect to that during normal operation, in order to this they had to open up to 100% a choke valve from one of the wells. An increase of the oil production above the normal operation values leads to a higher energy consumption, this is one of the main effects of this scenario.
- Second Scenario: the trainees had to originate a failure in the level controller of the HP-Separator, in order to do this they had to decrease the output of the control valve. This leads to a level increase in the HP-Separator, which activates an alarm, further, the level reaches the high-high limit and an Emergency Shutdown/Process Shutdown occurs.
- Third Scenario (“blind scenario”): The trainees ran the simulation and then a malfunction was triggered with the Exercise Manager. From the automatic assessment tool, the trainees were able to check if any change was happening in the system.

2.5. Automatic Assessment Tool

The automatic assessment tool consists in an extra graphic integrated to the list of graphics of the generic oil and gas model. It shows a live performance assessment i.e. the performance while carrying out a task. The performance values are shown on a scale between 0 and 100 %. The graphic shows a total performance value, which is a main performance indicator named abnormal situation management (ASM). This main performance indicator consists at the same time of four other indicators: oil production (OP), energy efficiency (EE), alarm activation (AA) and efficiency of the trainee (ET). The first three indicators are shown in the performance assessment graphic; the ET indicator is not shown to avoid putting more pressure on the users. Every indicator has a contribution to the total evaluation of the main performance indicator, these contributions were calculated with the implementation of the Analytic Hierarchy Process of Saaty (2008), further description about the calculations and the selected performance indicators can be found in Marcano and Komulainen (2016). When the blind scenario starts, all the indicators show a value of 100 %, after a while the values of the indicators start decreasing, which indicates that something is wrong in the system. If the performance of

the OP decreases, the trainee should check the equipment related to this indicator i.e. export pumps, HP-Separator, etc. If the performance of the EE decreases, they should check the export pumps or the compressor. Finally, if the performance of the AA decreases, they should check the alarm list.

3. Results

3.1. Qualitative Research: Questionnaire about the automatic assessment tool

Fig. 1 shows the results of the questionnaire about the automatic assessment tool (AAT). Six of the nine participants from USN answered the questionnaire, and from HiOA; four of the six participants did it. The first and second statement in the questionnaire were “I was able to understand the state of the system through the AAT” and “The AAT helped me to locate an abnormality in the system”, respectively. In both groups, all the students agree with the first two statements, and in both cases, half of the students strongly agree. The last statement was “Overall, the AAT was useful to solve the blind scenario”, all the students from the group at HiOA agree with this statement. The results from the students at USN present a variety of opinions, from strongly agree to one disagree.

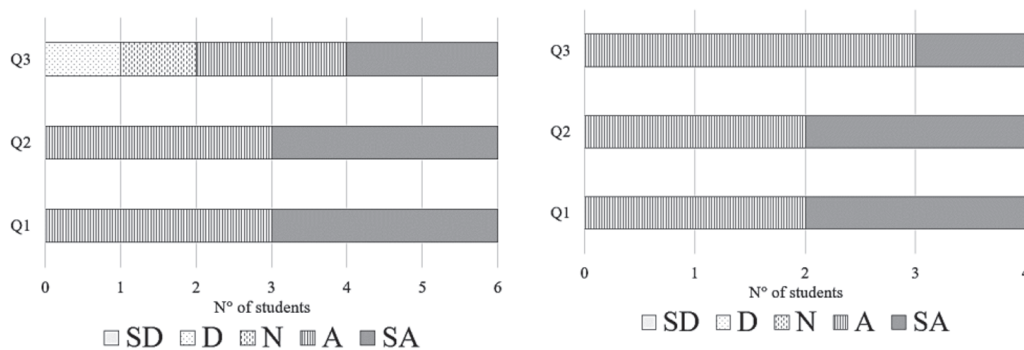


Fig. 1. Automatic Assessment Tool (AAT) Questionnaire. Left: USN. Right: HiOA. **Q1:** I was able to understand the state of the system through the AAT. **Q2:** The AAT helped me to locate an abnormality in the system. **Q3:** Overall, the AAT was useful to solve the blind scenario. SD: Strongly Disagree/D: Disagree/N: Neutral/A: Agree/SA: Strongly Agree.

3.2. Observations from the Simulation Sessions

The students were encouraged to work with a partner and discuss with each other during the tasks, however not all of them were willing to follow this strategy. During the debriefing session, the students were asked to discuss with their peers about what they have done and learned from the simulation session, so they could solve each other's doubts. Below some of the observations written during each simulation session are listed.

USN trainees: (a) during the first two scenarios, they seemed comfortable using the simulator. They asked few questions to the instructor and worked mostly independent. (b) During the blind scenario, they were able to understand, from the assessment tool, that there was an abnormality in the system. However, they had difficulties finding the source of the problem. The instructor needed to intervene more than expected.

Searching for better results from the second simulation session, the instructor did a more detailed briefing and motivated the trainees to ask questions and discuss more with each other during the first two scenarios.

HiOA trainees: (a) during the first two scenarios, the trainees seemed very engaged with the simulator and held some discussions with their classmates. (b) During the blind scenario, they seemed confident, they observed the information given by the assessment tool and tried to solve the problem. Five of the six trainees were able to solve the blind scenario independently.

3.3. Theoretical pre- and post-tests

Before and after the simulation sessions a theoretical multiple-choice test was imparted with basic concepts related to the session topic. The purpose of the test is to observe the students' improvement by the end of the simulation session. The test was developed in the learning platform Kahoot! (2017). The results from the tests are shown in Fig. 2. The figure shows the percentage of correct answers for each question, and the overall percentage is shown at the right end of each graph. When referring to each question, both groups had improvements or remained the same. In the case of the overall results, the group from USN went from 51 % to 71 %, thus having a normalized gain of 41 %. The group from HiOA went from 62 % to 79 %, which is a normalized gain of 45 %.

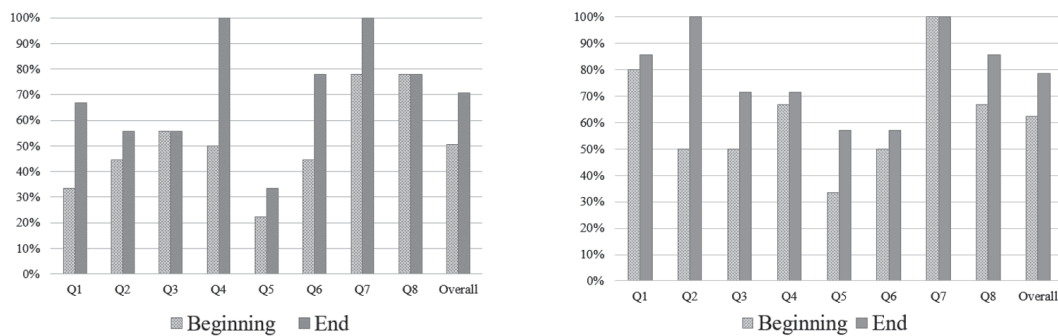


Fig. 2. Comparison of the test results before and after simulation session. Left: USN. Right: HiOA

4. Discussion

Based on the theoretical pre- and post-test, the prior knowledge of the second group (HiOA) was higher (USN 51 %, HiOA 62 %) and they also learned more during the simulation session (normalized gain USN 41 %, HiOA 45 %). We consider these to be good results that indicate that simulator training sessions gave successful learning outcomes. The results of the questionnaire gathered from the participants indicate that the majority (10/15 overall participants) considered that the automatic assessment tool helped them understand the state of the system, which is positive. On the other hand, when it was asked if the automatic assessment tool helped them to solve the blind scenario, the majority of the students from HiOA agreed, but the results from USN show that one student disagreed and one was neutral. Further, some of the students at USN commented that they liked that the instructor was there to guide them solving the scenarios. There is correspondence between the questionnaire results and the observations made. The assessment tool gives an awareness of the overall process, and makes it easier to find out if there is a problem affecting the system. However, it was also noticed that besides being able to understand the state of the system, the trainees also need relevant feedback to help them solve unexpected abnormalities in the process.

5. Conclusions

We set out with three research questions, the first of which was “how can an automatic assessment tool help the students achieving the learning goals of a simulator training session?” Our experience shows that the automatic assessment tool increases the students’ awareness of the process state. The implemented indicators in the automatic assessment helped to direct the students to the source of the problem faster. The second research question was “What role does the instructor play when automatic assessment tool is used?” Testing with the two groups shows that the instructor still plays a major role in the simulator training session and only a numerical assessment tool is not enough to “replace” the instructor’s guidance. Finally, how should the automatic assessment tool be developed further? Based on these experiences, the assessment tool could be a standalone tool if it can be improved further with the design of an online feedback function. This way, the simulation session could even be carried out without the instructor having to be around during the entire session, which can develop trainees to become more independent in their learning processes.

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D Effect of Automatic Feedback on Large-Scale Simulator Training

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Using the concept of data enclosing tunnel as an online feedback tool for simulator training

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Abstract

Feedback is one of the key factors that makes industrial simulator training an effective learning tool. Usually, the trainees receive feedback from the instructor, who guides them through the simulation tasks. However, nowadays the availability of expert instructors is scarce while the training demand is increasing. Therefore, there is a need for new simulator training practices that could allow the trainees to be more independent and decrease the need to rely so often on the instructor. This could be achieved by offering the trainees online automated feedback. This article presents a method for developing a tool meeting those requirements is presented. Simulation data were gathered representing different execution paths of the same scenario. Data were then analyzed and clustered using different clustering techniques. Interestingly, “good” and “bad” performances are shown to be separable using different techniques for clustering multivariate time series. Furthermore, we introduce the concept of enclosing data tunnel representing the trajectory of well-behaving execution paths in a reduced dimensional space. By conditioning the mal-behaving performances to be less than 20 % of the total simulation time inside the tunnel, an accuracy on 68 % was obtained. Being more flexible and allowing the mal-behaving performances to be inside the tunnel for a maximum of 35 % of the total simulation time, the accuracy of the enclosing tunnel was increased to 84 %.

Keywords: simulator training, online feedback, data clustering, enclosing tunnel, execution path

1 Introduction

A number of studies point out the importance of feedback during simulator training (Darken, 2009, Dozortsev, 2013, Håvold et al., 2015, Kluge et al., 2014, Kluge et al., 2009, Salas et al., 2012, Tichon and Diver, 2010). Feedback is a very effective learning mechanism that can be used to guide the trainees towards the development of a better performance. According to Salas et al. (2012) “Practice is most powerful when

combined with timely, constructive, and diagnostic feedback”. Usually, trainees receive feedback from an expert instructor who guides them through the simulation scenarios. Commonly, expert instructors are experienced operators who have accumulated a great knowledge of the system through years. This dependency on expert instructors has raised concern in different industrial sectors given that many of the experienced operators have retired or will retire in the near future (Alamo and Ross, 2017, Dozortsev, 2013, Manca et al., 2012). Consequently, the availability of expert instructors is continuously decreasing while the demand for operator training continues increasing. Therefore, there is need for new (tutoring) methods and techniques that could help the current instructors to cope with the training demands by allowing the trainees to be more independent. One way trainees can be more independent is by offering them online automated feedback about their performance during the training scenarios.

The topic of automated feedback for simulator training has been mentioned in several studies, some of them indicate that the use of instructional tools embedded in the simulator can improve the efficiency of training (Bell et al., 2008, Malakis and Kontogiannis, 2012). Further, there are studies that present a method (Manca et al., 2014) or an already developed tool (Dozortsev, 2013) to give automated feedback.

In this work, a procedure for developing an automated feedback tool for a simulator training is presented. The procedure developed is based on the analysis of the data collected from different variations of the same training scenario. The analysis of the data allows defining a good performance reference. This work builds on previous ideas from our position paper (Marcano et al., 2017b).

In order to be able to provide online automated feedback, it is necessary to know the state of the system at all times. The state of the system can be determined based on some key variables that together give a suitable overview of the process. These variables can be compared to the defined good performance reference.

Based on the results of the comparison the trainees can be informed whether they should reconsider the actions taken and try a different approach to solving the training task.

The case study we considered is a training scenario developed in K-Spice, a dynamic process simulation tool from Kongsberg Oil and Gas Technologies (Kongsberg, 2009). K-Spice resorts to a generic oil and gas production model. The goal of the studied training scenario is to increase the overall oil production flow with respect to the starting point.

