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A Framework to Integrate Human Reliability Data Obtained from Different Sources Based on the Complexity Scores of Proceduralized Tasks

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Abstract: For many decades, PSA (Probabilistic Safety Assessment) or PRA (Probabilistic Risk Assessment) techniques have been used to enhance the operational safety of nuclear power plants (NPPs) based on the consideration of potential hazards that could result in an unexpected consequence. As human error is one of the potential hazards, diverse human reliability analysis (HRA) methods have been proposed to provide a systematic way to estimate the likelihood of human errors (i.e., human error probability, HEP) in specific task contexts. Accordingly, it is evident that the quality of HRA results strongly depends on the credibility of HEP estimations. This implies that, in terms of enhancing this credibility, the collection of raw information (HRA data) that is helpful for understating when and why human errors occur is a crucial issue. In order to address this issue, in this study, the feasibility of a framework to integrate HRA data obtained from different sources is investigated based on the complexity of proceduralized tasks.

1. INTRODUCTION

Since the Three Mile Island accident, it is evident that the PSA (Probabilistic Safety Assessment) or PRA (Probabilistic Risk Assessment) has been used as one of the representative techniques to enhance the safety of nuclear power plants (NPPs) by visualizing the catalog of potential hazards in a systematic way. Since human error represents one of the potential hazards, diverse HFEs (Human Failure Events) should be incorporated into the development of the PSA model. Typical HFEs include “the purpose of the task cannot be achieved” or “the task fails to be completed” [1]. Accordingly, in terms of conducting the PSA, it is indispensable to quantify the likelihood of HFEs (or Human Error Probabilities, HEPs). For this reason, many kinds of HRA (Human Reliability Analysis) methods have been proposed in the last several decades.

In general, the HRA process can be done with three steps: (1) task analysis, (2) qualitative analysis, and (3) quantitative analysis. Brief explanations on these steps are as follows: “Task analysis is the process of collecting and analyzing relevant information on the major human actions considered in a PSA model. In qualitative analysis, performance shaping factors (PSFs) critical to error occurrences are analyzed in the context of each human action. PSFs refer to factors that influence human performance, including experience, stress, and task complexity. Lastly, based on the task analysis and qualitative analysis results, HEPs are estimated using quantitative analysis [2].” From this excerpt, it is obvious that the quality of information to be used in the HRA process (i.e., HRA data) is critical for ensuring the credibility of HRA results. This became the motivation of HRA data collection from many available sources including event investigation reports and simulator studies [3]. Unfortunately, it is also true that the quality of HRA data is one of the key limitations from the very beginning of HRA method development [4, 5]. To improve HRA, it is critical to determine how to soundly integrate HRA data from diverse sources.

In order to address this issue, in this paper, the framework of HRA data integration is investigated based on the complexity of proceduralized tasks. The underlying idea is to directly compare two sets of HRA data obtained from different sources. One data source is from a full-scope training simulator of NPPs, and the other is from a laboratory experiment using a simplified simulator). If there is a significant correlation between two sets of HRA data, then it is expected that we can have a relevant path forward to support how to integrate diverse HRA data. Otherwise, if the two data sets show different tendencies in terms of the complexity of proceduralized tasks, it is necessary to figure out which factors could result in these differences. Through this process, it is expected that a practical guideline can be established, which is able to support the integration of HRA data obtained from diverse sources.

This paper is organized as follows. Section 2 describes the background information about the TACOM (task complexity) measure for quantifying the complexity of proceduralized tasks. Section 3 briefly explains HRA data obtained from the full-scope simulator of Korean domestic NPPs with the results of existing studies supporting that the TACOM measure can be used as a relevant tool for characterizing HRA data. Section 4 outlines INL's Rancor Microworld simulator with associated HRA data obtained from a series of laboratory experiments using it. Section 5 presents the comparison results of two HRA data sets (from the full-scope training simulator and Rancor Microworld) with respect to TACOM scores. Finally, Section 6 draws conclusions with discussions pertaining to this study.

2. BACKGROUND INFORMATION ABOUT TACOM MEASURE

The safety of NPPs is the upmost goal to be achieved during their entire lifecycle. The fleetwide operating history of NPPs reveals that the consequences of incidents and/or accidents could be catastrophic in terms of the public and environmental effects. Fortunately, the frequency of high consequence events remains extremely low. Recent statistics reveal that one of the key contributors affecting the safety of NPPs is the degraded performance of human operators (e.g., human errors) [6]. It is imperative to provide effective countermeasures against performance degradation of operators. From this concern, the use of procedures has been regarded as one of the most effective countermeasures for preventing human errors [7]. Figure 1 depicts the typical structure of a procedure that consists of proceduralized tasks, procedural steps, and detailed actions.

