VTT Technical Research Centre of Finland

Dynamic human reliability analysis (HRA)

Liinasuo, Marja; Karanta, Ilkka; Kling, Terhi

Published: 11/03/2020

Document Version
Publisher's final version

RESEARCH REPORT

VTT-R-00193-20

Dynamic human reliability analysis (HRA) - a literature review

Authors: Marja Liinasuo, Ilkka Karanta, Terhi Kling

Confidentiality: Public

Report's title Dynamic human reliability analysis (HRA) - a literature review	
Customer, contact person, address VYR	**Order reference** SAFIR 3/2019
Project name New developments and Applications of PRA	**Project number/Short name** 122529/NAPRA
Author(s) Marja Liinasuo, Ilkka Karanta, Terhi Kling	**Pages** 27/
Keywords HRA, human reliability analysis, dynamic HRA, hybrid, control room	**Report identification code** VTT-R-00193-20

Summary

This report first clarifies the nature of human error and performance from a dynamic perspective, using two models, one relating to perception and another to situation awareness, as examples of that. The report also briefly describes the dynamic nature of the operating environment of the nuclear power plant operator.

Thereafter, the meaning of the concept of dynamic human reliability analysis (HRA) is presented as it is expressed in scientific literature. The concept is not always defined but apparently, the dynamic nature is seen either in the phenomena dynamic HRA focuses on or defined as the methods used in human reliability assessment. Furthermore, dynamic HRA tends to scrutinise human error as closely related to the contextual aspects, opposed to the presently central but also older, static approach, according to which human is prone to make errors as such. Various methods presently available for dynamic HRA are presented. The largest group of methods concentrate on the simulation and modelling of human cognitive processes. No comprehensive methodology for dynamic HRA is created but instead, each method tends to focus on some aspect or aspects considered relevant from the dynamic perspective. Due to the context of the present HRA study, the hybrid control room is also scrutinised from the perspective of dynamic HRA. The nature of control room does not seem to raise needs or requirements for a specifically dynamic approach.

Finally, conclusions are provided. Authors present their conception of dynamic HRA, discuss the need for the usage of dynamic HRA and contemplate the possibilities for the usage of dynamic HRA in the future.

In the Appendix, a research plan for dynamic HRA research in NAPRA project in 2020 is provided. The research will consist of a survey to stakeholders, and a related empirical study.

Confidentiality	Public

Espoo 11.3.2020

Written by	**Reviewed by**	**Accepted by**
Marja Liinasuo, Senior Scientist	Tero Tyrväinen, Research Scientist	Nadezhda Gotcheva, Research Team Leader

VTT's contact address
Vuorimiehentie 3, Espoo, P.O. Box 1000, FI, 02044 VTT, Finland

Distribution (customer and VTT)
SAFIR Extranet

Preface

This report is the deliverable of the task ‘Human reliability analysis’ (T3.2) of the project of ‘New Development and applications of PRA’ (NAPRA) on 2019.

The goal of NAPRA T3.2 is to define realistic or slightly conservative human error probability estimates and to identify the most relevant human failure events in hybrid control rooms. This realism includes dynamic HRA, contrasting the traditional static starting point of HRA.

This report presents a literature review of HRA, shedding light on what dynamic HRA means in current scientific literature.

The project is part of SAFIR2022 research programme, funded by VYR.

Espoo 11.3.2020

Authors

Contents

Abbreviations

ACT-R	Adaptive Control of Thought-Rational (cognitive architecture)
ADS-IDAC	Accident Dynamics Simulator-Information Decision and Action in Crew (an HRA method)
CFM	crew failure mode
D-OMAR	Distributed Operator Model ARchitecture
EHEA	Emergency Human Error Analysis
FAB	Feed And Bleed
GOMS	Goals, Operators, Methods, and Selection rules (a human performance modelling method)
HEMA	Human Error Modeling Architecture
HEP	Human Error Probability
HFE	Human Failure Event
HRA	Human Reliability Analysis
MIDAS	Man-machine Integration Design and Analysis System
NPP	Nuclear Power Plant
PIF	Performance Influencing Factor
PRA	Probabilistic Risk Assessment
PROCOS	PRObabilistic COgnitive Simulator
PSF	Performance Shaping Factor
SHERPA	a Simulator for Human ERror Probability Analysis
SOAR	State, Operator And Result (a cognitive architecture)

1. Introduction

Conventional human reliability analysis (HRA) relies mostly on static notions. Time, if considered at all, is present in time-probability curves that represent the probability that a human actor accomplishes a given activity (e.g. detecting failure) within a given time interval. Things like the history of events, the state of mind that a person goes through, and how all of this (context) affects the performance of the individual and the team are indirectly considered, if at all.

In the recent decade or two, a new paradigm called ‘dynamic HRA’ has entered the field of HRA. The concept of dynamic usually refers to continuous and productive activity or change (Merriam-Webster, 2019). Thus, it is rather positive adjective in nature, referring to something which does not remain the same in a productive way. ‘Dynamic system’ is a system or process in which motion occurs, or includes active forces, as opposed to static conditions with no motion (Corrosionpedia, 2019). Again, the change is emphasised in this definition as well, although the nature of the definition is more neutral than positive. Regarding dynamic HRA, the concept is even vaguer.

Traditionally, the estimates of human errors are based on static situations, even if the former events and situations affect the latter ones also in the context of human cognition and performance. Static HRA methods consider human performance at a point in time (R.L. Boring, 2007), without explaining how a change in one performance shaping factor (PSF) at one point affects PSFs and the events after that point. As PSFs are to capture the impact of the operating environment on human performance, this means that static methods are not sufficient when PSFs are likely to interact and change due to accident progression and the passing of time. Most HRA methods (including static ones) account for dependency (Spurgin, 2009). However, dependency is typically based on an overall human error probability (HEP) and does not systematically model the change of PSFs across events (R.L. Boring, 2007).

Thus, it is likely that HRA captures human errors and the probabilities of those errors best when applying a dynamic approach. The concept of dynamic HRA is, hence, highly relevant and represents a modern approach on human errors.

The objective of this study is to clarify the meaning or the variety of meanings of dynamic HRA. The means to reach this objective is to conduct a review on current scientific conceptions about dynamic HRA. Such scientific publications are selected, which deal with the dynamic matters in HRA.

This report first clarifies the nature of human error and performance from a dynamic perspective (section 2) as well as the dynamic nature of the operating environment of the nuclear power plant (NPP) operator (section 3), presenting these entities from a general perspective. Thereafter, the meaning of the concept of dynamic HRA is presented as it is expressed in scientific literature (section 4). In section 5, the different methods for dynamic HRA, described in literature, are presented. The context of the HRA studies in SAFIR2022 takes place in hybrid control rooms. Accordingly, in section 6, the hybrid control room is scrutinised from the perspective of dynamic HRA. Finally, conclusions (section 7) are provided.

2. Dynamics and errors in human performance

Human performance and the related psychological aspects, such as cognitive processes, e.g., decision making, and emotions, e.g., the ones related to stress, are complex phenomena. In this section, descriptive examples are provided about how dynamic human performance and the related errors can be tackled from a theoretical perspective.

Human performance and the related phenomena can be described as a loop or process. Briefly, Neisser (Neisser, 1976) describes the role of perception in the Perceptual Cycle Model (Figure 1) in which the individual cognitive map of the world directs perceptual exploration of the world; with perception, samples of the present environment are taken which, in turn, modify the cognitive map of the individual. Thus, human thought is in close connection with the person’s interaction with the world. The developing map of the world guides in seeking a specific type of information and can lead to anticipation over certain types of information (top-down processing). The map is also used in the interpretation of that information. On the other hand, information acquired from the world builds and modifies the cognitive map of the world (bottom-up processing).