In the next section, the procedure followed for developing the online feedback tool is described in detail, then the results obtained are presented, followed by the discussion, and finally some conclusions are drawn.

2 Methodology

The case study consists of a training scenario developed with the generic oil and gas production model integrated into the simulation tool K-Spice. Aim of the training scenario is to increase, in 30 min, the oil production flow with respect to the one given in the initial conditions of the simulation. The trainee must fulfill the goal without compromising the correct functioning of the process. In order to develop an online feedback tool for the case study, the following steps were followed.

2.1 Selection of variables

Figure 1 shows an overview of the generic oil and gas production model. The sections with the most relevant information of the process are the wells, the high-pressure separator (HP-separator), the export pump and the gas export compressor, the oil and gas export sections, and the high pressure flare (HP-flare). The variables studied were taken from these sections, being: 1) The total sum of outlet flows from the wells; 2) Inlet flow of the HP-separator; 3) Pump power consumption; 4) Compressor power consumption; 5) Oil export flow; 6) Gas export flow; and 7) HP-flare flow.

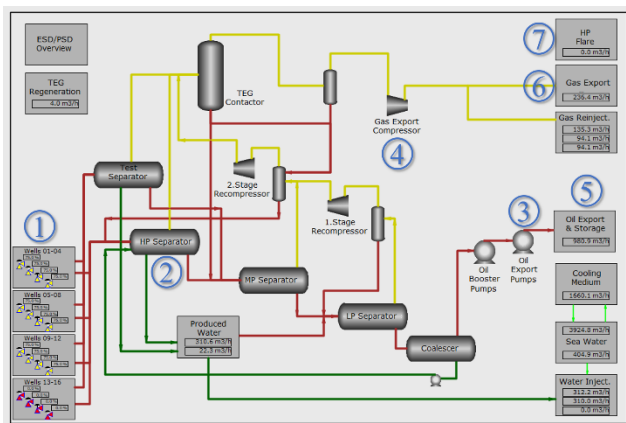


Figure 1. Overview of the generic oil and gas production process.

2.2 Data generation

In order to gather relevant data, a method to generate variations of the case study was developed. Each process variation was a random selection of five possible actions. The actions were defined based on the observations and results gathered from the simulator training sessions mentioned in Marcano et al. (2017a). During the development of the research (Marcano et al., 2017a), it was possible to extract knowledge about the students' understanding of the process and the probable actions they could execute. Based on this distilled knowledge, it was decided that a maximum of three actions could take place per variation of the case study, with a certain delay between them. The delay was set to 15 s, 45 s, 60 s, 120 s, and 180 s. These delays were chosen because during the simulator training sessions (Marcano et al. (2017a) we noticed that the trainees usually did not wait longer than 3 min to make changes in the simulation. The construction of one variation occurs as follows; first, a random action is chosen, and then, depending on the chosen first action there are some conditions that will determine the following random actions to choose among if any. The defined actions and the conditions triggering them are explained below.

1. Opening the choke valve from a well.

Opening a choke valve is the right execution path to follow when trying to increase the oil production in the process. Therefore, it is assumed that if the first decision of the trainee is to open a choke valve, then, if there are possible following actions, these will also be opening a choke valve. How much the choke is going to be opened is decided randomly between two options, being 85 % and 100 %. All choke valves in the simulation that are predetermined open, are open up to 75 %.

2. Closing the choke valve of a well.

Closing a choke valve is a wrong action to execute if the oil production needs to be increased. If the trainee is confused and closes a valve by mistake, then the next actions could, unfortunately, be to close even more valves. However, it could also happen that the student notices the mistake and tries to fix it by reopening the closed valve and opening an extra one. Then we randomly decide whether we will perform a sequence of 1 or 2 next actions. In case of choosing only one subsequent action, that second action could be either closing another valve or reopening the one closed. In case we choose two subsequent actions, then, the following two actions are to reopen the closed valve and open an extra one. How much the choke is going to be closed is decided randomly between two options, being 0 % and 65 %. For the opening, the same conditions explained in the first action are applied.

3. Opening the pulse-controlled valve to the test separator.

During the simulator training sessions carried out in Marcano et al. (2017a), it was noticed that few students

opened a pulse-controlled valve thinking that it was a choke valve. This mistake was also noticed during the simulator training sessions performed later in 2017. There were just a few students who made the mistake but it seems to be common to happen. Consequently, it was decided to take it into account. However, given that opening a pulse-controlled valve is a rare mistake if this action takes place first, then, it will be the only action to be executed and there will be no subsequent actions.

4. Opening the outlet control valve of the HP-separator.

Opening the outlet valve of the HP-separator might occur due to the misconception that by increasing the outlet flow from the HP-separator the oil production would increase as well. The next step is to choose whether to proceed with a sequence of one subsequent action or two subsequent actions. If we randomly chose to follow with two actions, then, these were set to be the opening of choke valves. If only one action is following, then, this could be either opening a choke valve or a pulse-controlled valve.

5. Increasing the pressure set point of the HP-separator.

Increasing the pressure of the HP-separator leads the system to switch on the high-pressure flare. This action was defined to ensure the possibility of analyzing execution paths with a negative environmental impact. If only one more action follows this one, then, it could be either opening a choke valve or a pulse-controlled valve. If two actions follow, then, both will be to open a choke valve.

2.3 Data clustering

The data gathered in this work consists of multivariate time series. It is necessary to identify from the data what corresponds to well-behaving performances and what corresponds to mal-behaving performances. This way it is possible to make balanced groups for training and validation. In order to cluster the data, it is necessary to use a notion of similarity. This can be done by calculating the distance between every possible combination of pairs of execution paths. In this work, three methods for distance calculation were evaluated namely: Euclidean distance, dynamic time warping (DTW), and symbolic aggregate approximation (SAX). This was done in order to determine and select the most accurate method among such distances.

Euclidean distance

Given two time series X and Y of the same length N , (1) defines the Euclidean distance between them. Figure 2a shows an intuitive representation of the Euclidean distance (Lin et al., 2003).

$$D(X, Y) \equiv \sqrt{\sum_{i=1}^N (x_i - y_i)^2} \quad (1)$$

Dynamic Time Warping (DTW)

The objective of DTW is to compare two (time-dependent) sequences $X := (x_1, x_2, \dots, x_N)$ of length $N \in \mathbb{N}$ and $Y := (y_1, y_2, \dots, y_M)$ of length $M \in \mathbb{N}$. These sequences may be discrete signals (time-series) or, more generally, feature sequences sampled at equidistant points in time (Müller, 2007). Being \mathcal{F} a feature space, $x_n, y_m \in \mathcal{F}$ for $n \in [1:N]$ and $m \in [1:M]$. To compare two different features $x, y \in \mathcal{F}$, a local cost measure is needed, also referred to as local distance measure, which is defined to be a function $c: \mathcal{F} \times \mathcal{F} \rightarrow \mathbb{R}_{\geq 0}$ (Müller, 2007).

Typically, $c(x, y)$ is small (low cost) if x and y are similar to each other, and otherwise $c(x, y)$ is large (high cost). Evaluating the local cost measure for each pair of elements of the sequences X and Y , the cost matrix $C \in \mathbb{R}^{N \times M}$ defined by $C(n, m) := c(x_n, y_m)$ is obtained. Then the goal is to find an alignment between X and Y having minimal overall cost (Müller, 2007). Each matrix element (i, j) corresponds to the alignment between the points x_i and y_j . A warping path is created, which consists of a contiguous set of matrix elements that defines a mapping between X and Y (Keogh and Ratanamahatana, 2005). The signal with an original set of points $X(\text{original}), Y(\text{original})$ is transformed to $X(\text{warped}), Y(\text{original})$. However, even though DTW measures a distance-like quantity between two given sequences, it does not guarantee the triangle inequality to hold (Müller, 2007).

SAX (Symbolic Aggregate approXimation)

SAX allows a time series of arbitrary length N to be reduced to a string of arbitrary length w , ($w < N$, typically $w \ll N$). The alphabet size is also an arbitrary integer a , where $a > 2$. SAX uses an intermediate representation between the raw time series and the symbolic strings. First, the data is transformed into the Piecewise Aggregate Approximation (PAA) representation and then symbolize the PAA representation into a discrete string (Lin et al., 2003).

In dimensionality reduction via PAA a time series X of length N can be represented in a w -dimensional space by a vector $\bar{X} = \bar{x}_1, \dots, \bar{x}_w$. The i^{th} element of \bar{X} is calculated as follows (Lin et al., 2003):

$$\bar{x}_i = \frac{w}{N} \sum_{j=\frac{N}{w}(i-1)+1}^{\frac{N}{w}i} x_j \quad (2)$$

Having transformed a time series database into PAA, a further transformation to obtain a discrete representation can be applied. SAX uses a discretization technique that produces symbols with equiprobability (Lin et al., 2003). If the original subsequences in the Euclidean distance are transformed into PAA representations, \bar{X} and \bar{Y} , using (2), then a lower bounding approximation of the Euclidean distance between the original

subsequences can be obtained (3), this is illustrated in Figure 2b (Lin et al., 2003).

$$DR(\bar{X}, \bar{Y}) \equiv \sqrt{\frac{N}{w}} \sqrt{\sum_{i=1}^w (\bar{x}_i - \bar{y}_i)^2} \quad (3)$$

If the data is further transformed into the symbolic representation, a MINDIST function that returns the minimum distance between the original time series of two words can be defined by (4), which is illustrated in Figure 2c (Lin et al., 2003).

$$MINDIST(\hat{X}, \hat{Y}) \equiv \sqrt{\frac{N}{w}} \sqrt{\sum_{i=1}^w (dist(\hat{x}_i, \hat{y}_i))^2} \quad (4)$$

The *dist()* function can be implemented using a table lookup as shown in Table 1. Table 1 is for an alphabet of cardinality 4. The distance between two symbols can be read off by checking the corresponding row and column. For example, *dist(a,c) = 0.67* (Lin et al., 2003).

Table 1. A lookup table used by the MINDIST function. This table was taken from Lin et al. (2003).

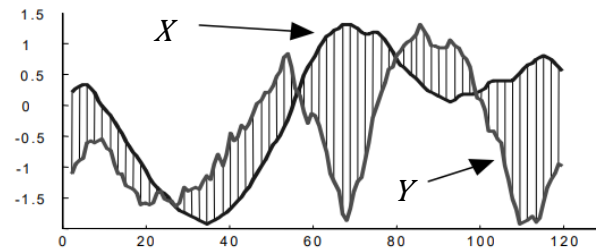
	a	b	c	d
a	0	0	0.67	1.34
b	0	0	0	0.67
c	0.67	0	0	0
d	1.34	0.67	0	0

Hierarchical clustering

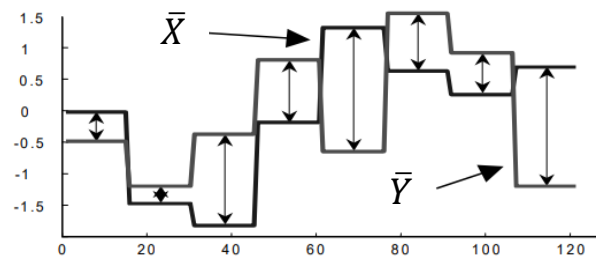
Hierarchical clustering groups data over a variety of scales by creating a cluster tree. The tree is not a single set of clusters, but rather a multilevel hierarchy, where clusters at one level are joined as clusters at the next level. This allows deciding the level or scale of clustering that is most appropriate for the application required (MathWorks, 2018).

2.4 Samples selection

For this study, 75 out of 1145 possible variations were generated the way described in Section 2.2, this represents 6.5 % of all the possible combinations. The data were classified using the methods described in Section 2.3. Of the 75 variations, 2/3 of the data corresponding to the well-behaving execution paths, and 2/3 of the data corresponding to the mal-behaving execution paths were used for training i.e. 50 variations in total. The rest of the data was used for validation i.e. 25 variations (1/3 of the good performances, and 1/3 of the bad performances). For each time series, one sample was taken every 12 s during 30 min i.e. 150 data points, plus one additional point at time zero.