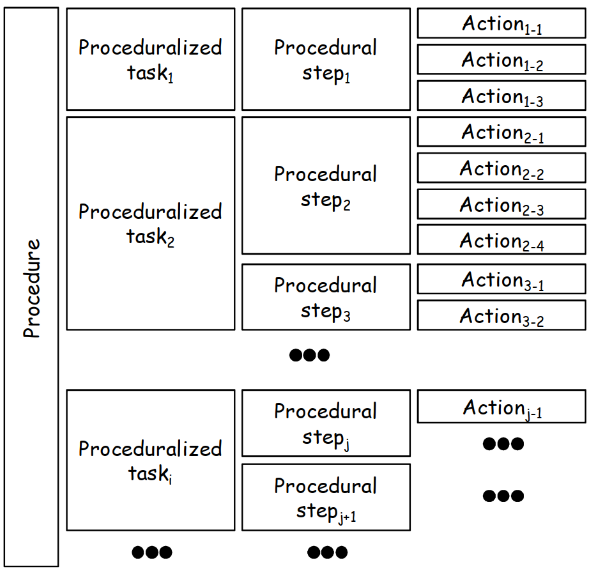

Figure 1: Proceduralized task, procedural step, and detailed action; adopted from [7]

As can be seen from Fig. 1, a procedure specifies both what has to be conducted by human operators (i.e., proceduralized tasks) and how to accomplish it (i.e., a series of actions included in procedural steps) with a clear structure. Due to these characteristics, Park and Jung stated that good procedures are effective for: (1) reducing workload, (2) preventing the occurrence of human errors, and (3) minimizing the variability of human performance [8]. The abovementioned advantages are very important for human operators who are responsible for the operation of NPPs, including during off-normal conditions. That is, as an off-normal condition may challenge the performance of human operators (e.g., distractions due to rapidly changing process parameters and tough decision-making under stressful conditions), most NPPs manifest their conduct of operations with strict adherence of procedures as written. Here, if human operators have to follow procedures as written (or as much as possible at least), it is reasonable to expect that the baseline of a task complexity can be soundly determined by the contents of proceduralized tasks. For this reason, the TACOM (Task Complexity) measure was developed based on the consideration of five sub-measures that represent distinct complexity factors: (1) number of actions, (2) amount of information, (3) logical entanglement, (4) amount of domain knowledge, and (5) difficulty to establish a decision criterion [9-12]. Table 1 shows the physical meaning of each complexity factor with the associated sub-measure.

Table 1: Five complexity factors with associated sub-measures; adopted from [12]

Complexity factor	Sub-measure	Physical meaning
Step information complexity	SIC	Complexity due to the amount of information to be processed by human operators
Step size complexity	SSC	Complexity caused by the number of actions to be conducted by human operators
Step logic complexity	SLC	Logical complexity originated from the sequences of actions to be followed by human operators
Abstraction hierarchy complexity	AHC	Complexity resulted from the amount of domain knowledge required by human operators
Engineering decision complexity	EDC	Complexity varied with respect to the amount of cognitive resources required by human operators, which is needed to establish an appropriate decision criterion

Based on the five complexity factors, the TACOM score of a specific prodedural task can be quantified by the following formula that includes three kinds of complexity dimensions [14]. Table 2 summarizes the meaning of each complexity dimension with the complexity factors shown in Table 1.

$$\text{TACOM} = \{0.621 \cdot (\text{TS})^2 + 0.239 \cdot (\text{TR})^2 + 0.140 \cdot (\text{TU})^2\}^{1/2}$$

$$\text{TS} = 0.716 \cdot \text{SIC} + 0.284 \cdot \text{SSC}$$

$$\text{TR} = 0.891 \cdot \text{SLC} + 0.109 \cdot \text{AHC}$$

$$\text{TU} = \text{EDC}$$

Table 2: Meaning of each complexity dimension; modified from [12]

Complexity dimension	Definition	Related complexity factor
Task scope (TS)	Representing the breadth, extent, range, or general size of a task being considered	SIC and SSC
Task structurability (TR)	Representing whether or not the sequence and the relationship between subtasks are well structured	SLC and AHC
Task uncertainty (TU)	Representing the degree of predictability or confidence in a task	EDC