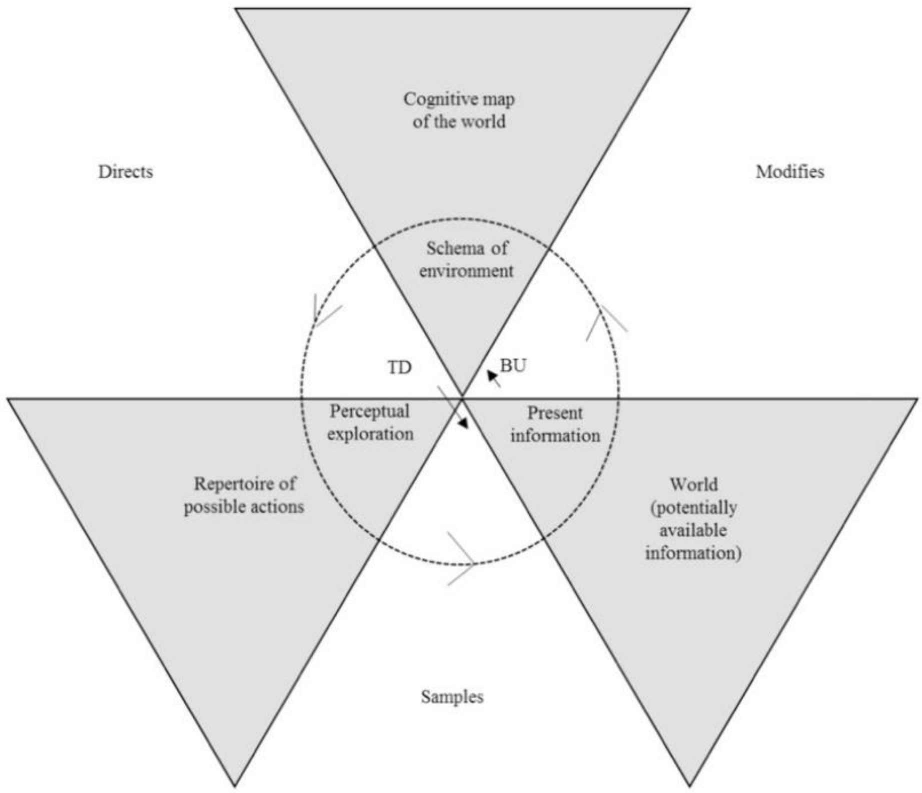

Figure 1. The Perceptual Cycle Model (adapted from Neisser (Neisser, 1976)*). TD refers to top-down processing and BU bottom-up processing.*

Regarding human errors, the source of the errors can be, based in Perceptual Cycle model, in an erroneous or incomplete cognitive map of the world as a whole, or in the schema of environment; in what is available in the environment for perceptual exploration; and in the nature of the information provided in the environment.

Perceptual Cycle model has been used in exploring systemic decision-making processes, in the context of retrospective accident analysis (Plant & Stanton, 2012)(Banks, Plant, & Stanton, 2018). Specifically, the Schema Theory, incorporated in the Perceptual Cycle framework, was used for identifying causal relationships accounting for human error (Plant & Stanton, 2012) or for identifying the underlying cause to be “designer error” instead of a user’s (in that case, driver’s) one (Banks et al., 2018).

Accordingly, situation awareness can be defined as firstly, the perception of the elements in within space and time, thereafter, the comprehension of their meaning, and finally, the projection of the status of those elements in the near future (Endsley, 1995). Defined like this, situation awareness includes both the understanding of present situation and the anticipation of the situation in the future. Situation awareness, in turn, may impact decision making, which affects person’s ability to carry out the correct action (Endsley, 1995) (Figure 2).

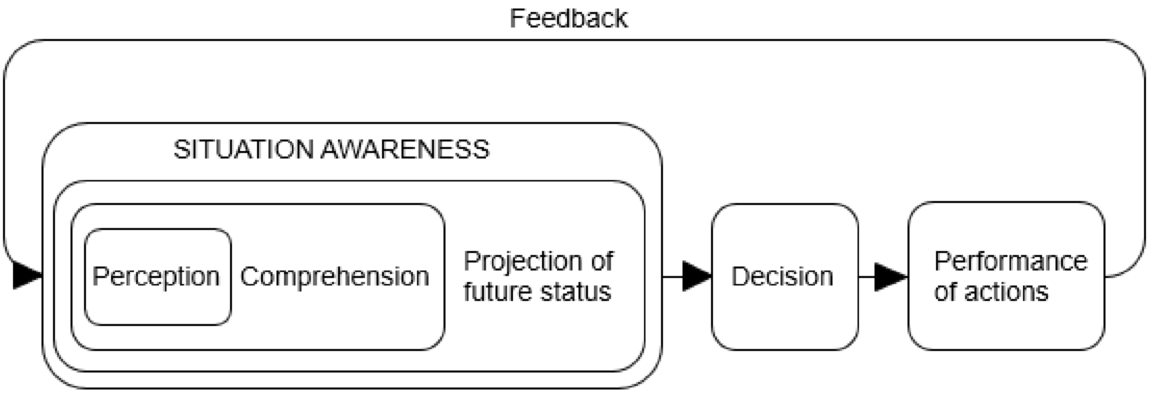

Figure 2. Model of situation awareness in dynamic decision making (simplified, adopted from Endsley (Endsley, 1995)*).*

The formation of situation awareness is not straightforward. Individuals vary in their ability to extract information; the quantity and quality of information the environment provides varies; and also, person-dependant factors may affect the formation of situation awareness. Indeed, the model of situation awareness in Figure 2 is a simplification of the original model. The core, presented in Figure 2, is affected by both task or system related factors and individual factors (Endsley, 1995). Task and system related factors are, according to (Endsley, 1995), both outside-world related factors such as system capability, interface design and automation, and person-related matters of stress and workload. The factor of complexity, considered as a task or system factor by Endsley (Endsley, 1995), can be regarded as an objective feature of the outside world and as something, which depends on the individual (some object can be complex to somebody and not complex to somebody else). Individual factors, according to (Endsley, 1995), are goals, objectives and preconceptions as well as information processing related matters (information processing mechanisms, long-term memory stores and automaticity) and factors affecting information processing (abilities, experience and training). These individual factors are more permanent in nature than the task and system related, more contextual ones.

Scrutinising human errors briefly through this model of situation awareness (Figure 2), the error may lie in an ambiguous nature of the matters to perceive, person’s ability to comprehend those matters as such and the ability to foresee what these matters mean for the future situation. Furthermore, the ability to make appropriate decisions may be weakened due to temporary or permanent person, task or system related matter. Finally, error may occur even if all the preceding phases were conducted appropriately if there is something, which hinders the intended performance of correct actions.

Thus, even these simplified models shed light on the nature of human performance in the real life. Human performance is dynamic in nature. Different matters are perceived, depending on the cognitive map, or mental model, of the situation, and the environment, which may present clearly or hide the relevant information, from the perspective of a person in that specific situation. Not only the outside situation changes but also the matters depending on the person change as perception and the related cognitive processes are both person and context dependent. People are affected differently by, say, stress, perceived familiarity of the situation, as well as uncertainty and complexity of the situation. Hectic situations may support some individuals to excel themselves and exhaust others, and some endure long-lasting stressful situation when others are fatigued. Emotions may intervene and affect teamwork and individual decision-making and consequently, the operations made.

Universally accepted definition of human errors does not exist. The most widely recognised definition is by Reason (Reason, 1990); according to it, human error is “a generic term to encompass all those occasions in which a planned sequence of mental or physical activities fails to achieve its intended outcome, and when these failures cannot be attributed to the intervention of some chance agency” (p. 9). Human error models can be categorised as either person models, concentrating on errors made by an individual operator, or system models, focussing on the interaction between wider systemic failures and errors made by individual operators (Salmon, Lenné, Stanton, Jenkins, & Walker, 2010).

The dynamic nature of human performance, depending on human or system characteristics or both, makes the identification of the cause of human errors more complex. When no stationary reasons or permanent characteristics are assumed, the analysis of human error and human reliability requires carefully considered approach.

3. Dynamics in the operating environment

There are many dynamic or change-related factors in the operational context of the NPP operator. These contextual or objective factors (opposed to cognitive and subjective factors related to human performance) are about changes, which take place in the operating and surrounding circumstances as well as in the event or accident progression.