(a)



(b)

$$\hat{X} = \mathbf{b a a b c c b c}$$

$$\hat{Y} = \mathbf{b a b c a c c a}$$

(c)

Figure 2. a) Euclidean distance between two time series. b) Distance measure defined for the PAA. c) SAX representations of two time series. This figure was taken from Lin et al. (2003).

2.5 Introducing the concept of enclosing tunnel

2.5.1 Data processing and dimensionality reduction

The training data was processed using PCA. In order to compare with each other all the variations in the training data, a PCA analysis was done for different time slots of the time series. For each time slot, the average of the data within the range was taken. The time moving average was calculated using the sliding window algorithm, with a window size of 35 samples. Which means that the first PCA calculated describes all the variations in the time span between the first and the 35th sample. The second PCA describes all the variations in the time span between the second and the 36th sample, and so forth until the entire time-range of 30 min (151 samples) is covered. After testing different sizes for the sliding window algorithm, a size of 35 samples was selected given that it was the one that resulted in the smoothest graphical representation of the data. The variance results show that the first and second principal components (PC1 and PC2, respectively) are the most representative, as shown in Figure 3. Figure 3a shows the first 19 sliding windows, it can be seen that the first two principal components describe approximately 70

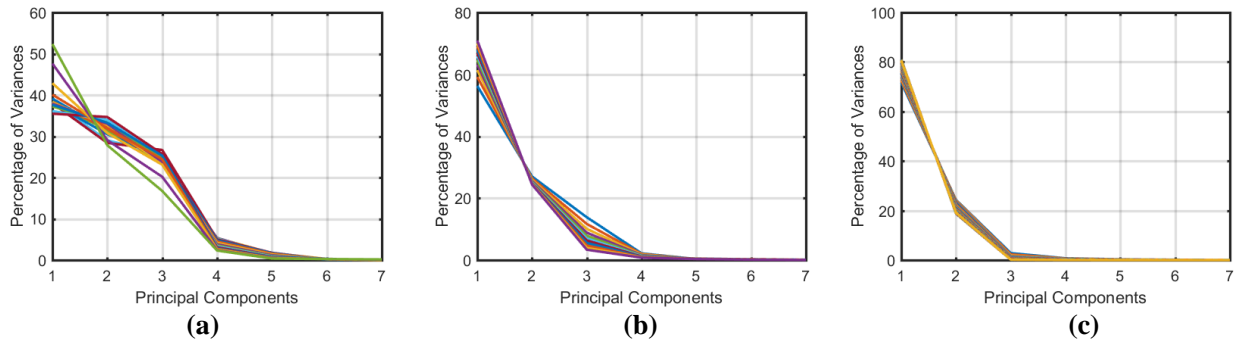


Figure 3. Variances. a) Variances of the first 19 sliding windows. b) Variances from the 20th to the 30th sliding window. c) Variances from the 31st to the 117th sliding window.

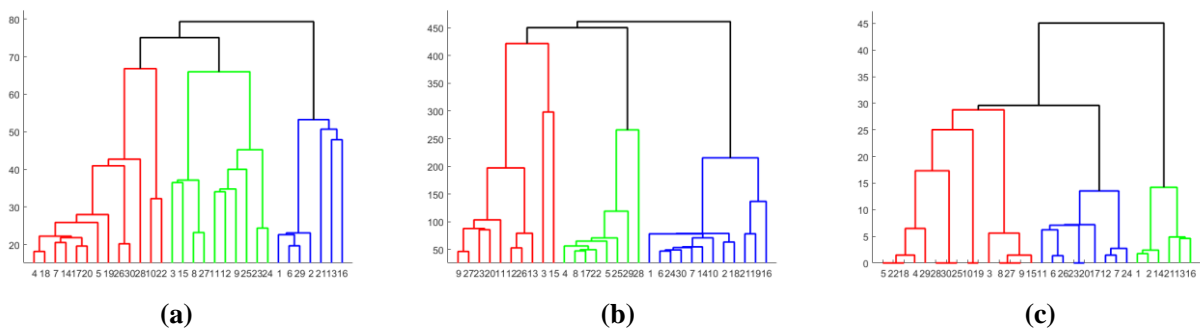


Figure 4. Hierarchical clustering based on time series distances. a) Euclidean b) DTW c) SAX.

80 % of the data. Further, Figure 3b and Figure 3c show that the first two principal components describe approximately 90% of the data. Therefore, all analyses made are based on the first two principal components.

2.5.2 Data delimitation using an enclosing tunnel

The structure of the enclosing data tunnel is based on five main circles. The enclosing circles were calculated based on the data projected on the 2D plane formed by the data scores from PC1 vs the scores from PC2. In order to frame the data projected on this plane we resort to the minimal enclosing circle problem. The minimal enclosing circle problem consists of finding the circle of smallest radius that contains a given set of points in its interior or on its boundary. Jung’s theorem states that every finite set of points with geometric span d has an enclosing circle with radius no greater than $d/\sqrt{3}$ (Weisstein, 2018). Each circle is located in a moment in time in which the well-behaving execution paths show a significant tendency of change. The data enclosing tunnel was constructed by creating a surface that connects each of the sections formed between the minimal circles.

3 Results

We started by clustering the raw data to separate the well-behaving and mal-behaving performances. The

data clustering was carried out implementing the three methods described in the methodology. Once the distances were calculated with the three methods, they were clustered using hierarchical clustering. Figure 4 shows the three clustering trees obtained with each of the methods. In general, it can be seen that there are three main clusters formed by the data, given that three main groups (green, red and blue) were obtained with each method. However, the two main branches of the cluster tree obtained with the SAX method (Figure 4c) are more noticeable than the two main branches of the other two methods, Euclidean and DTW (Figure 4a, Figure 4b), which indicates that the clusters formed by the SAX method are defined more clearly. Numerically this is checked with the cophenetic correlation coefficient, which resulted to be 0.9347 for the clustering tree calculated with the Euclidean distances, 0.8769 for the clustering tree calculated with the method DTW, and 0.9392 for the clustering tree calculated with the method SAX. Therefore, the results obtained with SAX were the one used for classifying the data as good and bad performances.

Figure 6 shows the results of the data processing using PCA. Figure 6a depicts a 3D representation of the variation along time, of the scores obtained with the first two principal components. It can be noticed that there are three different patterns in the data. Figure 6b corresponds to an upper view of the previous one. It

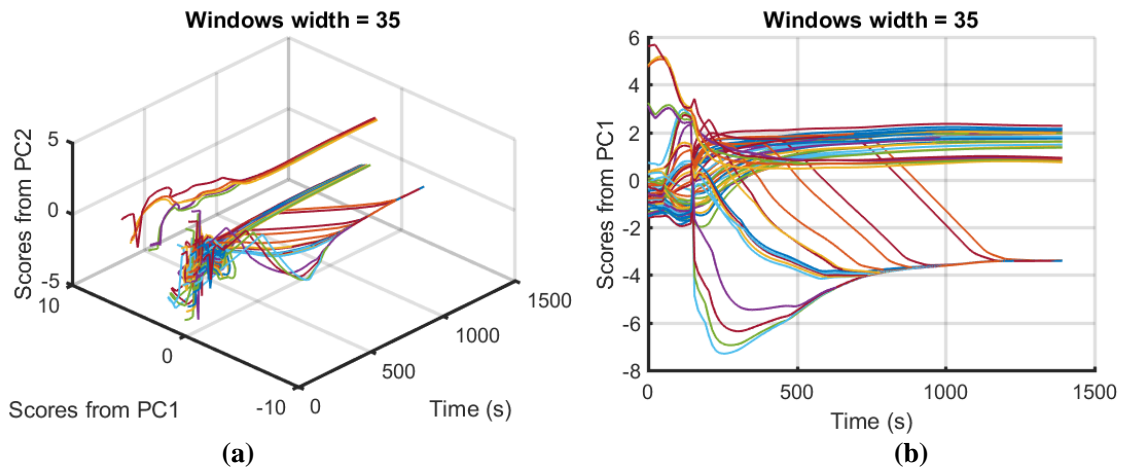


Figure 5. a) 3D view of the enclosing tunnel. **b)** 2D view of the enclosing tunnel.

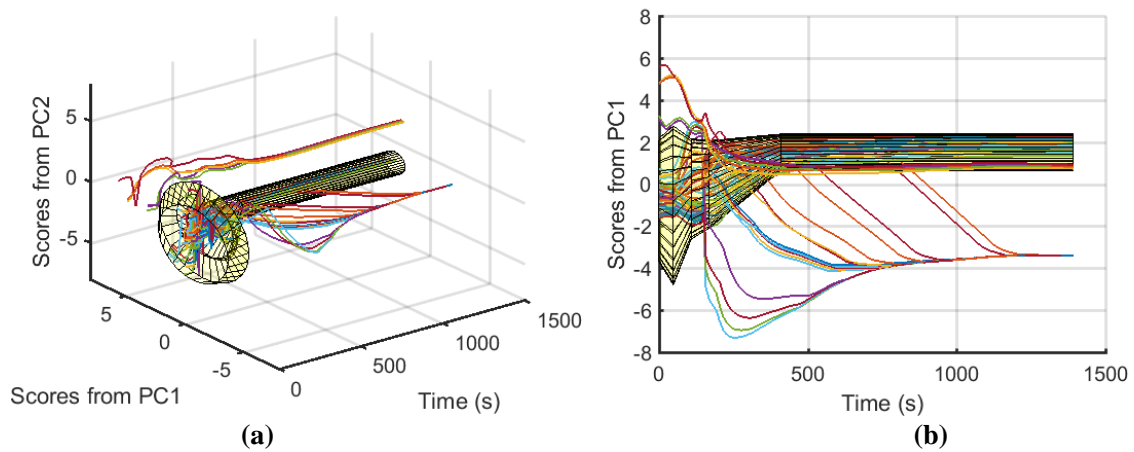


Figure 6. a) Data scores from PC2 vs Data scores from PC1 vs Time. **b)** Data scores from PC1 vs Time.

shows the variation of scores obtained with the first principal component versus time, and three different tendencies of the data can also be appreciated.

Figure 5 shows a 3D and 2D view of the tunnel enclosing the data that correspond to the good performances. The tunnel consists of five different circular sections that correspond to the minimal enclosing circle of the well-behaving execution paths in each section. All data that do not fall inside the tunnel corresponds to a bad performance. The trends that start being inside the tunnel but then go totally outside correspond to those actions where the outlet controlled valve of the HP-separator is opened. The trends that are above the tunnel correspond to those actions where the pressure set point of the HP-separator was increased.

In order to test the accuracy of the tunnel, the data left aside for validation was used. First, the validation data was projected on the PCA space calculated with the training data. Next, the processed validation data was plotted with the tunnel, as shown in Figure 7. Finally, the accuracy of the tunnel was determined by calculating the total amount of time that each good and bad

performance spent inside the tunnel. In the case of the well-behaving execution paths, it was expected that they would be inside the tunnel at least 80 % of the total simulation time. While in the case of the mal-behaving execution paths, it is expected that they wouldn't be inside of the tunnel more than 20 % of the total simulation time. Based on these limits the accuracy calculated for the tunnel resulted to be 68 %, as shown in the confusion matrix presented in Figure 8a. The diagonal of the confusion matrix (green squares) represents the correct classifications. Figure 8a shows that 12 execution paths were correctly classified as "good", and 5 execution paths were correctly classified as "bad". On the other hand, the red squares show the incorrect classifications, and it can be seen that 8 execution paths were wrongly classified as "good", these are false positives. In order to improve the accuracy of the tunnel, the tolerance of the bad performances inside of the tunnel was increased to 35 % of the total simulation time. This way the false positives were reduced from 8 to 4, given as a result an improved accuracy of 84 % as can be seen from Figure 8b.