3. CHARACTERIZING HRA DATA OBTAINED FROM A FULL-SCOPE SIMULATOR USING THE TACOM MEASURE

3.1. HRA Data Obtained from a Full-scope Simulator

As briefly stated in Section 2, a procedure is a very important tool to enhance the safety of NPPs, because it is effective for ensuring the performance of human operators in diverse off-normal conditions. However, the provision of the procedure does not guarantee this expectation without relevant educations and trainings for its use. For this reason, human operators working in the main control room (MCR) of domestic Korean NPPs (for convenience, the term MCR operators will be used hereafter) have to be regularly trained using a full-scope training simulator that is the replica of an MCR installed in their home plants. Since the purpose of this simulator training session is to enhance the competence of MCR operators in coping with diverse off-normal conditions, MCR operators are usually exposed to a wide spectrum of training scenarios that could emulate either familiar and typical off-normal conditions or extremely difficult and rare events. This implies that the response of MCR operators observable from the simulator training session is one of the most important information sources to understand when and why the degradation of human performance occurred.

At the same time, however, there are pros and cons in terms of HRA data collection from simulator training sessions [13]. For example, Kim et al. stated the pros and cons of as follows: "Human reliability data collection often requires considerable expertise and resources to handle the following complicating factors. First, human errors in fields engaging highly trained operators are infrequently observed. To collect data for such kind of human error, many tasks or events should be attempted. Second, the contexts that contribute to error occurrences, as represented by the performance influencing factors (PIFs) in HRA, are diverse. The identification of such contexts necessitates an in-depth understanding of human and machine interactions. The collection and analysis of data to estimate the PIFs' effects on HEPs could be thus resource-intensive. Lastly, the administrative process for gaining access to PIF information from the simulated or real-world incidents could be tedious [14, p. 896]." Accordingly, it is necessary to establish a sound framework that facilitates the collection of HRA data from simulator training session. For this reason, Korea Atomic Energy Research Institute (KAERI) proposed the HuREX (Human Reliability data Extraction) framework [15].

Based on the HuREX framework, KAERI accomplished two large data collection projects. The main objective of the first project is to collect the performance data of MCR operators who are working in an analog environment equipped with analog human machine interfaces (HMIs) such as alarm tiles, chart recorders, push buttons and rotary switches. The performance data of MCR operators in the analog environment were stored in the form of the information gathering templates (IGTs) provided by the HuREX framework. One of the representative HRA data sources available from the HuREX framework is detailed contexts for the occurrence of human errors including errors of omission (EOOs) and errors of commission (EOCs).

Similarly, in the second project, the performance data of MCR operators were also collected from simulator training sessions. In the second project, the HuREX framework is used and a lot of performance data are successfully gathered. The unique feature distinguishing the second project from the first one is the working environment of MCR operators. That is, the full-scope training simulator used in the second project is a replica of a fully digitalized MCR that is installed in one of the Korean domestic NPPs that recently started its commercial operation. Accordingly, MCR operators had to accomplish their required tasks by using up-to-date digital HMIs including an advanced alarm system, computerized procedure system, large display panel, and soft control system. In this condition, KAERI successfully collected diverse HRA data paralleling those of an analog environment.

3.2. Existing Studies related to the Comparison of HRA Data with TACOM Scores

Based on human performance data collected from the abovementioned projects, KAERI explored insights that are helpful for understanding the nature of human performance degradations (e.g., when and why human performance degradations occurred). For example, Jang et al. observed a significant correlation indicating that the number of human errors is proportional to the increase of TACOM scores [16]. In addition, Park et al. claimed that there seems to be a significant relation between TACOM scores and the occurrence probability of human errors in an analog environment [17]. Here, the term 'occurrence probability' means not the probability of human errors but the chance of occurrence in a specific task environment. That is, if the occurrence probability exceeds 0.5, then the chance of human errors is higher than that of no human error, or vice versa. Accordingly, the occurrence probability would be more meaningful for distinguishing whether or not human errors are more likely to occur in a given condition. Figure 2 shows the result of comparisons reported by Jang et al. [16].

The interesting point is that TACOM scores are also attributable to the occurrence probability of human errors that were identified from a digital environment. Figure 3 clarifies this claim [18]. For example, the left of Fig. 3 shows the result of the logistic regression between TACOM scores and the occurrence probability of all human errors including error of omissions (EOOs) and error of commissions (EOCs).