To start with, the situation in the plant is not self-evidently static. Shutdown, start-up, maintenance work, incidents and accidents are dynamic by nature or cause changes in the state of the plant. Only the state of full power is not dynamic as such, even if the state of the plant slightly changes in accordance with the abrasion of components and parts of the plant system.

Regarding incidents and accidents, the starting point may trigger some other events and the situation changes by time. The situation evolves also when it proceeds as expected. Thus, new alarms may appear, and others disappear. Additionally, as operators are to control the nuclear processes, they intervene the proceeding of events when needed and this is especially true if an accident takes place. Each involvement changes the situation and operators are to manage the situation and update their situation awareness constantly. The possibility of having flawed measurements and erroneous alarms, which originate from false measurements or no measurement at all add changes to a situation.

Also, natural or other, not nuclear-originated disaster may affect the situation, making it more unpredictable. Examples of such disasters are earthquake, tsunami, forest fire, war, and cyber-attack. Even if they would not take place at the NPP site, they can break connections for vehicles to the site and diminish or destroy the possibilities to get more resources to the site. They can also isolate the site so that it is not possible to get food, water or electricity to the site. These external threats also develop by time, possibly adding uncertainty and risks related to safety and security.

Multi-unit sites have the potential to have incidents and accidents that have interrelations between each other (Schroer & Modarres, 2013), adding the complexity and unexpected changes to the situation. A simple example of this is the potential lack of personnel if some accident takes place at both plants in the same site simultaneously.

The situation may worsen when some critical point, not necessarily known beforehand, is reached. This can take place during an accident but also in a day when apparently nothing unexpected has happened before something happens. This can be when, for example, a weakness not identified earlier has grown enough to cause some damage, such as when a slightly loose screw gradually opens and at some point, it is open enough for a flange to come off.

Finally, the changes in personnel add changes to the situation. Each person has his or her own competences and style, affecting, for example, how operations are performed and the successfulness of communication. Shift changes affect operations, even if they are neutral events by nature. Also the support from the outside of the main control room changes the situation; it can be good but also bad, if, for example, the new person has such a powerful status that operators kind of forget to think by themselves, trusting this new person in a wrong way. A less probable but still possible situation is that one operator falls ill or becomes too stressed to handle a demanding situation.

4. The meaning of 'dynamic HRA'

A practical driver of increased interest in dynamic HRA is the need to consider long time windows that has emerged in the wake of the Fukushima Daiichi nuclear accident. Conventionally the time windows considered in HRA have been limited to 24 hours, but in Fukushima it took two or three days from the initiating event for some events significantly affecting accident progression to take place (IAEA, 2015). The first initiating event (IE), the Great East Japan Earthquake, occurred on March 11, 2011, at 14:45. The last IE, the second tsunami, hit the site at 15:36. It has been estimated that the core of Unit 3 uncovered at 13 March 04:15, indicating an imminent core damage, almost two days after the first IE.

Accordingly, Tyrväinen et al. (Tyrväinen et al., 2019) carried out a state-of-the-art review on long time windows in PRA and important related topics. Longer time windows bring in the need to model and analyse more recovery actions and component repairs, which are usually governed by procedures and typically evaluated using HRA methods. In this context, existing (static) HRA methods may not be suitable for the following reasons:

- Static HRA methods usually have a too simplistic view on the variety of the ways a component can fail, as well as the needed repair time and factors that affect it. This is in accordance with the fact that HRA of field workers other than operators (such as maintenance personnel) has not received much attention. Consequently, sufficient data might not exist to estimate the parameters of a repair time probability distribution, and proper modelling may require a lot of expert work.
- Static HRA methods usually have not been developed to quantify the human error probabilities (HEPs) associated with the transportation, placement, connection, or local control of portable equipment. These activities, however, take frequently place in NPPs.
- The typical available times for nuclear power plant level 1 human actions are from 30 minutes to 1 or 2 hours. The existing HRA methods are developed to cope with this situation. In the real world, human actions follow each other in a faster pace.

The modelling of recovery and repair increases HRA model complexity. Modelling of dependencies between recoveries and repairs and other human actions has not received much attention, but it could make the analysis more realistic. Another potentially important aspect of long-term scenarios is the impact of shift changeover on the reliability of measure. Shift changeovers may lead to a loss of information or situational awareness, thus inducing additional sources of human error. In a longer time scenario, the plant crisis organisation would be in place. The potential impacts of multiple decision makers on the performance should be considered realistically. Furthermore, a lot of information is missing related to human performance: parameters of an actual repair time probability distribution (although average repair times are estimated based on repair conducted during normal power production); human error probabilities associated with various matters (see the list above); the intervening factors in long scenarios such as fatigue; and a wider view of human performance, exceeding the one of operators in the main control room. Thus, in the case of long time windows, some issues are related to the dynamic features in the situation not included in HRA currently, and others related to other type of missing information.

Dynamic HRA can be scrutinised as compared with static HRA. In static HRA (and PRA), events are analysed for an assumed, e.g., typical, window of time. The probability or nature of HFE for static HRA does not change as a function of time or the event progression. Either the analysis represents a very generic context in which the event would occur, or the analysis is agnostic to time, meaning that time evolution is simply not factored into the calculation of the human error probability (HEP). Other performance shaping factors (PSFs) apart from time drive the quantification of the HEP (Boring 2017). Boring (R.L. Boring, 2007), among others, explains the conceptual shift from static HRA to dynamic HRA. Key aspects of this shift are the transition from predictions based on fixed models of accident sequences into predictions based on direct simulation of an accident sequence, with explicit consideration of timing of key events.

Dynamic HRA has also been referred to in the context of the dynamic nature of human performance (R.L. Boring, 2007). Specifically, the dynamic progression of human behaviour is of interest in HRA when it leads up to and follows human failure events (HFEs) (R.L. Boring, 2007).

Time-dependent nature of events is also regarded as part of dynamic HRA as human performance may alter depending on time and the changing situation. The changes in situation can be based on the appearance of new events and phenomena (objective changes) as well as changes in the personal evaluation of the situation, changes in the experienced stress etc. (subjective changes).

Thus, the concept of dynamism can also refer to the dynamic nature of the situation in which human error is possible. However, regarding HRA in a dynamic context, the concept of ‘dynamic HRA’ is not necessarily used. Instead, dynamic PRA environment has been used (Mosleh & Chang, 2004). Additionally, causality between cognitive factors and operator behaviour can be regarded as part of this concept (Mosleh & Chang, 2004). This causes confusion in the concepts of dynamic and static HRA.

This twofold view on dynamism in the concept of dynamic HRA is parallel to the division of models of human error. The focus can be on the nature of human or the one of the situations. In both cases, variation in the probability of human error is central but the main or only source is regarded to be in the human or the context in which the human is.

Dynamic HRA has also been defined through the methodology that is suggested to be used in HRA. From that perspective, it has been stated (R. L. Boring & Rasmussen, 2017) that for greater accuracy in overall risk modelling, virtual operator models should be integrated with virtual plant models; that human cognition and action should be dynamically modelled; and that these elements should be incorporated into PRA framework. These elements were stated to be the key elements for dynamic HRA (R. L. Boring & Rasmussen, 2017).

5. The methods of dynamic HRA

5.1 Background

Currently, the dichotomy of first-generation and second-generation HRA is assumed. First-generation HRA (Spurgin, 2010) assume correspondence in the performance of human and a machine and, accordingly, in the errors of them. In this approach, human performance is considered to consist of tasks; each task can be divided into task units and the status of each task unit can be described in terms of success or failure. Thus, in first-generation methods, the internal states and cognitive processes of the human are disregarded. Furthermore, these methods are not applicable to such situations in which human decision-making guides the proceeding of performance as the mental processes are considered as black box if anything and, furthermore, usage of first-generation methods requires that human performance, i.e., the tasks, is predefined.