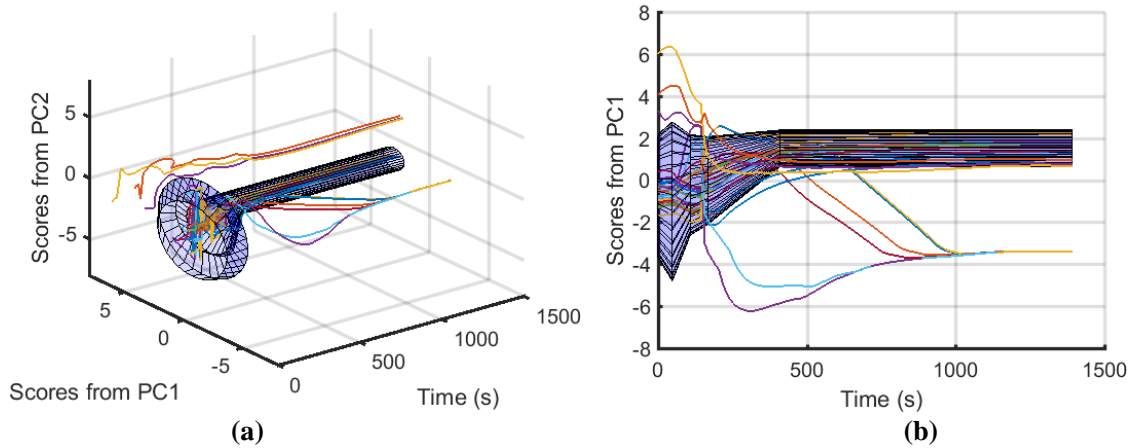


Figure 7. a) Validation data and 3D view of the enclosing tunnel. b) Validation data and 2D view of the enclosing tunnel.

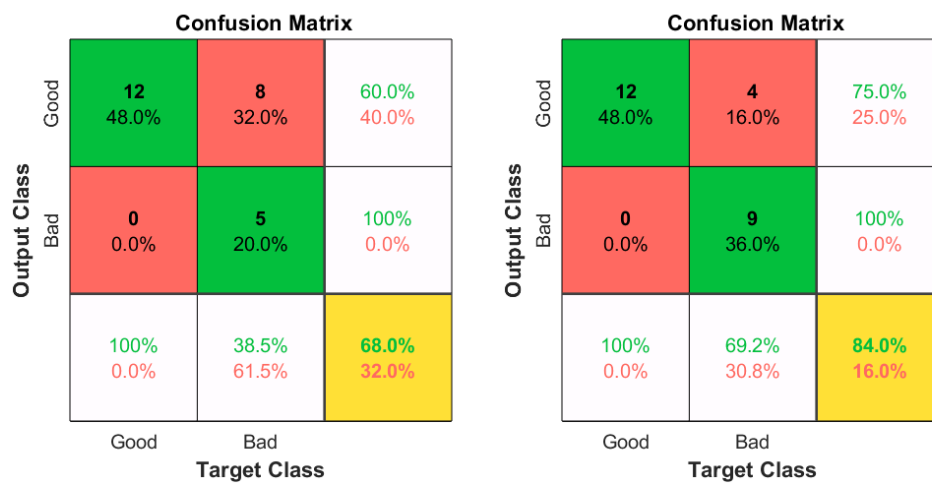


Figure 8. a) Confusion matrix: mal-behaving execution paths inside of the tunnel for 20 % of the total simulation time. b) Confusion matrix: mal-behaving execution paths inside of the tunnel for 35 % of the total simulation time.

4 Discussion

In this work, the construction of the online feedback tool was based on the well-behaving execution paths. Consequently, it was necessary to find methods that could ease the laborious task of clustering data and identifying their typology. The results obtained with the data clustering techniques show that these are effective methods for finding similarities among data. Which is very useful when handling a large amount of data, such as those produced from simulator training scenarios.

The proposed enclosing tunnel could be used as an effective tool for generating online feedback. The data of a new trainee could be monitored, for instance, every two minutes. The first set of data should be projected on the PCA space, and later compared with the tunnel, if it is observed that the execution path is outside the tunnel a warning can be given to the trainee. If the execution path is inside the tunnel no warning should be generated. Later, in the next two minutes, the data of the last four minutes could be analyzed, and once again depending

on the data trend it is decided if a warning should be given to the operator or not. This sequence should be repeated online over the total duration of the simulation scenario. Further, depending on the data behavior we could also determine the type of mistake made by the trainee, and more detailed feedback could be generated. This refers particularly to the cases in which the outlet valve of the HP-Separator is opened, and when the pressure set point of the HP-Separator is increased. These two cases present a very differentiated behavior around the tunnel, therefore it could be easy to identify them. However, the trends for the cases where the outlet control valve of the HP-Separator is opened may take several minutes before leaving the tunnel. These are the cases that were classified correctly by allowing them to be inside the tunnel 35 % of the total time.

In general, this method could be used for different training scenarios. This procedure shows that an enclosing tunnel, based on good performances, can be designed for any kind of scenario, thus online feedback can be offered to the operators, giving them more training independence.

5 Conclusion and future work

The data clustering methods implemented, Euclidean distance, DTW, and SAX showed to be effective for finding similarities among data. Of the three methods, SAX is shown to be the most effective of all with a cophenetic correlation coefficient of 0.9392. The clustering of the data helped to identify among the entire data set the well-behaving execution paths, which were used to design the online feedback tool for simulator training. The online feedback tool designed consists of an enclosing data tunnel. The tunnel developed has in principle an accuracy of 68 %. This value was calculated by allowing the mal-behaving execution paths to be inside the tunnel no more than 20 % of the total simulation time. However, with a more flexible tolerance (bad performances allowed to be inside the tunnel 35 % of the total simulation time) the total accuracy of the tunnel could be increased up to 84 %. It was demonstrated that it is possible to develop a method that can be used to generate automated online feedback, thus opening the possibility of more independent simulator training sessions.

Future work includes improving the accuracy of the tunnel without increasing the tolerance for mal-behaving execution paths. This could be done by increasing the amount of training data, so more differences can be noticed among the time series. Additionally, the method should also be improved so that it can detect if more specific requirements have been fulfilled by the operator. Furthermore, enclosing tunnels constructed for different training scenarios should be compared to each other in order to determine if a single generic tunnel could be designed to be used for different training scenarios.

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F Methodology for Building a Data-Enclosing Tunnel for Automated Online-Feedback in Simulator Training

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METHODOLOGY FOR BUILDING A DATA-ENCLOSING TUNNEL FOR AUTOMATED ONLINE-FEEDBACK IN SIMULATOR TRAINING

A PREPRINT

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ABSTRACT

Extensive research confirms that feedback is the key to effective training. However, in many domains including engineering, human trainers that can provide feedback to trainees is considered not only to be a costly resource but also a scarce resource. Therefore, for trainees to be more independent and successfully train by themselves, effective automated feedback must be provided. In this work, we resort to elements from the theory of data mining to devise a data-driven automated feedback system. We propose a novel concept reckoned as a data-enclosing tunnel, which can be used to detect deviations from correct operation paths and be the base for automated feedback. Two case studies were developed to demonstrate the viability of this methodology and its usefulness in two industrial simulation scenarios involving K-Spice, an oil and gas simulation platform. The data-enclosing tunnel constructed for each case study was validated and compared to three other simpler methods. The accuracy of each method was determined by calculating how precisely each of them classified new data. The most elaborate and complex approach, namely, our proposed data-enclosing tunnel yielded the highest accuracy, 94.3 %. Future work includes creating an interface for the feedback tool and testing it with trainees.

Keywords data analysis · data mining · automated feedback · industrial training · simulator training

1 Introduction

Feedback is a crucial factor in effective simulator training [1], [2], [3], [4], [5], [6]. Typically, an expert instructor is responsible for guiding the trainees through the simulation task, providing relevant feedback when necessary. Nevertheless, the availability of expert instructors is decreasing, mainly due to retirement [7], [8]. Therefore, industries are facing the challenge of fulfilling the increased training demand with a limited number of instructors. This situation could be overcome with the implementation of simulator training practices that allow the trainees to be more independent so that the need for expert instructors can be alleviated [9].

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One way of helping trainees to be more independent during simulator training consists of offering real-time automated feedback [10], [11], [12]. If trainees receive automated feedback, they will not have to rely exclusively and often on the instructor. Further, with automated feedback, trainees can receive comments and guidance faster, since they will not have to wait until the instructor is available. Also, automated feedback allows remote training, which can represent a cost reduction for industries. If remote training for technical skills is promoted before on-site training, the time needed in the training center could be compressed. Thus, costs related to the operators' mobility could be saved. Automated online feedback can also motivate operators to train more often by themselves since they will count on having relevant and prompt guidance, and they will be able to train at their own pace. On the other hand, automated feedback could also be used as a support tool for novice instructors. It could guide inexperienced instructor on what kind of feedback to give to the trainees.

Automated feedback for simulator training is not a new concept. Automated feedback has been already an active topic for research especially in health-care education [13], [14]. There is also extensive research on intelligent tutoring systems (ITSs) as an educational tool to help trainees outside the classroom, to learn a new language, and even in serious games [15], [16], [17]. Gonzalez-Sanchez et al. [18] indicate that ITSs could become a steady and economical alternative to human instructors. However, little research can be found specifically on automated feedback for industrial simulator training [12], [19]. Research has been done on how to improve operators performance based on the analysis of operational records [20], [21], [22], nevertheless not with the aim of developing automated feedback.

In this paper, we develop a novel data mining based approach for providing automatic feedback to trainees. Our approach resorts to a novel concept called data-enclosing tunnel, which can be seen as a data envelope describing the expected evolution of the simulation process. We show that by using the data-enclosing tunnel we can automatically detect deviations from correct executions paths and issue an automated corrective feedback to the user. As an industrial large-scale simulation use case, we consider the dynamic process simulator K-Spice [23], from Kongsberg Digital.

2 Methodology

An overview diagram of the different steps of the methodology developed is shown in Figure 1. The methodology presented in this work is based on a data mining approach. Data mining is the process of examining large amounts of data to discover novel and useful information [24]. The steps in the methodology are described in detail in the following sub-chapters (2.1-2.8).

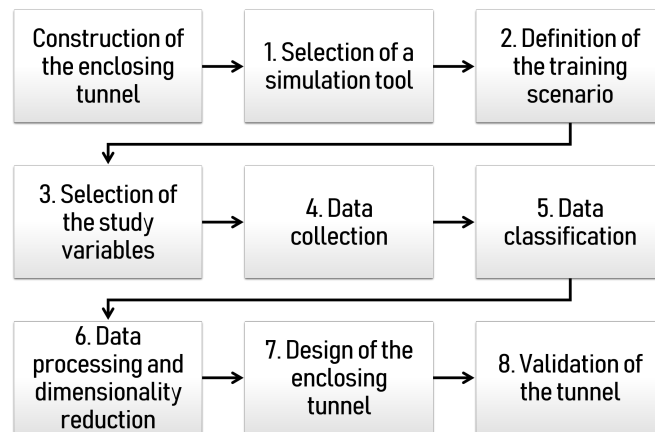


Figure 1: Overview diagram of the methodology for constructing a data-enclosing tunnel.

2.1 Simulation tool

The simulation tool should be a dynamic model of the process. It should have functionalities for saving and exporting historical data. It should have training scenarios available, or it should offer the possibility to create them. In the cases in which the feedback message cannot be generated on the simulation tool, the tool should be able to connect with a server to send the data to an external program where the feedback message can be generated online.

2.2 Defining a training scenario

The training scenario for the automated feedback can be selected from the available ones (in the simulator) or created from scratch. The studied scenario should have clear operational goals and well-defined learning objectives. The performance of the user can be tracked based on whether they are reaching the established goal or not.

2.3 Selection of study variables

The selection of monitoring variables depends on the case study. Variables related to the operational goals and learning objectives should be chosen. On the other hand, the complexity of the process also plays an important role when it comes to selecting the study variables. Complex processes may require studying a large number of variables [25]. In these cases, Key Performance Indicators (KPIs) and Operator Performance Indicators (OPIs) are valuable tools. Performance indicators can be useful metrics based on the combination of several variables. KPIs refer to the production efficiency of an entire process, while OPIs refer to human performance [26], [27]. The use of performance indicators can be useful to simplify the number of variables to study.

2.4 Data collection

Many research highlights the great value that can be found in the analysis of process operational data [20], [22], [28]. It is necessary to gather data describing different ways in which a training scenario can be carried out. This data should be rich enough to document different possible ways a task can be solved or may fail so that a useful feedback tool can be developed based on the analysis of these records.