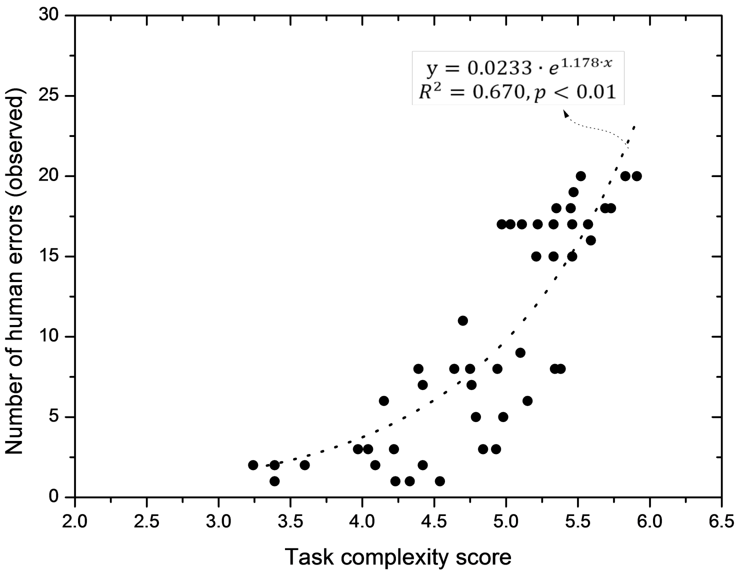

Figure 2: Comparison result between TACOM scores and the number of human errors observed from an analog environment; modified from [16]

In contrast, the right of Fig. 3 depicts two kinds of the logistic regression results that show the change of occurrence probabilities for EOOs and EOCs with respect to TACOM scores. Accordingly, it is possible to say that the TACOM measure can be used as a baseline to distinguish the characteristics of human performance data that were gathered from different environments.

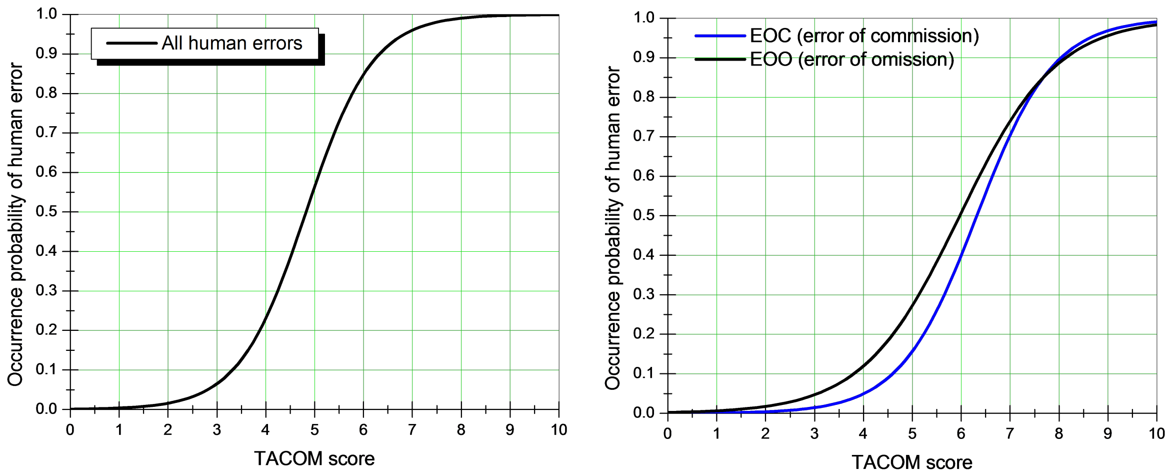

Figure 3: Comparison results between TACOM scores and the occurrence probability of human errors identified from a digital environment; modified from [18]

4. HRA DATA FROM THE RANCOR MICROWORLD SIMULATOR

4.1. Overview of the Rancor Microworld Simulator

The Rancor Microworld Simulator (called simply "Rancor") is a reduced order model simulator developed to represent a nuclear process control environment [19]. The simulator provides the basic functionality found in a full-scope simulator for a pressurized water reactor, but it does so in a highly simplified fashion that allows naïve participants, such as students, to quickly learn the system and complete experimental scenarios. Furthermore, the simplified platform is also suitable for quickly training experienced nuclear operators to serve as participants. The aim of this approach is to provide rapid data collection to support research on human performance aspects of nuclear process control.