Second-generation HRA evolved later, emphasising the cognitive and other mental processes affecting human performance and the related errors. The classification of human performance according to the three levels, the ones of skill, rule, and knowledge (Rasmussen, 1983) is an example of this approach. The proceeding of cognitive processes is the same among individuals so the reliability of human performance is not considered to depend primarily on cognitive processes but on the context, which may be of the kind where errors are more or less probable.

In such a categorisation, the first-generation methods are claimed to be, e.g., limited in addressing the most risk-significant errors and in finding causal relationships in the error and its reasons (Mosleh & Chang, 2004). The more advanced second-generation methods appear as suitable for scrutinising human error related performance in a demanding, dynamic context. The shift from static to dynamic HRA has been stated to take place along with the transition from predictions based on fixed models of accident sequences into predictions based on direct simulation of an accident sequence, with explicit consideration of timing of key events (R. L. Boring & Rasmussen, 2017). In static HRA, HFE does not change as a function of time or during the progression of the event; as a whole, evolution is not included in the calculation of HEP (R. L. Boring & Rasmussen, 2017).

Presently, widely used HRA methods are static. They do not provide a dynamic account of human actions or how the PSFs can dynamically modify the HEP over time (Boring, Joe, & Mandelli, 2015). Given this simplified approach, once the HEP is calculated based on PSFs that modify the nominal HEP, it remains unchanged over the available time. Contrasting to this, dynamic HRA does not rely on a fixed set of events and fault trees to model event outcome. Rather, it builds the event progression dynamically, as a result of ongoing actions (Boring & Rasmussen, 2017). In the following, the HRA methods with a dynamic approach are presented. It is not self-evident what techniques are suitable for assessing dynamic HRA. Several scientists, according to Boring (R.L. Boring, 2007), have expressed, firstly, the need for dynamic HRA and, secondly, have begun developing new HRA methods, or have modified existing ones, to account for the dynamic progression of human behaviour, leading to and following human failure events.

It has been suggested (R.L. Boring, 2007) that specifically cognitive modelling and simulation address the dynamic nature of human performance and the accompanying human errors. When the prediction based, fixed models of accident sequences are substituted by simulation of an accident sequence, timing of key events must be explicitly considered and the multitude of possible human actions relevant to an event must be simulated as well (R.L. Boring, 2007). Thus, as most plant actions are currently controlled by operators, the means to have a non-idealised model of plant performance is to account for operator’s controlling actions; a high-fidelity (i.e., real) representation of a nuclear power plant requires an accurate model of its human operators (R. L. Boring & Rasmussen, 2017). Accordingly, fusion of simulation and modelling with HRA has been suggested (e.g., (Mosleh & Chang, 2004).

However, the way simulation and modelling should be used is an open question. It is clear that there is considerable variation in operators' performance, in spite of procedures guiding this performance (Forester et al., 2012)(Forester et al., 2012)(Forester et al., 2012)(Forester et al., 2012)(Forester et al., 2012). Thus, describing operator actions by describing the activities based on procedures is not enough. Should the modelling, for example, follow the performance of the operators and produce a model about that; or should some predefined model of human cognition be taken as granted and then assume the cognitive functioning and the related error proneness in some specific situations based on theory; or should interviewing or some other method be used instead. An example of one of the possibilities listed above is presented by Cacciabue et al. (Cacciabue, Cojazzi, & Parisi, 1996) who suggested the usage of error probability assessment based on cognitive simulation and the related taxonomies of erroneous behaviour.

According to (R. L. Boring & Rasmussen, 2017), dynamic HRA is essentially about following the evolution of the event and in that case, the modelling in the subtask level is important. They state that computational techniques, namely simulation and modelling, are needed to integrate virtual operator models with virtual plant models, and dynamic modelling of human cognition and actions is the other key element in dynamic HRA. Thus, the modelling should be performed regarding the operator cognition (invisible activities, on which behaviour is based), operator behaviour (visible activities) and plant behaviour.

5.2 Early approaches

As early as 1993, dynamic event tree was presented in scientific literature (Acosta & Siu, 1993). It provided a framework for treating stochastic variation both in operating crew states and in hardware states. With an example analysis of a steam generator tube rupture, authors showed how important operator behaviour patterns could be represented with the method and how sources of dependencies between failures were better defined with it.

Another early contribution on dynamic HRA was made in 1999. Many HRA methods that time, in 90's, give a rather static description of man–machine system performance, and consider human contribution to risk in a too straightforward way. Holmberg et al. (Holmberg, Hukki, Norros, Pulkkinen, & Pyy, 1999) developed an approach to analyse operators' decision making and to perform human reliability analysis (HRA) for accident sequences. In the approach of Holmberg and colleagues (Holmberg et al., 1999), description of the activity context, probabilistic modelling, and psychological analysis form an iterative interdisciplinary sequence of analysis in which the results of one subtask may be input to another. Decision analytic dynamic reliability model (Holmberg et al., 1999) integrates probabilistic and psychological approaches in human reliability. The aim is to provide a conceptual interface between these approaches and to design such an analysis process that supports the formation of the integrated view, not to design an actual HRA method. The analysis of the context is carried out first with the help of a common set of conceptual tools. The resulting descriptions of the context promote the probabilistic modelling, through which new results regarding the probabilistic dynamics can be achieved. The more comprehensive description of the human activity context takes better into account the dynamic nature of the man–machine interaction by creating a conceptual interface between the probabilistic reliability analysis and contextual psychology.

The analysis process proceeds in two levels or phases, in the description of the context, and in psychological and probabilistic modelling. In probabilistic analysis, data is collected and applied in a statistical manner to validate the model structure and to estimate the probability parameters. In psychological analysis, data is used in a descriptive manner for the analysis of the operators' actual performance and its effect on risk. Operators' activities are observed so that critical diagnostic process information and the relevant decision alternatives are formulated beforehand, to support observation. Also, expert judgements are used, and operators can be interviewed. In the process, operator decision making is of central importance, concluded from the analyses described above. Decisions influence risks and the probabilistic analysis handles actions as components of the risk assessment of the studied sequence. The challenges they are trying to meet are the following (Holmberg et al., 1999):

- Operators controlling hazardous processes work in a dynamic environment, requiring interpretation of the situation and decision making.
- The operators' ability to manage the situations depends on the state of the process and on the available resources to regulate.
- The reliability of the operators in process control is sensitive to the context e.g. process information, procedures, co-operational resources (the number and competence of operators) and division of labour.
- The contextual nature of human activities has conventionally been reduced to the assessment of situation specific performance shaping factors in risk analysis. Interaction between operators and the context of their activity have not been explicitly included in the models in a deeper sense.

The benefits of the framework are based on conscious, conceptually shared communication between approaches during the analysis process. Even if the approach was not labelled as focusing on the dynamic aspect of human performance, the dynamic dimension is interwoven in it.

5.3 Cognitive simulation

Simulation is generally used in the analysis of plant response for PRA, and its purpose is to mimic the behaviour of the plant in the given scenario. Therefore, it is natural to consider mimicking the behaviour of humans in a given scenario. The purpose of cognitive simulation is just that, or more precisely, mimicking human decision making.

In the context of dynamic HRA, cognitive simulation means the simulation of a cognitive model with respect to time. A cognitive model, in its turn, represents human cognitive processing, which can be defined, with the aim of having a relevant definition for HRA purposes, as including perception, diagnosis and decision-making. Also action can be included as the final phase of cognitive processes, even if strictly taken, action is not cognitive but behavioural. A cognitive model is based on a cognitive architecture, the structural properties of the modelled system or, as defined by the Institute of Creative Technologies of the University of Michigan, "hypothesis about the fixed structures that provide a mind, whether in natural or artificial systems, and how they work together - in conjunction with knowledge and skills embodied within the architecture - to yield intelligent behaviour in a diversity of complex environments". In artificial intelligence, cognitive architecture may refer both to such a theory about the structure of the human mind, and to a computer implementation of such a theory.