Since the feedback tool is developed to support people, ideally the data collected should be records of the performance of actual users when solving the proposed training scenario. However, sometimes data from actual users is not available or cannot be collected on time to develop the feedback tool. In those cases, the data can be generated. An algorithm that makes different combinations of plausible actions can be developed. A repository of several probable actions, good and bad, should be produced based on the knowledge gathered from observing actual trainees using the simulator. The algorithm has to be programmed to randomly choose one or several options from the repository and create different combinations of them to solve the scenario, thus ensuring human unpredictability.

2.5 Data classification

The data gathered from one user corresponds to one sample of the total data. Each sample consists of multivariate time series. It is necessary to identify among the samples what correspond to good execution paths and what correspond to bad execution paths, to make balanced groups for training and validation. The simplest way to do this is to label the data records of the actual user right after they solved the training scenario. On the other hand, in the case of generated data, the data should be labelled along with its creation.

Nevertheless, if the data is not labeled there are different methods to cluster it based on its characteristics. In order to cluster data, it is necessary to use a notion of similarity. This can be done by calculating the distance between every possible combination of pairs of execution paths. Marcano et al. [29] present a detailed explanation of three different methods that can be used to calculate the distances between the execution paths.

2.6 Data processing and dimensionality reduction

If the training data is multi-dimensional, it is preferable to comprise it [25]. In the following, we describe the approach applied in the case study using principal component analysis, PCA. The PCA analysis must be done for different time slots that include all the training data. This is to ensure that all samples in the training data are compared with each other.

Each time slot is defined using the sliding window algorithm. The number of elements must be chosen for the window size. If the number chosen is N , this means that the first time slot covers the range from the first to the N th element of each sample. The second time slot covers the range from the second to the N th plus one element of each sample and so forth until the entire time-range for each sample is covered. The average of the elements within each range is taken for each sample. Each average corresponds to a row in a matrix that will have as many rows as there are samples in the training data. The first PCA corresponds to the first matrix formed with averages of the first time slot. The second PCA will correspond to the matrix formed with the averages of the second time slot, and so forth. The number of elements used for the window size depends on the PCA projection. The number should be adjusted until the graph of the scores of PC1 vs the scores of PC2 vs time is smooth.

2.7 Enclosing tunnel

To construct the enclosing tunnel, first, the data projected on the PCA plane, corresponding only to the good execution paths, must be observed to identify the points in time where the data makes drastic changes. Then, the data must be studied right on each of these points; to do this it should be observed from the 2D plane formed by the scores of PC1 vs the scores of PC2. Next, the points projected on this plane are framed using the minimal enclosing circle problem [30]. Eventually, there will be as many circles as the points where data changes. The enclosing tunnel is constructed by drawing a surface around all those circles.

2.8 Validation of the tunnel

The validation data must be reduced using the PCA models obtained with the training data. Then, the projected validation data should be plotted together with the enclosing tunnel. Later, it must be determined which execution paths fall inside the tunnel, which ones outside and for how long. Based on this, together with the data labels, the accuracy of the tunnel can be calculated. Two metrics were established to determine the accuracy of the tunnel to compare different results:

1. Execution paths outside the tunnel more than 35 % of the total scenario time are considered bad.
2. Execution paths outside the tunnel more than 50 % of the total scenario time are considered bad.

The validation results of the tunnel must be compared also with a state of the art method, which could be used as a baseline.

3 Case studies

We implemented the methodology presented in this work to develop the enclosing tunnel for two training scenarios. Below is explained how each step was implemented.

3.1 Simulation tool for the case studies

The dynamic process simulator K-Spice [23], from Kongsberg Digital was used in this study. The training scenarios were simulated with K-Spice generic oil and gas production model.

3.2 Training scenarios

This study presents the analysis of two training scenarios:

Scenario 1 (SC1): the aim is to increase, in 30 min, at least +10 % the oil production flow compared to the initial conditions of the simulation.

Scenario 2 (SC2): the aim is to decrease, in 30 min, –10 % of the gas production compared to the initial conditions. The trainee must fulfill the goals without compromising the correct operation of the process.

3.3 Variables chosen for the case studies

In the generic oil and gas production model, the sections with the most relevant process information for the two training scenarios are the wells, the high-pressure separator (HP-separator), the export pump and the gas export compressor, the oil and gas export sections, and the high-pressure flare (HP-flare). The variables studied were taken from these sections: 1) total sum of outlet flow rates from the wells; 2) inlet flow rate of the HP-separator; 3) pump power consumption; 4) compressor power consumption; 5) oil export flow rate; 6) gas export flow rate; and 7) HP-flare flow rate, as shown in Figure 2.

3.4 Data collection for the case studies

In this work, the data gathered was generated with an automatic method that ensured different execution paths of the training scenarios. Each path was built based on random selections from several possible actions. The actions were defined based on the observations and results gathered from the simulator training sessions mentioned in previous work [31]. Only one main action, with a maximum of two subsequent actions, could take place per execution path. For SC1, the delays for the main action and the following actions were set to 15 s, 45 s, 60 s, 120 s, and 180 s. These values were

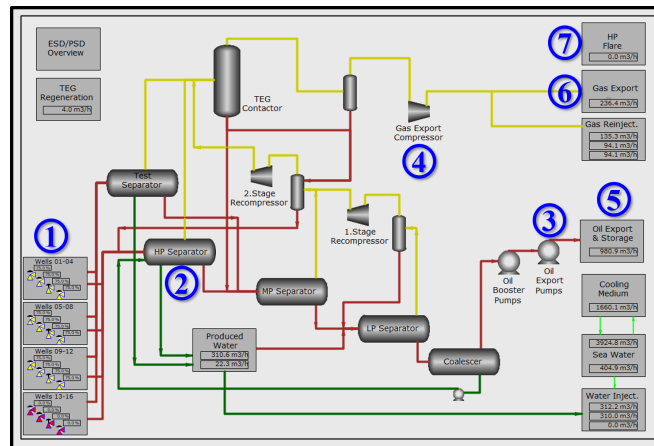


Figure 2: Overview of the generic oil and gas production process and study variables. 1) Total sum of outlet flow rates from the wells. 2) Inlet flow rate of the HP-separator. 3) Pump power consumption. 4) Compressor power consumption. 5) Oil export flow rate. 6) Gas export flow rate. 7) HP-flare flow rate.

chosen because during the simulator training sessions we noticed that the participants did not wait more than 3 min to make changes in the simulation. For SC2, the delays for the main action was the same as for SC1. The delays for the subsequent actions in SC2 were set to 180 s, 240 s, and 300 s to give enough time to evaluate the percentage change of the gas flow rate. The construction of one execution path occurs as follows: first, the main action is chosen randomly among the main options. Then whether the main action will be followed by one, two or no more actions is also decided randomly. The main actions of each scenario studied are explained below.

3.4.1 Scenario 1: Increase oil production

1. Increasing the flow from a well

Increasing the flow from a well is the right decision when trying to increase oil production; this can be done by opening a choke valve. We assumed that if the first decision of the trainee is to open a choke valve, then, the following actions, if any, should be to open more choke valves. Once the first choke valve is opened, whether one, two or no more valves will be opened is decided randomly. The opening of the choke valves is also a random decision between two options: 85 % and 100 %. In the simulation, all choke valves predetermined to be open, are already open up to 75 %.

2. Decreasing the flow from a well

Decreasing the flow from a well is an incorrect approach if the oil production needs to be increased. To decrease the flow from a well, a choke valve must be closed. If the trainee is confused and closes a valve by mistake, the next actions could be to close even more valves. However, the trainee might notice the error and try to fix it by reopening the closed valve and opening an extra one. Whether the action of closing a choke valve will be followed by one, two or no more actions is decided randomly. In the case of choosing one more action, this one could be either closing another valve or reopening the one that was closed. In the case of two subsequent actions, these will be to reopen the closed valve and open an extra one. How much a choke valve is closed is also a random decision between two options: 0 % and 65 %. For the opening, the same conditions explained for the first main action are applied.

3. Opening an Emergency Shutdown (ESD) valve

During the simulator training sessions described in [31], it was noticed that some participants opened an ESD valve thinking that it was a choke valve. This mistake was also observed during the simulator training sessions performed later in 2017 and 2018. Therefore, it was considered. Given that the opening an ESD valve is a rare mistake we did not define subsequent actions for it.

4. Increasing the pressure set point of the HP-separator

Opening the outlet valve of the HP-separator might occur due to a misconception. Some trainees think that by increasing the outlet flow from the HP-separator, the oil production would increase as well. The next step is to choose whether to proceed with one, two or no more actions. If two actions are chosen, these are set to be the

opening of two choke valves. If only one more action is following, this can be opening either a choke valve or an ESD valve.

5. *Opening the outlet control valve of the HP-separator*

Increasing the pressure of the HP-separator leads the system to switch on the high-pressure flare. This action was defined to ensure the possibility of analyzing execution paths with a negative environmental impact. If only one more action follows this one, it can be opening either a choke valve or an ESD valve. If two actions follow, both will be to open a choke valve.

3.4.2 Scenario 2: Decrease gas production

1. *Decreasing the flow from a well*

Decreasing the opening of a choke from 75 % to 60 % is the right decision when trying to decrease 10 % of the initial gas production. If this is done, it will be enough to reach the goal, so no more actions will follow.

However, a trainee might consider closing a choke valve entirely or down to values that might not be suitable for reaching the scenario's goal. Therefore, s/he will have to reopen the choke valve. Then, if the trainee opens the valve too much, s/he might have to close it again. Several options were defined to represent some of the possibilities described; these are presented in Table 1.

Table 1: Defined options when the first action is closing a choke valve

Sequence condition	Close choke valve down to (%)	Reopen choke valve up to (%)	Reclose choke valve down to (%)
If only main action	60	-	-
If main action followed by one action	0	40	-
	40	50	-
	70	60	-
If main action followed by two actions	0	40	60
	40	50	60
	70	65	60

2. *Increasing the flow from a well*

Increasing the flow from a well is an incorrect approach if the gas production needs to be decreased. If the trainee is not sure of what they are doing, they might make this mistake. On the other hand, the trainee could notice the error and try to fix it by closing the opened valve. One, two, or no more actions may follow the opening of a choke valve. Table 2 shows the available options for this case.

3. *Closing the Emergency Shutdown (ESD) valve of a well.*

The trainee could choose to close the ESD valve of a well. This action would decrease the gas production, by much more than 10 %, so it is an incorrect approach. Closing the ESD valve of a well affects drastically the flow coming from it. Therefore, only one subsequent action may follow this one, and it will be to open the ESD valve again.

4. *Closing the Emergency Shutdown (ESD) valve of the HP-separator to the Contactor*

The trainee could be mistaken and think that if the gas flow from the HP-separator decreases, the gas production would drop too. Due to this, they might reduce the opening of the ESD valve of the HP-separator that regulates the flow to the Contactor. Then, when noticing that this decision barely affects the gas production flow, they could continue closing the valve until the gas accumulates in the system, then pressure increases and finally the high-pressure flare must be operated.

3.5 Classification of the case studies data

In the case of SC1, 75 different samples were generated, of which two-thirds were used for training and one-third for validation, i.e. 50 samples for training and 25 for validation. Each group had a balanced number of good and bad execution paths. The data generated for the first scenario was not labelled, so it was clustered using the distances

Table 2: Defined options when the first action is opening a choke valve

Sequence condition	Open choke valve up to (%)	Close choke valve down to (%)	Reopen choke valve up to (%)
If only main action	85	-	-
	100	-	-
If main action followed by one action	85	0	-
	100	50	-
If main action followed by two actions	85	0	20
		50	60
	100	0	20
		50	60

between every possible pair of execution paths and the hierarchical clustering method. A detailed explanation of how the data was classified can be found in [29].

For SC2, 200 different samples were generated, of which 65 % were used for training and 35 % for validation, i.e. 130 samples for training and 70 for validation. Again, it was ensured that each group had a balanced number of good and bad execution paths. The data generated for the second scenario was labelled.

3.6 Data processing and dimensionality reduction of the case studies

In the case of SC1, the time moving average was calculated using a window size of 35 elements. For SC2, the most suitable windows size was of 20 elements. Figure 3 and Figure 4 show the graphs of the training data scores of PC1 vs the scores of PC2 vs time, for SC1 and SC2 respectively.