A brief description of components and their arrangement is provided below for the base Rancor configuration. Though there are several variants of Rancor configured to represent different types of designs, the base configuration is a two-loop pressurized water reactor design. In this base configuration, Rancor can be divided into two main segments which are the primary and secondary systems. The primary system contains the reactor vessel, recirculating coolant pumps, and valves to regulate flow through the reactor and the steam generators tubes. The secondary side includes the steam generator shell, main steam lines, turbine, generator, feedwater pumps, and valves to control flow. Indications for these components are arranged in a piping and instrumentation diagram (P&ID) representation (see Fig. 4). Controls are located below the P&ID, and the alarms are arranged along the top of an overview display along the left edge of the simulator interface.

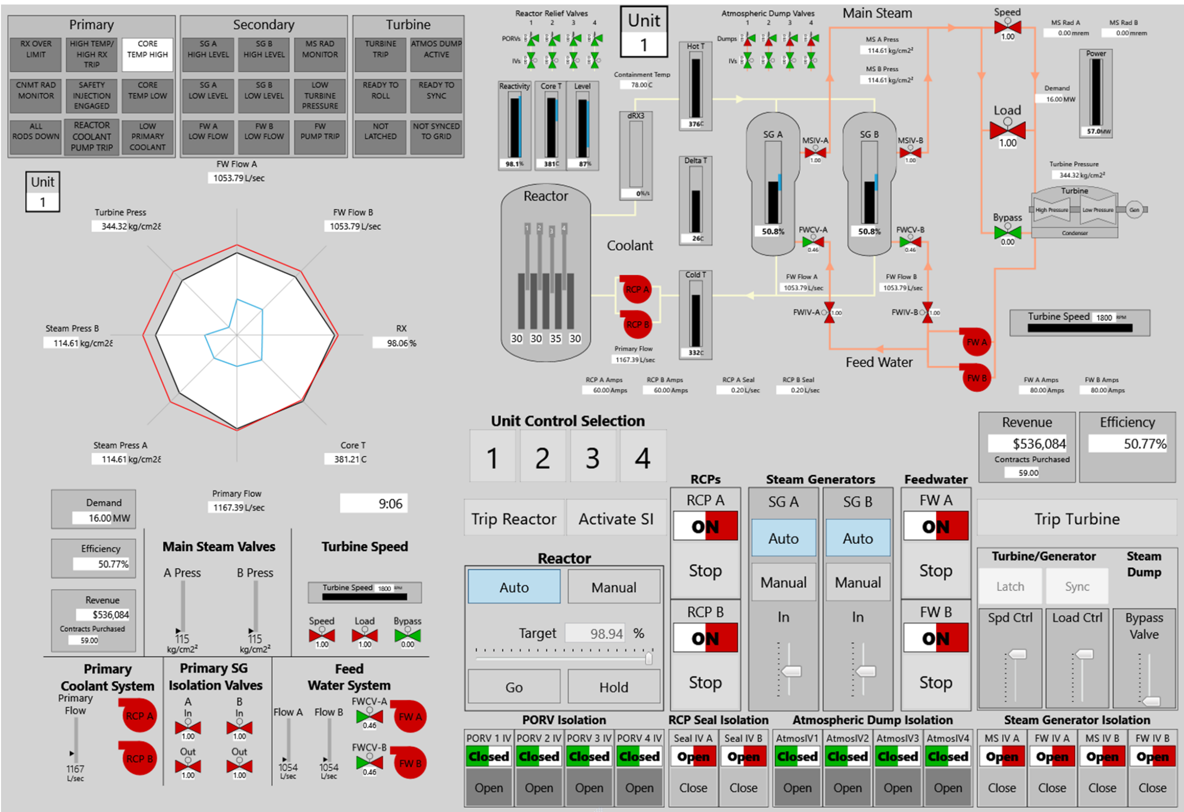

Figure 4: Rancor simulator human-machine interface depicting an overview display with alarms on the left, a piping and instrumentation diagram of components on the top right and the controls on the bottom right.

Rancor supports both normal operations and abnormal operations in which a malfunction is inserted into the system and the user must respond accordingly to mitigate the induced transient and restore the operating envelope. Initial conditions with scripted time and event driven malfunctions can be loaded to support various types of plant contexts. This is important to evaluate human performance issues during abnormal operations in which the timely diagnosis of the root cause failure and an expedient response are crucial to avoiding a potential system failure. Furthermore, it supports manual control and automatic control strategies to support analysing human-automation interaction topics. To support the various scenario types, Rancor has a suite of paper procedures as can be seen in Table 3. A computer-based procedure module is under active development and is planned for the next Rancor release.