In the human factors literature, cognitive modelling is often referred to as human performance modelling. It has been widely applied especially in the aviation sector, see for example (Pew, 2008) or (Zhang & Xue, 2013). Several useful contributions have been developed in human performance modelling, for example GOMS (Goals, Operators, Methods, and Selection rules) (Card, Moran, & Newell, 1983). GOMS is a ystematic description of how to calculate the time to accomplish tasks, based on the time that is spent in physical and mental actions required of the task.

5.3.1 Modelling paradigms and platforms

There are several modelling paradigms that can be utilized in cognitive modelling:

- symbolic cognitive architectures rely on explicit conceptual models of the domain and their manipulation on the symbol level. They can be implemented by rule-based systems, belonging to logical programming,
- sub symbolic approaches are based on numerical models as a formalism for representation and analysis. The most important sub symbolic approach to cognitive modelling, neural networks (Levine, 2019), provide a way of constructing models that have analogies to the functioning of the brain at the neural level. However, they require data for learning the model parameters, it is not easy to get an explanation to why a given decision was made, and it is trivial to model human errors in this paradigm. Therefore, they are not among the most promising approaches to cognitive modelling for HRA. Another sub symbolic approach that seems to be gaining more popularity is Bayesian cognitive modelling (Lee & Wagenmakers, 2013),
- hybrid architectures combine symbolic and sub symbolic approaches,
- other paradigms that have been utilized include discrete event simulation (Lockett, 1997) and network models (Siegel & Wolf, 1969).

A popular means of organizing a cognitive architecture is intelligent agents (Resconi & Jain, 2004). Wikipedia defines an intelligent agent as "an autonomous entity which acts, directing its activity towards achieving goals (i.e. it is an agent), upon an environment using observation through sensors and consequent actuators (i.e., it is "intelligent")". Thus, an intelligent agent may be seen as a rough analogue to a human individual.

Various tools and platforms can be utilised in the implementation of cognitive simulation. Some have a very wide scope of application outside cognitive simulation, others have been constructed from the beginning to this purpose.

Saint is a general purpose discrete-event simulation language (implemented in the computer program Micro Saint, currently available as Micro Saint Sharp, developed by Ailon Science and Technology) that has been used widely to model task performance in military and other applications, see, e.g., Lockett (Lockett, 1997). It is likely that other major discrete-event simulation platforms such as Arena, Simul8 and SimPy are also suitable for cognitive simulation purposes.

Soar (State, Operator, And Result) (Laird, 2012) is a major general-purpose cognitive architecture that relies largely on symbolic constructs. It aims to provide means for complete simulation of an intelligent agent. Procedural knowledge is represented by rules, and semantic knowledge by relational graph structures. Its output is a complete simulation from which various measures of performance can be derived. It is available open-source and free.

ACT-R (Adaptive Control of Thought-Rational) is a general-purpose cognitive architecture. It is "perhaps the most widely used cognitive architecture" (Pew, 2008). According to Wikipedia, it "aims to define the basic and irreducible cognitive and perceptual operations that enable the human mind". It has been inspired by the progress of cognitive neuroscience. The computer implementation of ACT-R is written in the Common Lisp programming language, and is available open-source and free.

Other notable platforms include MIDAS (Man-machine Integration Design and Analysis System) (Gore & Jarvis, 2005), developed by NASA Ames Research Laboratory, and D-OMAR (Distributed Operator Model Architecture) developed by Bolt Beranek and Newman.

5.3.2 Cognitive simulators for HRA

Cognitive simulators have been proposed or applied also in HRA (see also the list of cognitive simulators in the article of Trucco and Leva (Trucco & Leva, 2007)).

A framework for using MIDAS for HRA has been proposed (Ronald L. Boring, Dudenhoeffer, Hallbert, & Gore, 2006) but not implemented.

Human Error Modeling Architecture (HEMA) (Fotta, Byrne, & Luther, 2005) has been designed on the basis of ACT-R. Based on a set of general error mechanisms that have been specified, it has been identified where ACT-R can be used, where it has to be modified, and where new mechanisms or models would be needed. The system is in conceptual design phase.

The Accident Dynamics Simulator-Information Decision and Action in Crew (ADS-IDAC) system (Chang & Mosleh, 2007a) was developed for HRA applications. Its scope is to “probabilistically predict the responses of the nuclear power plant control room-operating crew during an accident for use in probabilistic risk assessments”. Operator response include cognitive, emotional and physical activities. It is presented with more detail in section 5.4.

PRObabilistic COgnitive Simulator for HRA studies (PROCOS) is based on a “semi-static” approach to combine first-generation HRA methods with cognitive modelling. The dynamism comes from cognitive simulation, which, in turn, is based on a cognitive flow chart. Two flow charts are introduced, one for operator behaviour in normal operations, and one for recovery phase. The inputs to the simulation come largely from ordinary HRA analysis: PSFs, hardware involved and its possible states, steps of the task (from task analysis), and a set of error modes.

A Simulator for Human ERror Probability Analysis (SHERPA) (Di Pasquale, Miranda, Iannone, & Riemma, 2015) combines, like PROCOS, cognitive simulation with HRA methods. Error probability is estimated as a function of the task, PSFs, and the time spent on the task. SHERPA has been later enhanced into a HRA model called Emergency Human Error Analysis (EHEA) that aims to “evaluate human error probability in emergency conditions in industrial plants and critical infrastructures” (Petrillo, Falcone, De Felice, & Zomparelli, 2017).

Cognitive simulation (perhaps combined with plant simulation) may be used in the following ways to capture and generate data for HRA purposes (R.L. Boring, 2007; Di Pasquale et al., 2015):

- simulation runs produce logs that can be used in expert judgment to produce human error probabilities.
- simulation can be used to produce estimates of PSFs.
- simulation can be used to produce task performance times and other performance measures. These can be combined with performance criteria set for the task (e.g. maximum time allowed) to produce frequentist estimates of human failure probability.

There are several cases showing where cognitive simulation would be a major benefit for HRA. Firstly, it is needed, when the “safety of novel equipment and configurations” (R.L. Boring, 2007) needs to be assessed. This is when main control room simulator, operators, or indeed even a plant, are not available. Thus, cognitive simulation allows HRA analyses in the design phase of a new NPP.

Secondly, cognitive simulation allows also estimates of human error probabilities for human actions for which simulators or data are not available or applicable, such as repair or maintenance actions.

Finally, cognitive simulators can also be used in scenarios for which simulator data is not available and is not practicable to produce. For example, it is likely that very little data is available concerning human actions with long time windows (e.g. 48 hours), because this would require the involvement of operators and simulator personnel for a very long time. Another example of impracticability of producing real data is when a human error is a priori judged to be very rare. To produce enough data for estimating such a low probability would require a very large number of simulator experiments (say, tens or hundreds of thousands). Then, cognitive simulation provides a means to get at least some data.

The main problem and constraint of currently existing HRA applications of cognitive simulation is that the models are very narrow, concentrating on single scenarios, and that they lack generality. Also their construction is tedious.

5.4 Crew behaviour

Complex technological systems are usually operated and maintained by teams of humans and the team performance is strongly affected by the communication and collaboration among operators under a dynamic situation. Since the human cognitive processes heavily depend on the context in the real environment, Shu et al. (Shu, Furuta, & Kondo, 2002) propose a team behaviour network model that can simulate and analyse response of an operator team to an incident in a dynamic and context-sensitive situation. The model is an attempt to find the all likely event chains for the given initial event. Considering collaboration and communication, which is triggered by individual factors, organization structure and type of task, they are aiming to analyse team cognitive process after an initiating event has occurred and predict team performance under possible event sequence. Comparison of the results between simulation and an experiment of FAB (feed and bleed) operation in PWR (pressurized water reactor) shows that the operators' actual performance can be simulated approximately. Details of the simulation result, however, differ from the experiment because of some idealistic assumptions in the team model. The model was built based on expert judgement.