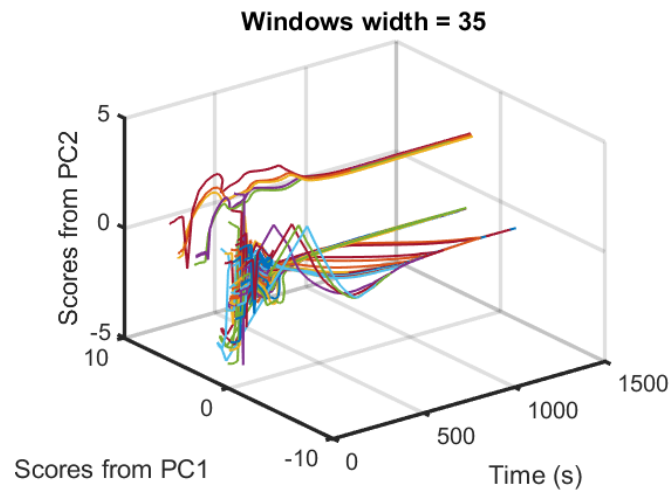


Figure 3: SC1 – Scores from PC2 vs Scores from PC1 vs Time.

3.7 Enclosing tunnels of the case studies

The enclosing tunnel designed for SC1 has five different radiuses, Figure 5 shows the SC1 training data plotted together with its corresponding data-enclosing tunnel. In the case of SC2, the tunnel designed has eleven different radiuses; Figure 6 presents the SC2 training data plotted together with its related data-enclosing tunnel.

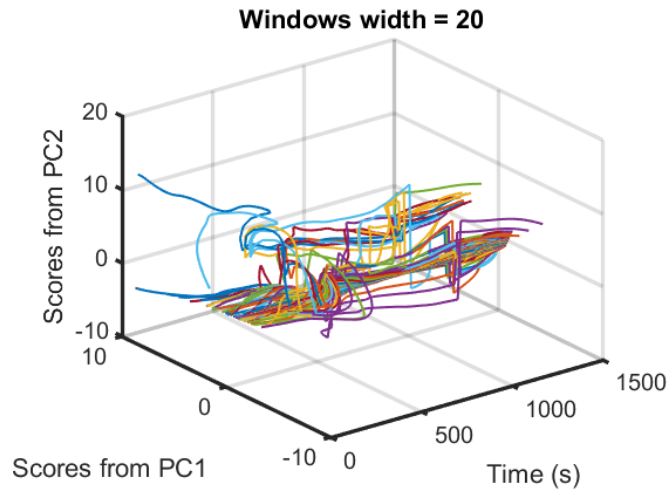


Figure 4: SC2 – Scores from PC2 vs Scores from PC1 vs Time.

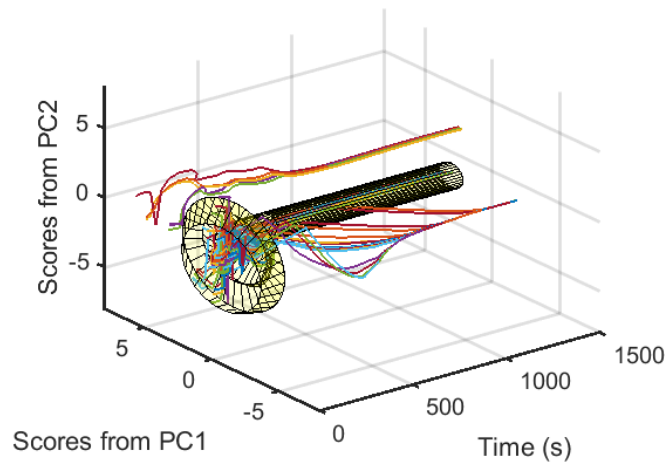


Figure 5: SC1 – Data-encloding tunnel and training data.

3.8 Validation of the tunnels of the case studies

As indicated in the methodology, the validation of the tunnel was made by calculating how many of the execution paths in the validation data ended correctly inside or outside the enclosing tunnel. Figure 7 and Figure 8 show the tunnels from each scenario plotted together with the validation data.

Nevertheless, with the aim of having different benchmarking points, we developed a method more straightforward than the enclosing tunnel. We created an enclosing band, which evaluates separately each studied variable, without dimensionality reduction. The building of the band consists in choosing or defining a reference path from the good execution paths. Once a reference path is established, the enclosing band is created by setting a limit above and below the reference path. The enclosing band was generated three times, each one with a different and simpler approach than the previous one; all of them were compared with the tunnel. Each of the three approaches for developing the enclosing band is explained in the following.

3.8.1 Enclosing band: Approach 1 (AP1)

1. *Reference path*: For the first approach, the reference path was defined by making a curve fitting for each of the studied variables. The curve fittings were done using only the good execution paths of the training data.

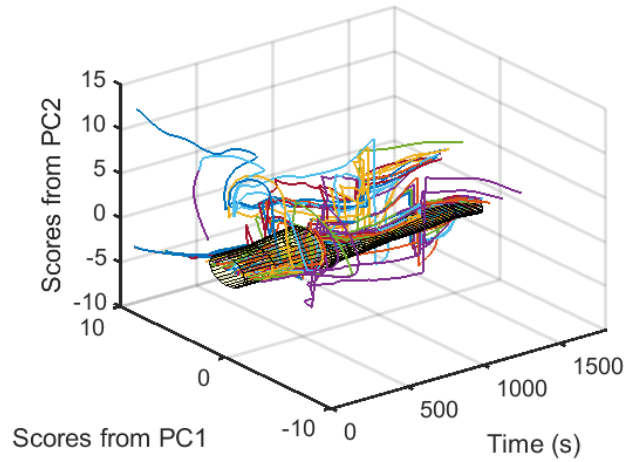


Figure 6: SC2 – Data-enclosing tunnel and training data.

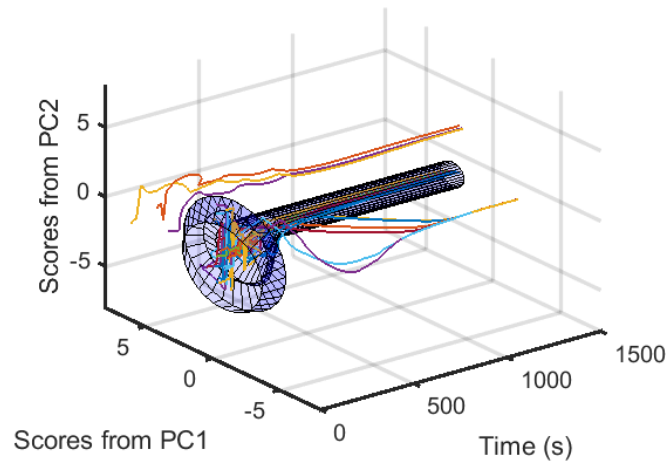


Figure 7: SC1 – Data-enclosing tunnel and validation data.

Figure 9 and Figure 10 show the curve fitting for the variables oil production and gas production of SC1 and SC2, respectively.

2. *Data scaling*: The training data was grouped per variables, one matrix for each variable. Given that in both of our case studies seven variables were monitored, there were seven matrices in the end, with as many columns as samples in the training data of each case study. The mean values and the standard deviations of each of the matrices were calculated. These parameters were used later to scale the reference path and the validation data.
3. *Enclosing band*: After establishing the reference path and scaling, the following step was to design the enclosing band. In this approach, the band was created by summing up and subtracting from the scaled reference path the radiuses of the tunnel.

Figure 11 and Figure 12 show the enclosing band together with the scaled validation data of SC1 and SC2, respectively. Figure 11 corresponds to the scaled variable, oil production, of SC1. Figure 12 corresponds to the scaled variable, gas production, of SC2.

3.8.2 Enclosing band: Approach 2 (AP2)

1. *Reference path*: For the second approach, the reference path was chosen from the good execution paths of the training data. The reference was selected by observing the execution paths of one variable only. The variable observed was the one that represents better the achievement of the scenario objective. In the case of SC1, the

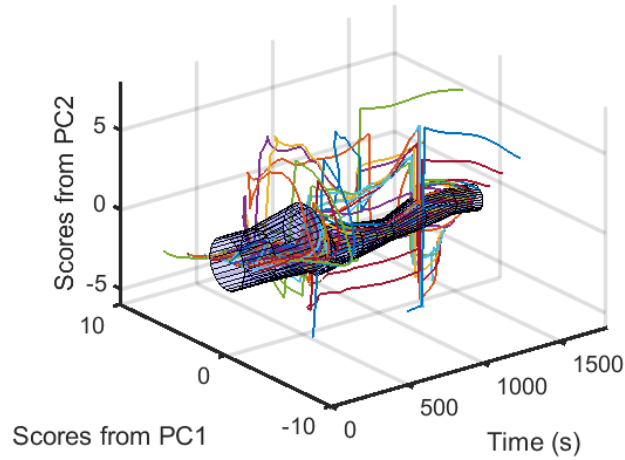


Figure 8: SC2 – Data-enclosing tunnel and validation data.

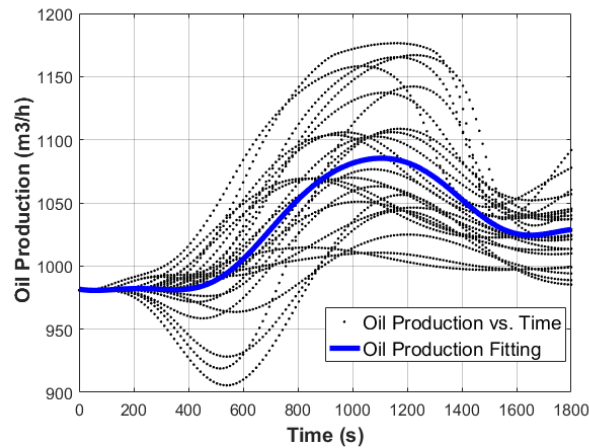


Figure 9: SC1 – Curve fitting of the variable oil production.

variable observed was oil production, while for SC2 it was gas production. Figure 13 and Figure 14 show the chosen reference paths for SC1 and SC2, respectively.

2. *Data scaling*: The scaling was done in the same manner as in AP1.
3. *Enclosing band*: After choosing the reference path and scaling, the enclosing band was created also by summing up and subtracting from the scaled reference path the radiuses of the tunnel. Figure 15 and Figure 16 show the enclosing band together with the scaled validation data of SC1 and SC2, respectively. It can be noticed that the results with AP1 and AP2 seem to be very similar, even though the reference paths were established differently.

3.8.3 Enclosing band: Approach 3 (AP3)

1. *Reference path*: For the third approach, the reference paths were the same as in AP2 (see Figure 13 and Figure 14), chosen reference paths.
2. *Data scaling*: In the third approach, the data was not scaled.
3. *Enclosing band*: AP3 consisted in creating the enclosing band using a generic factor. The factor was calculated by assuming that the tunnel radiuses were scaled data. The radiuses were transformed into “actual variables” using the scaling parameters determined in the previous two approaches. Once the radiuses were converted into their version of each of the seven variables, the resulting matrix was compared with the chosen reference

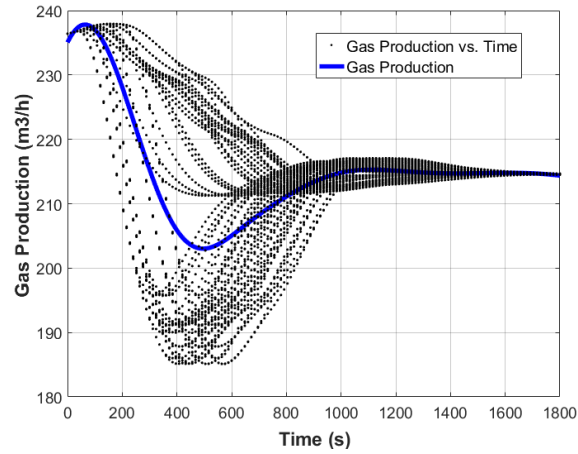


Figure 10: SC2 – Curve fitting of the variable gas production.