ADS-IDAC (Chang & Mosleh, 2007b) is a method to probabilistically predict the responses of the control-room crew during an accident. The response includes cognitive, emotional, and physical activities. ADS refers to Accident Dynamics Simulator, which is a dynamic PRA computer simulation program, developed in part to implement the IDAC model. IDAC, in turn, refers to the model of Information Decision and Action in Crew. IDAC model suits best for computer simulation - accordingly, ADS has been used to test IDAC and the feasibility of integrated dynamic PRA for NPP risk applications. The evolution of IDAC and ADS has provided a framework to integrate many of the findings and developments from various related disciplines into a common predictive HRA model, with a reasonable chance for meeting key scientific validity criteria. Once fully developed, in addition to its use as a full-scale dynamic PRA environment, ADS–IDAC can also support classical PRA and HRA analyses, and further research and development activities in the area of operator response modelling. A key difference between ADS-IDAC and other dynamic PRA methodologies is that ADS has the IDAC cognitive model integrated to perform automatic, systematic, and probabilistic simulation of human-system interactions. IDAC models the individual and group behaviour of the operating crew. Each individual operator model includes elements of the IDAC cognitive architecture (e.g., performance-influencing factors (PIFs), memory architecture) and model of cognitive process (e.g., information processing model). In modelling cognition, IDAC combines the effects of rational and emotional dimensions through a small number of generic rules-of-behaviour that govern the dynamic responses of the operator. These responses include information pre-processing (I), diagnosis and decision-making (D), and action execution (A). Mental state is a representation of an operator's mind. The interaction between mental state and the I–D–A activities is a dynamic process of mutual influences.

The model (Chang & Mosleh, 2007b) has three generic types of operator: decision maker, action taker, and consultant. Each of them has: defined tasks and responsibilities, defined formal communication channels, defined knowledge and experience bases, and unique psychological and physical characteristics. Crew influences on individual operator response through the IDAC team-related PIFs. Crew interaction has two main features: communication and coordination. Crew interacts with the system through the actions of its individual members. The ADS code simulates accident scenarios and generates information about the external world (i.e., system state and environmental variables). This information is then used as input to the crew model (i.e., IDAC), which in turn simulates various types of operator response including actions on the system.

PHOENIX (Ekanem, Mosleh, & Shen, 2016) is a method for producing HFEs and likely scenarios leading to each event. It utilizes “crew response trees” that provide a structure for capturing the context of HFEs, for errors of commission and omission. It also brings the Information, Decision and Action cognitive model to team level, and uses “macro-cognitive” abstractions of crew behaviour, and findings from scientific literature and operating experience “to identify potential causes of failures and influencing factors”.

IDHEAS (J. Xing et al., 2017) models the errors made by trained crews performing required responses to plant disturbances. It addresses post-initiator, internal at-power events at nuclear power plants. The crews modelled are NPP control room crews. It also utilizes crew response trees. The qualitative analysis part includes a cognitive task analysis process where analysts “identify and graphically represent crew response paths and critical tasks needed for success”. The quantitative part analyses a set of crew failure modes (CFM) and their performance influencing factors (PIF). The HEPs of the CFMs under various combinations of PIFs are estimated by formal expert judgment.

Still one way to model crew behaviour is multi-agent modelling. Considerable research literature exists on combining agents (see section 5.3.1) - intelligent or otherwise - to multi-agent systems (Weiss, 1999). It has turned out that multi-agent systems provide a natural and useful platform for the simulation of teams and crews (Sycara & Lewis, 2008).

5.5 Other approaches

Gertman (Gertman, 2012) focuses on the dynamic environment and calls for sensitivity to complexity in advanced digital environments. He has identified three complexity factors and proposes a rating scale approach that suits for HRA purposes. The complexity factors are based on the model proposed by Xing and Manning (Jing Xing & Manning, 2005), approaching complexity from the viewpoints of

- quantity (number of steps it takes to solve a problem),
- variety (switching between patterns of information that may be emerging, variety in interaction metaphors for system devices in the same control room, and variety in the types of tasks being performed) and
- relations (rules, structures, interconnections).

GOMS-HRA (R. L. Boring & Rasmussen, 2017) concentrates on categorising subtasks as the so-called GOMS primitives. G represents Goals, i.e., the high—level tasks the human seeks to complete; O is for Operators, that is, the available actions the human can take; M for Methods, the steps or sub goals the human takes towards the goals; and Selection rules for S, i.e., the decisions humans make. GOMS has been used for various purposes. This solution is developed because dynamic HRA, following the evolution of the event, often requires modelling at the subtask level. GOMS-HRA states that the performance shaping factor and its’ influence on operator’s performance can change over time; the final effect is that the human error probability varies over time. Regarding HRA, GOMS brings the idea that each step of an operator is coded, resulting to a model with such additional information that makes HRA possible. Presently, GOMS-HRA provides a useful technique enabling crew modelling in dynamic HRA. However, only future research will refine and implement GOMS-HRA into dynamic HRA.

Dynamic methods may also be used to provide data for HRA methods. Groth et al. (Groth, Smith, & Moradi, 2019) present an algorithm for using causal models and multiple types of HRA data for cognitively based HRA methods such as PHOENIX and IDHEAS. It uses causal models that utilise data from cognitive literature, systems engineering, existing HRA methods, simulator data and expert opinion. These causal factors are combined with team tasks and events to formulate Bayesian network models, and finally, Bayesian parameter updating is utilised.

6. Dynamic HRA in hybrid main control room

According to Jiang et al. (Jiang et al., 2018), the traditional cognitive model cannot be quite qualified with the human reliability evaluation of digital human-computer interface, because there are differences in the human cognitive behaviour compared with traditional human-machine interface, for example: 1) operators need to observe and analyse more parameters, perform emergency procedures, plan secondary tasks, search navigation information, etc.; 2) the parameters and procedures are dynamic changes; 3) the positions to display information and procedures on screens are not fixed. Taking a nuclear power plant as research background, Jiang et al. propose a cognitive reliability model for digital human-computer interface based on Bayesian networks, to be able to consider the multiple states of human, randomness, uncertainty and relevance between variables. Thus, it is indirectly stated that digital and analogue control rooms call for different approaches. Based on this, it can be concluded that HRA for hybrid control rooms is more complex to perform.

Accordingly, complexity has been stated to be the distinguishing feature among performance shaping factors regarding advanced control room design (Gertman, 2012). Diversity in instrumentation is stated to heighten complexity (Gertman, 2012); this claim is originally about small modular reactors but is true in any control room. Furthermore, diversity is emphasised in hybrid control rooms where units to be used by operators are of two different nature, that is, the one of analogue and another of the digital type.

To conclude, there is no expressed demand in scientific literature that hybrid control room (or any type of control room) would require a dynamic approach. The assumed complexity may result in dynamic changes in the operating environment, though, and may also initiate more complex cognitive processes, increasing the possibility of also erroneous actions.

7. Conclusions

This report briefly clarifies the nature of human error and performance from a dynamic perspective, using two models, one relating to the process of human perception (by Neisser) and another to situation awareness (by Endsley), as examples of that. The report also briefly describes the dynamic nature of the operating environment of the nuclear power plant operator. Thus, the dynamic nature of the target of HRA is taken as a starting point.

Also the meaning of the concept of dynamic HRA is presented as it is expressed in scientific literature. The concept of dynamic HRA is somewhat unclear in scientific discussion. It often seems to be referred to as a generally known concept but closer scrutiny shows that sometimes the dynamic phenomena to be assessed are seen as defining the essence of dynamic HRA, whereas in other cases, the methods with which HRA is conducted are conceived as factors defining dynamic HRA.

Furthermore, dynamic HRA tends to scrutinise human error as closely related to the contextual aspects, opposed to the presently central but also older, static approach, according to which human is prone to make errors as such. Thus, dynamic HRA represents a more modern view on human performance. The view including the contextual factors in human erroneous performance is more open to see the human also as an actor capable of compensating flaws in the technical environment. Even if HRA as such concentrates on, naturally, human errors, the possibility to perceive human also as capable of such safety supporting, flexible activities technology can never accomplish is a perspective and possibility to add safety in the nuclear domain.

The various methods presently available for dynamic HRA are presented in the review. The largest group of methods concentrate on the simulation and modelling of human cognitive processes. No comprehensive methodology for dynamic HRA is created but instead, each method tends to focus on some aspect or aspects considered relevant from the dynamic perspective.

Due to the context of the present HRA study, that is, HRA in hybrid control rooms, the hybrid control room is also scrutinised from the perspective of dynamic HRA. The nature of control room does not seem to raise needs or requirements for a specifically dynamic approach.

According to the conception of the authors of this review, humans, the nuclear power plant, and the objectives for human work form the entity, which should be included in HRA. The concept - or perhaps even the paradigm - of ‘dynamic HRA’ emphasises the context of human perceptions, decisions and actions, and time as an essential aspect of the context. The concept has been necessitated by empirical evidence that reveals how complex the reasons of human error often are and enabled by advances in cognitive psychology on the one hand, and computer-based modelling and simulation on the other. Parallel to this, the operating context, i.e., the NPP, in which the human operator acts, is not static either. Gradual degradation and latent flaws call for rapid corrective actions and in the case of an incident or accident, the situation is continuously changing and humans are to constantly update their situation awareness and perform accordingly. Thus, the qualities of the target of assessment cannot be separated from the methods with which these phenomena are to be assessed.

Long-lasting events and, especially, event sequences increase the demand for a dynamic approach. Not all situations are long-lasting and still, it can be stated that dynamic approach is needed. Reality is dynamic, be it either inside the human (i.e., mental states and cognitive processes) or outside of it (such as group dynamics as expressed in crew collaboration and the changing state of a nuclear power plant). As a consequence, dynamics in HRA, from the perspectives of the target of assessment and the assessment method, makes HRA more realistic and hence, in principle, provides more possibilities for HRA to be more accurate and, consequently, more reliable.

Dynamic phenomena are more demanding to take into account than assuming a static approach. This is probably the reason for having static HRA as the mainstream approach. With static methods, results are obtained with a reasonable time and effort. However, methods develop by time and it is both probable and desirable that dynamic approach will gradually gain momentum. It is also possible that some specific event will cast the possibility and need of dynamic approach to general knowledge. Unfortunately, these events may also negative ones, like Fukushima accident raised the topic of multi-unit accidents to the discussions in the nuclear domain.

The strengths, weaknesses and targets for applications of dynamic HRA represent part of HRA. One way the nuclear domain may proceed to a more dynamic approach is to apply dynamic HRA to the most dynamic and critical part of the human related phenomena in the nuclear domain while using the static HRA in the remaining areas. The presently ongoing updating of control rooms, resulting first in hybrid and finally in digital control rooms, does not seem to increase the demand of dynamic approach, at least as reflected in the scientific literature. The development of the nuclear domain may add pressure to a more dynamic approach based on other phenomena, though. It is possible that in the future, nuclear authorities start to require more dynamic HRA methods because the usage and risks related to nuclear power plants seem to become more dynamic in the future. This is true related to small modular reactors, which are expected to organise production in a flexible way, making load-following a highly dynamic process on a daily basis.

The next step in this study will be a survey on how HRA (PRA) professionals in Finland understand the dynamic HRA and what their potential practices and needs related to that are. An empirical study will be performed based on survey results.

References

Acosta, C., & Siu, N. (1993). Dynamic event trees in accident sequence analysis: application to steam generator tube rupture. *Reliability Engineering & System Safety*, *41*(2), 135–154. Retrieved from https://doi.org/10.1016/0951-8320(93)90027-V

Banks, V. A., Plant, K. L., & Stanton, N. A. (2018). Driver error or designer error: Using the Perceptual Cycle Model to explore the circumstances surrounding the fatal Tesla crash on 7th May 2016. *Safety Science*, *108*(August 2017), 278–285. https://doi.org/10.1016/j.ssci.2017.12.023

Boring, R. L., & Rasmussen, M. (2017). GOMS-HRA: A method for treating subtasks in dynamic human reliability analysis. *Risk, Reliability and Safety: Innovating Theory and Practice - Proceedings of the 26th European Safety and Reliability Conference, ESREL 2016*, 154. https://doi.org/10.1201/9781315374987-144

Boring, R.L. (2007). Dynamic Human Reliability Analysis: Benefits and Challenges of Simulating Human Performance. *Proceedings of the European Safety and Reliability Conference (ESREL 200/)*, 1043–1049. Retrieved from https://www.osti.gov/biblio/912477

Boring, Ronald L., Dudenhoeffer, D. D., Hallbert, B. P., & Gore, B. F. (2006). Modeling Human Reliability Analysis Using MIDAS. *International Workshop on Future Control Station Designs and Human Performance Issues in Nuclear Pow*. Retrieved from https://www.osti.gov/biblio/911648

Boring, Ronald Laurids, Joe, J. C., & Mandelli, D. (2015). Human Performance Modeling for Dynamic Human Reliaiblity Analysis. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *9184*, 223–234. https://doi.org/10.1007/978-3-319-21073-5

Cacciabue, P. C., Cojazzi, G., & Parisi, P. (1996). A Dynamic HRA Method Based on a Taxonomy and a Cognitive Simulation Model. *Probabilistic Safety Assessment and Management '96*, 138–145. Retrieved from https://link.springer.com/chapter/10.1007/978-1-4471-3409-1_23

Card, S. K., Moran, T. P., & Newell, A. (1983). *The psychology of human-computer interaction*. Mahwah, NJ: Lawrence Erlbaum Associates.

Chang, Y. H. J., & Mosleh, A. (2007a). Cognitive modeling and dynamic probabilistic simulation of operating crew response to complex system accidents. Part 1: Overview of the IDAC Model. *Reliability Engineering and System Safety*, *92*(8), 997–1013. https://doi.org/10.1016/j.ress.2006.05.014

Chang, Y. H. J., & Mosleh, A. (2007b). Cognitive modeling and dynamic probabilistic simulation of operating crew response to complex system accidents. Part 4: IDAC causal model of operator problem-solving response. *Reliability Engineering and System Safety*, *92*(8), 1061–1075. https://doi.org/10.1016/j.ress.2006.05.011

Corrosionpedia. (2019). Corrosionpedia, the words "dynamic system." Retrieved November 19, 2019, from https://www.corrosionpedia.com/definition/424/dynamic-system-material-science

Di Pasquale, V., Miranda, S., Iannone, R., & Riemma, S. (2015). A Simulator for Human Error Probability Analysis (SHERPA). *Reliability Engineering and System Safety*, *139*, 17–32. https://doi.org/10.1016/j.ress.2015.02.003

Ekanem, N. J., Mosleh, A., & Shen, S. H. (2016). Phoenix - A model-based Human Reliability Analysis methodology: Qualitative Analysis Procedure. *Reliability Engineering and System Safety*, *145*, 301–315. https://doi.org/10.1016/j.ress.2015.07.009

Endsley, M. R. (1995). Toward a theory of situation awarenss in dynamic systems. *Human Factors*, Vol. 37, pp. 32–64. https://doi.org/10.1518/001872095779049543

Forester, J., Dang, V. N., Bye, A., Lois, E., Massaiu, S., Broberg, H., … Nelson, P. (2012). The international HRA empirical study - lessons learned from comparing HRA methods predictions to HAMMLAB simulator data. *Nureg-2127*. Retrieved from http://www.nrc.gov/reading-rm/doc-collections/nuregs/staff/sr2127/

Fotta, M., Byrne, M., & Luther, M. (2005). Developing a Human Error Modeling Architecture (HEMA). In *Proceedings of Human-Computer International 2005* (CD).