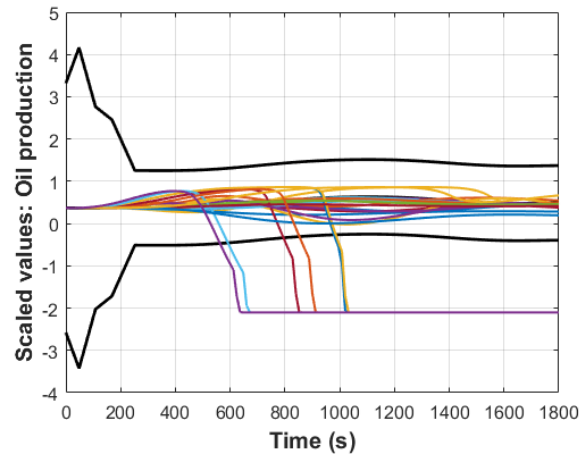


Figure 11: SC1 – AP1 – Enclosing band and validation data. Variable: Scaled oil production.

path to determine the relationship between them. By doing so, a factor was calculated for each of the two training scenarios. The average between the two factors was taken to get a final generic value which was 15 %. The enclosing band was created by summing up and subtracting from the reference path that generic factor. Figure 17 and Figure 18 show the enclosing band together with the validation data of SC1 and SC2, respectively.

3.8.4 Validation of the enclosing bands

For each of the case studies, there were seven bands, one for each of the monitoring variables. Therefore, to validate the enclosing band, first, the percentage of residence of each variable path inside its corresponding band was calculated. If any of the variables falls outside of its associated band more than 35 or 50 % of the total time, the execution path related to such variable is classified as bad. Next, the validation of the enclosing band is the same way as it happened for the tunnel. It is based on calculating how many of the execution paths in the validation data are correctly classified by the enclosing band.

3.8.5 Comparison of the methods

Table 3 and Table 4 present the different accuracies obtained for each of the methods studied. We consider four subgroups of classification: 1) true positives (TPs), which denote the good execution paths that fall inside the tunnel/band; 2) true

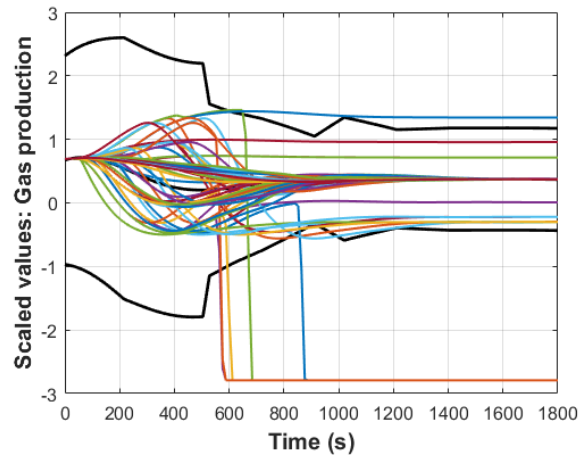


Figure 12: SC2 – AP1 – Enclosing band and validation data. Variable: Scaled gas production.

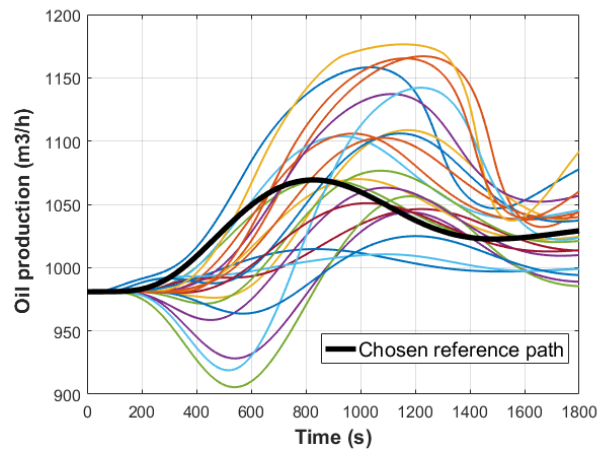


Figure 13: SC1 – Chosen reference among the oil production paths.

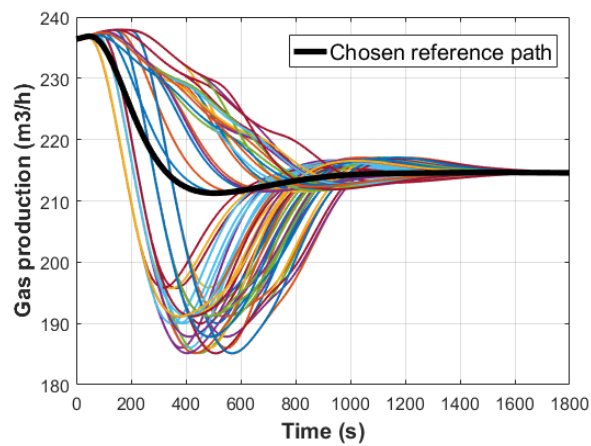


Figure 14: SC2 – Chosen reference among the gas production paths.

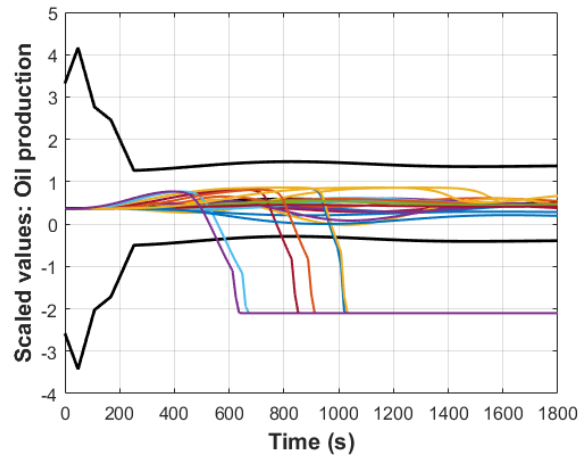


Figure 15: SC1 – AP2 – Enclosing band and validation data. Variable: Scaled oil production.

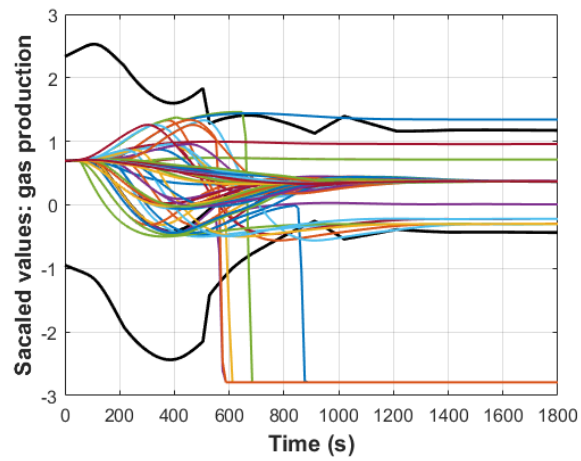


Figure 16: SC2 – AP2 – Enclosing band and validation data. Variable: Scaled gas production.

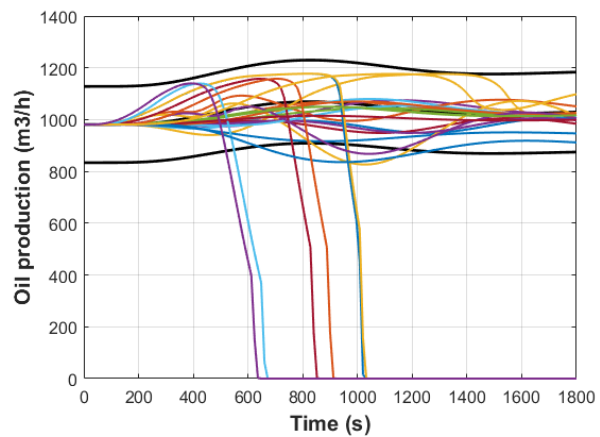


Figure 17: SC1 – AP3 – Enclosing band and validation data. Variable: Oil production.

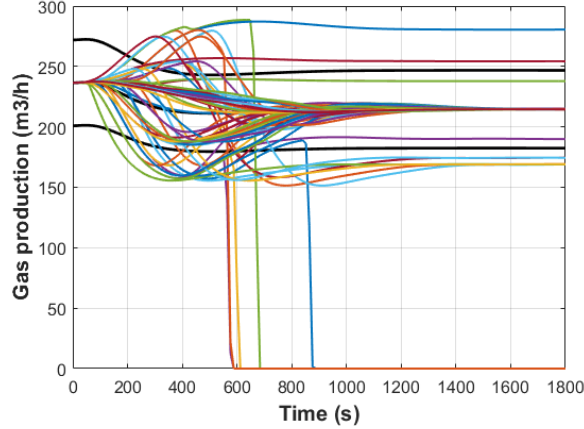


Figure 18: SC2 – AP3 – Enclosing band and validation data. Variable: Gas production.

negatives (TNs), which denote bad execution paths that fall outside the tunnel/band; 3) false positives (FPs), which refer to bad execution paths that fall inside the tunnel/band; and 4) false negatives (FNs), which refer to good execution path that fall outside the tunnel/band. The accuracy is defined as follows:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

In the case of SC1 (Table 3), the accuracy is the same for all the methods when Metric 1 is used (a path is considered bad if it falls outside the tunnel/band more than 35 % of the total time). When using Metric 2 (a path is considered bad if it falls outside the tunnel/band more than 50 % of the total time), AP1 and AP2 have a lower accuracy while the accuracy of the enclosing tunnel and AP3 remains the same.

The results of SC2 are notoriously different from those of SC1. When it comes to SC2, Table 4 shows that the tunnel method is the most accurate regardless of the implemented metric.

Table 3: Comparison of the accuracy of the methods for Scenario 1.

Method	Metric 1: 35 % outside is "bad"					Metric 2: 50 % outside is "bad"				
	FP	FN	TP	TN	Acc. (%)	FP	FN	TP	TN	Acc. (%)
SC1 Tunnel	3	0	12	10	88	3	0	12	10	88
SC1 AP1	3	0	12	10	88	5	0	12	8	80
SC1 AP2	3	0	12	10	88	6	0	12	7	76
SC1 AP3	0	3	9	13	88	0	3	9	13	88

The subgroups of classification can also be analyzed with a confusion matrix. A confusion matrix is a table that describes the performance of a classification method on a set of test data for which the true values are known [32]. Figure 19 shows how to read a confusion matrix. The values in the diagonal (green boxes) are the correct classifications, i.e. the true positives and the true negatives. The final values in the diagonal (yellow box), correspond to the overall correct classifications, i.e. the accuracy, and the overall incorrect classifications. The values outside the diagonal (red boxes) correspond to misclassifications, i.e. false positives and false negatives. Reading the confusion matrix vertically, the results presented in the last row of the first column refer only to the actual number of good execution paths, it shows the percentage of good execution paths that were classified correctly and the percentage of good execution paths that were misclassified. The same is true for the last row of the second column, but in this case referring only to the actual number of bad execution paths. Reading the confusion matrix horizontally, the values shown in the last column of the

Table 4: Comparison of the accuracy of the methods for Scenario 2.

Method	Metric 1: 35 % outside is "bad"					Metric 2: 50 % outside is "bad"				
	FP	FN	TP	TN	Acc. (%)	FP	FN	TP	TN	Acc. (%)
SC2 Tunnel	4	0	35	31	94.3	10	0	35	25	85.7
SC2 AP1	13	0	35	22	81.4	18	0	35	17	74.3
SC2 AP2	9	17	18	26	62.9	15	0	35	20	78.6
SC2 AP3	21	0	35	14	70.0	21	0	35	14	70.0

first row refer to the total amount of predicted positives; it shows the percentage of correct and incorrect positives. In the case of the last column of the second row, these values refer to the total amount of predicted negatives; it shows the percentage of correct and incorrect negatives. Figures 20, 21, 22 and 23 respectively show the confusion matrix of each of the methods using Metric 1, for SC2.

		Actual good	Actual bad	
Output class	Predicted good	N° of True Positives % with respect to total amount of samples	N° of False Positives % with respect to total amount of samples	% of correct positives % of incorrect positives
	Predicted bad	N° of False Negatives % with respect to total amount of samples	N° of True Negatives % with respect to total amount of samples	% of correct negatives % of incorrect negatives
		% of good executions paths classify correctly % of misclassifications of good execution paths	% of bad executions paths classify correctly % of misclassifications of bad execution paths	% of overall correct classifications % of overall incorrect classifications
		Target class		

Figure 19: Explanation of the confusion matrix.