Gertman, D. I. (2012). Complexity: Application to human performance modeling and HRA for dynamic environments. *Proceedings - 2012 5th International Symposium on Resilient Control Systems, ISRCS 2012*, 19–24. https://doi.org/10.1109/ISRCS.2012.6309287

Gore, B. F., & Jarvis, P. A. (2005). New integrated modeling capabilities: MIDAS' recent behavioral enhancements. *SAE Technical Papers*, (February). https://doi.org/10.4271/2005-01-2701

Groth, K. M., Smith, R., & Moradi, R. (2019). A hybrid algorithm for developing third generation HRA methods using simulator data, causal models, and cognitive science. *Reliability Engineering and System Safety*, *191*(June), 106507. https://doi.org/10.1016/j.ress.2019.106507

Holmberg, J., Hukki, K., Norros, L., Pulkkinen, U., & Pyy, P. (1999). Integrated approach to human reliability analysis - decision analytic dynamic reliability model. *Reliability Engineering and System Safety*, *65*(3), 239–250. https://doi.org/10.1016/S0951-8320(99)00003-4

IAEA. (2015). The Fukushima Daiichi Accident Report by the Director General. *Director General*, 1–222. https://doi.org/10.1037/a0018137

Jiang, J., Wang, Y., Zhang, L., Wu, D., Li, M., Xie, T., … Zhang, A. (2018). A cognitive reliability model research for complex digital human-computer interface of industrial system. *Safety Science*, *108*(August 2017), 196–202. https://doi.org/10.1016/j.ssci.2017.07.016

Laird, J. E. (2012). *The Soar Cognitive Architecture*. Cambridge, Massachusetts: The MIT Press.

Lee, M. D., & Wagenmakers, E.-J. (2013). *Bayesian cognitive modeling - a practical course*. Cambridge, UK.

Levine, D. S. (2019). *Introduction to neural and cognitive modeling, third edition* (3rd ed.). New York: Routledge.

Lockett, J. F. (1997). Task network modeling of human workload coping strategies. In R. J. K. M.J. Smith, G. Salvendy (Ed.), *Proceedings of the HCI International '97 Conference* (pp. 71–74). Amsterdam: Elsevier.

Merriam-Webster. (2019). Merriam-Webster, the word "dynamic."

Mosleh, A., & Chang, Y. H. (2004). Model-based human reliability analysis: Prospects and requirements. *Reliability Engineering and System Safety*, *83*(2), 241–253. https://doi.org/10.1016/j.ress.2003.09.014

Neisser, U. (1976). *Cognition and reality: Principles and implications of cognitive psychology*. San Francisco: WH Freeman/Times Book/Heny Holt & Co.

Petrillo, A., Falcone, D., De Felice, F., & Zomparelli, F. (2017). Development of a risk analysis model to evaluate human error in industrial plants and in critical infrastructures. *International Journal of Disaster Risk Reduction*, *23*(March), 15–24.

https://doi.org/10.1016/j.ijdrr.2017.03.012

Pew, R. W. (2008). More than 50 years of history and accomplishments in human performance model development. *Human Factors*, *50*(3), 489–496. https://doi.org/10.1518/001872008X288493

Plant, K. L., & Stanton, N. A. (2012). Why did the pilots shut down the wrong engine? Explaining errors in context using Schema Theory and the Perceptual Cycle Model. *Safety Science*, *50*(2), 300–315. https://doi.org/10.1016/j.ssci.2011.09.005

Rasmussen, J. (1983). Skills, Rules, and Knowledge; Signals, Signs, and Symbols, and Other Distinctions in Human Performance Models. *IEEE Transactions on Systems, Man and Cybernetics*, *SMC-13*(3), 257–266. https://doi.org/10.1109/TSMC.1983.6313160

Reason, J. (1990). *Human Error*. Cambridge: Cambridge University Press.

Resconi, G., & Jain, L. C. (2004). *Intelligent agents - theory and applications*. Berlin Heidelberg: Springer-Verlag.

Salmon, P. M., Lenné, M. G., Stanton, N. A., Jenkins, D. P., & Walker, G. H. (2010). Managing error on the open road: The contribution of human error models and methods. *Safety Science*, *48*(10), 1225–1235. https://doi.org/10.1016/j.ssci.2010.04.004

Schroer, S., & Modarres, M. (2013). An event classification schema for evaluating site risk in a multi-unit nuclear power plant probabilistic risk assessment. *Reliability Engineering and System Safety*, *117*, 40–51. https://doi.org/10.1016/j.ress.2013.03.005

Shu, Y., Furuta, K., & Kondo, S. (2002). Team performance modeling for HRA in dynamic situations. *Reliability Engineering and System Safety*, *78*(2), 111–121. https://doi.org/10.1016/S0951-8320(02)00111-4

Siegel, A. I., & Wolf, J. J. (1969). *Man-machine simulation models: psychosocial and performance interaction*. New York: Wiley-Interscience.

Spurgin, A. J. (2009). Human reliability assessment theory and practice. In *Human Reliability Assessment Theory and Practice* (1st ed.). https://doi.org/10.1201/9781420068528

Spurgin, A. J. (2010). *Human reliability assessment - theory and practice*. CRC Press.

Sycara, K., & Lewis, M. (2008). *Agent-based approaches to dynamic team simulation*. Millington, TN.

Trucco, P., & Leva, M. C. (2007). A probabilistic cognitive simulator for HRA studies (PROCOS). *Reliability Engineering and System Safety*, *92*(8), 1117–1130. https://doi.org/10.1016/j.ress.2006.06.003

Weiss, G. (Ed.). (1999). *Multiagent systems - a modern approach to distributed artificial intelligence*. Cambridge, Massachusetts: The MIT Press.

Xing, J., Parry, G. W., Presley, M., Forester, J. A., Hendrickson, S., & Dang, V. (2017). An Integrated Human Event Analysis System (IDHEAS) for Nuclear Power Plant Internal Events At-Power Application, Vol. 1. *Nureg-2199*, *1*.

Xing, Jing, & Manning, C. A. (2005). *Complexity and automation displays of air traffic control: Literature review and analysis*. Retrieved from https://apps.dtic.mil/dtic/tr/fulltext/u2/a460107.pdf

Zhang, X., & Xue, H. (2013). Pilot performance models. In V. Duffy (Ed.), *International Conference on Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management* (pp. 134–140). Berlin, Heidelberg: Springer.

Appendix: Research plan on dynamic HRA in NAPRA project, 2020

Survey on dynamic HRA

This survey is targeted to HRA experts (or PRA experts with some experience in HRA) of the Finnish stakeholders (STUK, Fennovoima, Fortum, TVO). The objective of the survey is to clarify the present conception, needs and analysis practices related to dynamic HRA among nuclear safety professionals in Finland. The outcome will be a summary of survey results. The following themes will be addressed in the survey.

Theme A: Present conception of dynamic HRA (what dynamic HRA means, how familiar the respondents are with the concept).

Theme B: Present methods to handle dynamics in human actions utilized in the field (are dynamic phenomena handled in HRA, how they are handled or why they are not handled).

Theme C: Needs for dynamic approaches in HRA (do the respondents see needs or value in dynamic approaches regarding human action and error, in what context dynamic approaches are needed, what kind of support could future research on dynamic HRA provide for respondents, e.g. the content of the empirical study (see below)).

Empirical study

Based on the results of the survey, the method of the empirical study will be decided. The objective of the empirical study is to identify the conceptions, impressions and experiences related to dynamic phenomena in pre-accident and accident situations. In each option, the outcome will be a summary and qualitative analysis of the study results. The following tentative options are provided.

Option 1: Interviews.

Interviewing may be used as the research method. Interviewees will be main control room operators.

Dynamic phenomena consist of contextual factors inducing dynamicity in the situation, and cognitive factors related to dynamicity in the human mind.

Interviews deal with phenomena, situations and conceptions that the operators associate with dynamicity. Some of the questions will be forced-choice questions, and other questions are open.

Option 2: Analysis of recorded simulator tests

VTT has recorded operator performance in simulator tests as part of human factors studies. These recordings may be used for analysing dynamic features in operator performance.

First a set of criteria for recognizing dynamic phenomena in operator performance will be specified, and a note-taking practice will be defined. During the viewing, the defined methodology will be applied.

Option 3: Analysis of simulator tests

A set of simulator runs will be specified and conducted. In the runs and the analysis of the results, dynamic phenomena will be emphasized.

First a set of criteria for recognizing dynamic phenomena in operator performance will be specified, and a note-taking practice will be defined. During the viewing, the defined methodology will be applied.