4 Discussion

This work presented a methodology for constructing a data-enclosing tunnel to be used as an online feedback tool for simulator-training scenarios. The design of the data-enclosing tunnel is based on a data mining approach; good examples of how the scenario of interest can be solved are used to construct the tunnel. Thus, the data-enclosing tunnel can automatically detect deviations from correct executions paths. When the tunnel is used online, what will be determined is whether the new data received falls inside or outside the tunnel. If the data falls outside the tunnel, then feedback should be given to the user, so they are aware that something wrong is happening in the process. Given that the tunnel is constructed based on the most relevant variables that characterized the training scenario for which it was built, it is possible to give feedback related to the specific variable deviating from normal or safe conditions.

Further, this work presents two case studies of the methodology introduced. A data-enclosing tunnel was built for two different training scenarios to demonstrate the usefulness and viability of the methodology presented and to validate it.

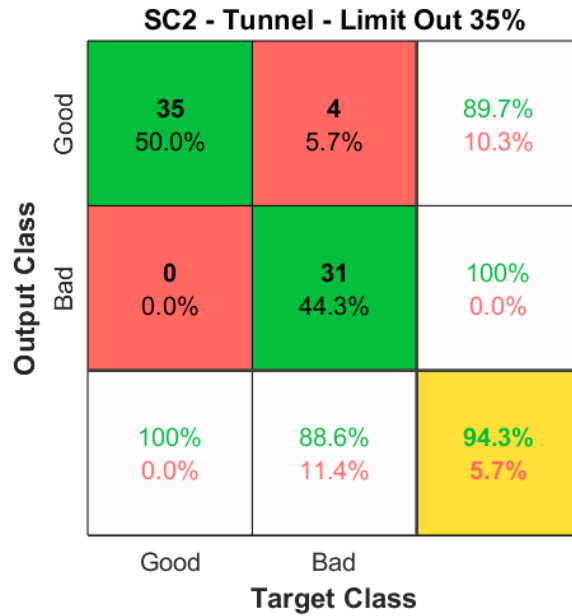


Figure 20: SC2 – Confusion matrix of the data-enclosing tunnel using Metric 1.

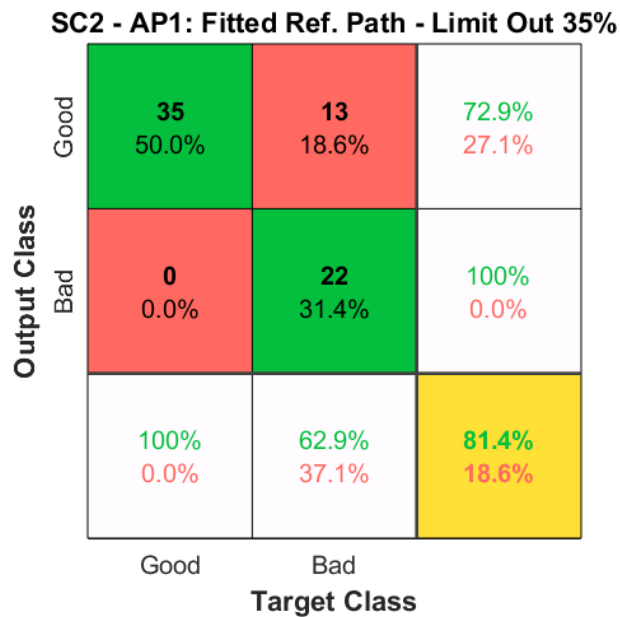


Figure 21: SC2 – Confusion matrix AP1 using Metric 1.

The two training scenarios studied were based on a generic oil and gas production model, using the simulation tool K-Spice, from Kongsberg Digital. The goal of the first scenario was for the trainees to increase the value of the oil production flow given on the initial conditions of the simulation. The objective of the second scenario studied was to decrease 10 % of the value of the gas production flow provided with the initial conditions of the model. In both scenarios, the same seven variables were monitored.

Given that we did not have available actual user data, the data was generated with an algorithm. The algorithm could choose randomly from a repository of possible actions that were defined based on the authors' previous experience

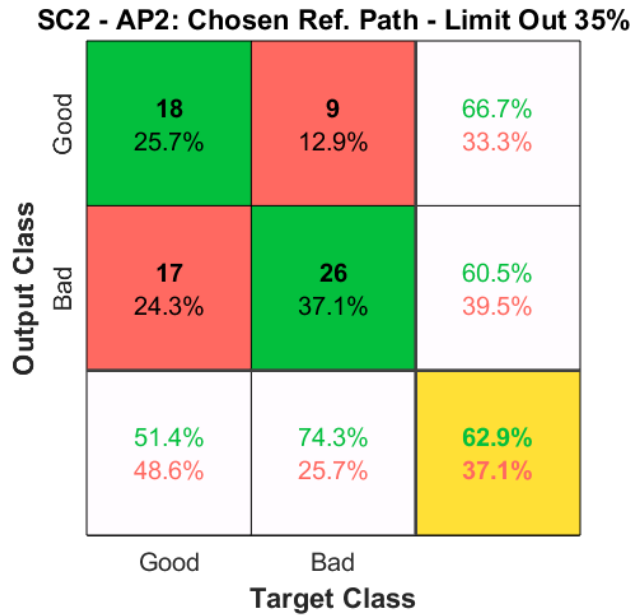


Figure 22: SC2 – Confusion matrix AP2 using Metric 1.

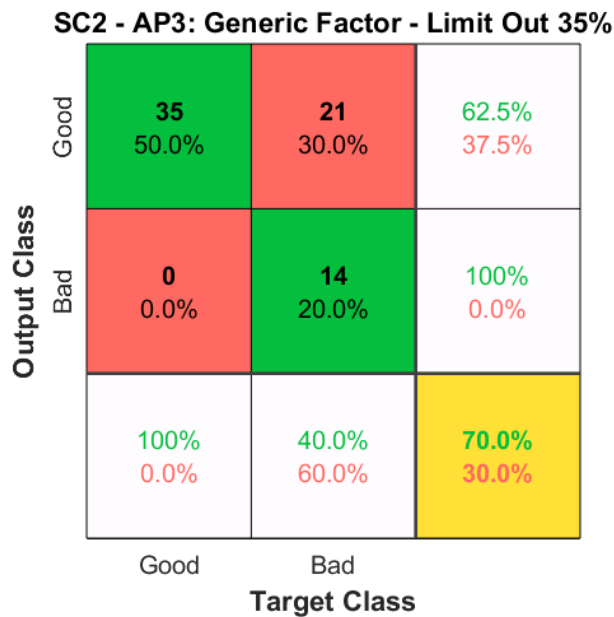


Figure 23: SC2 – Confusion matrix AP3 using Metric 1.

working with simulator training for novices. In the case of SC1, the data was not labeled. Therefore, a classification method was used. On the other hand, the data generated for the second scenario was labeled. Thus, we illustrate the different possible situations when using the methodology presented. Moreover, the data generated for the second scenario was larger than the data generated for the first one, also with the aim to show the performance of the data-enclosing tunnel under different circumstances.

To validate the tunnels built for each of the training scenarios, it was determined how many of the execution paths in the validation data ended correctly either inside or outside the tunnel based on the classification labels of the data. Besides,

we developed a simpler method, an enclosing band. The enclosing band aims to compare our enclosing-tunnel method with another that represents the state of the art. There is not much research related to online feedback for simulator training based on the evaluation of good execution paths [33]. Therefore, we developed a simpler method that works in a 2D plane without dimensionality reduction, which means that all variables are studied individually.

The band was built in three different ways, each one with a simpler approach than the previous one. For AP1 and AP2 the band was built using the tunnel radiuses as limits above and below the reference path. The difference between these approaches was the way the reference path was established. For AP1 the reference path was determined by making a curve fit of the good execution paths in the training data, while for AP2 the reference path was chosen from the good execution paths in the training data. Finally, the third band, AP3, was built using a generic factor to calculate the limits above and below the reference path, which was the same reference path used in AP2. The aim of having different comparison methods was to determine how the complexity of each method affects its accuracy.

Table 3 shows the accuracy results obtained for SC1. In the case of Metric 1, the same accuracy, 88 %, was obtained with all the methods studied. With Metric 2, the accuracy of AP1 and AP2 is lower. This can be explained by observing the number of false positives, which increases in both cases when using Metric 2. Given that Metric 2 has a higher tolerance towards the time an execution path can fall outside the tunnel/band without being considered bad, some execution paths get misclassified. The tunnel and AP3 have the same accuracy using both metrics. The lack of variation in the accuracy of the methods for SC1 can be due to the size of the data, which could be considered small, given that it had only 50 samples for training and 25 for validation. Consequently, SC1 is a simple problem, and all the information that is possible to get from the data is reached with all the tested methods.

On the other hand, the accuracy results obtained for SC2 are more versatile, as shown in Table 4. When observing only the results obtained with Metric 1, it can be seen that the tunnel is the most accurate among four methods. Also, AP1 is more accurate than AP2. We can argue that the accuracy of AP1 is higher since the reference path used to create the enclosing band was determined more meticulously than for AP2. A curve fit represents better the behavior of all the good execution paths than only one good path chosen randomly as a reference. AP2 and AP3 are the less complex of the four methods, and it can be seen that the accuracies obtained with these two methods are the lowest.

If the results obtained with Metric 2 are observed (Table 4), it can be seen that again the tunnel is the most accurate of the four methods. However, the accuracy of the tunnel when using Metric 2 decreases. If we study the number of false positives in this case, it can be seen that a more flexible metric for SC2 leads to a larger number of misclassifications of the bad paths. The same is observed with AP1 (Table 4). On the contrary, the accuracy of AP2 increases when Metric 2 is used, which indicates that having a more flexible metric for this case helped to classify correctly the execution paths that with Metric 1 did not enter in the right category, i.e. the number of true positives of AP2 increases when using Metric 2. In the case of AP3, the accuracy remains the same with each of the metrics, which was also the case for SC1. This could be due to the simplicity of AP3, so not much variance can be obtained from the method.

The variety of the results obtained for SC2 may also be due to the size of the data, which in this case is larger than the one for SC1, having 130 samples for training and 70 for validation. In general, based on the results with SC2 which have a notorious variability, it can be said that the tunnel is the most accurate of all the methods studied using any of the two metrics, and AP3 is the less accurate.

5 Conclusions

The methodology presented in this work was effectively implemented in two case studies. It was demonstrated how to use the methodology and how to follow each of the related steps with two industrial cases, developed with the dynamic process simulator K-Spice, from Kongsberg Digital. The data mining results from each of the scenarios were presented: classification, processing, and dimensionality reduction of the data. Further, different situations that the user could encounter when using the methodology were illustrated, as well as how to deal with such conditions as non-labeled data or not available data from actual simulator users.

The two data-enclosing tunnels developed for each of the case studies were validated and compared with three other simpler methods. It was noticed that the size of the data had a significant influence on the accuracy of the methods. When doing the data mining process, the larger the data the most information can be extracted from it, and more variability can be observed among the results. The complexity of the methods also has a significant influence on their accuracy. The most elaborate and complex methods had more substantial accuracy than the simplest ones. This means that the data-enclosing tunnel is the most accurate of all the methods evaluated, which indicates that the tunnel is the method that could detect more efficiently if a trainee deviates from the good execution paths.

On the other hand, even though less accurate, the simplest approach also has some advantages. As long as there are not so many variables to evaluate individually, in our case studies we had seven, when it refers to reaction time, the simplest

method (AP3) would be the fastest in detecting that the trainee is deviating from the good execution path, given that the data does not need to be reduced or scaled. However, since the simplest method is less accurate, using it encompasses the risk of not giving any feedback to the trainee when they are taking wrong actions. Further, as mentioned above, it is also advisable to consider the number of monitoring variables. Complex processes require a large number of variables to be monitored, the larger the number of variables, the longer the time that will be needed to determine if they do not fall inside the established limits of the enclosing band. This would not be the case of the data-enclosing tunnel, given that it has the advantage of dimensionality reduction. Nevertheless, further work needs to be done to evaluate and corroborate these hypotheses.

Moreover, future work also includes the development and testing of a user interface for the automated feedback tool. The interface should show guiding messages using natural language so that the trainee does not have to read more values on the screen. The testing of the tool should be carried out with actual trainees that could give their opinion on their experience using it.

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