Table 3: Procedures used to support scenario testing using the Rancor simulator

Procedure	Description	Procedure	Description
OP-001	Startup	AOP-001	Rapid Shutdown
OP-002	Shutdown	EOP-E-1	Loss of Primary Coolant

OP-010	Manual Reactor Control	EOP-E-2	Loss of Feedwater
OP-011	Manual Feedwater Control	EOP-E-3	Steam Generator Tube Rupture

4.2. HRA Data Collection Using Rancor Microworld Simulator

INL has attempted to collect HRA data through the Simplified Human Error Experimental Program (SHEEP), which relies on simplified simulators (i.e., the Rancor Microworld [19], and the Compact Nuclear Simulator (CNS) [20]) and student operators [21]. Figure 5 shows the SHEEP framework. INL's approach to implementing this framework is to complement full-scope studies by suggesting a way to infer full-scope data for estimating nominal/basic HEPs needed in the HRA quantification process, based on experimental data collected from students operating simplified simulators. The goal of the SHEEP framework is to lower the entry point for collecting useful HRA data by securing large sample sizes at a reasonable amount of cost and labor while also guaranteeing a high degree of freedom when designing experiments.

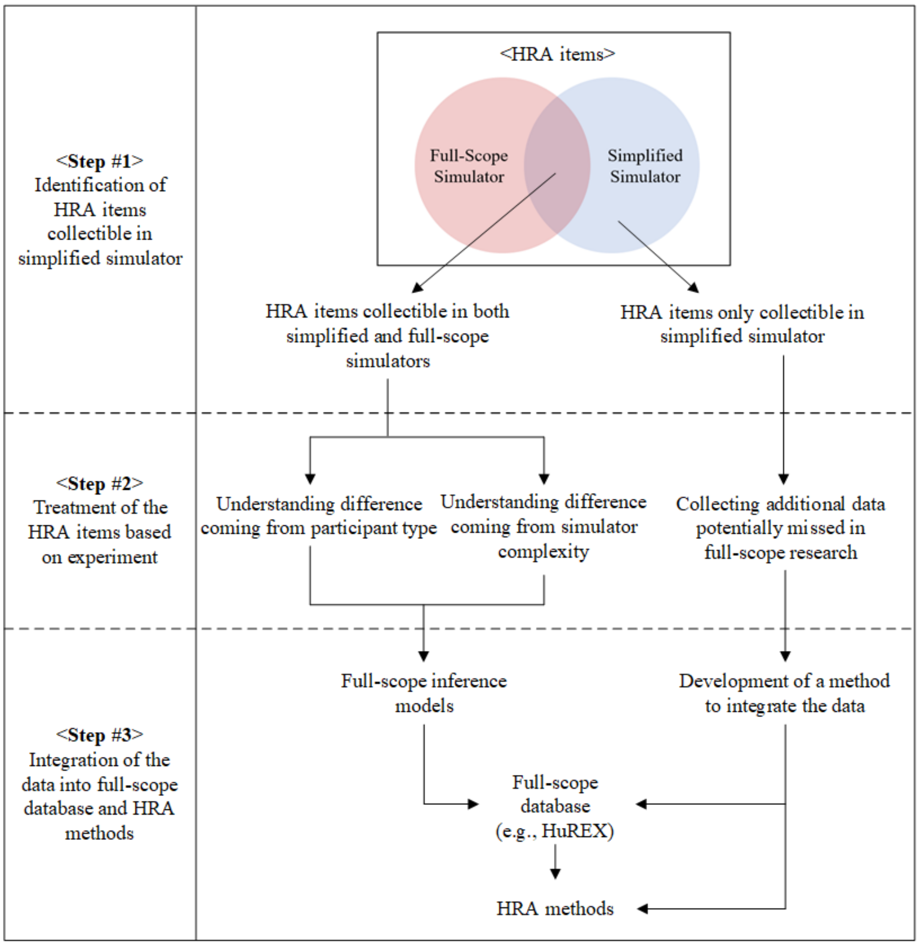

Figure 5: The SHEEP (Simplified Human Error Experimental Program) framework

In this light, the authors' previous research [21] investigated whether data collected from the SHEEP framework could support the HuREX database. Specifically, student/operator errors when using the Rancor Microworld were incorporated into the HuREX framework and then quantitatively compared with the HuREX error data. Also, human performance differences between professional and student operators when using Rancor were analysed to understand the lack of fidelity of the simplified simulators and student operators within the SHEEP study [22]. In ongoing research efforts, INL keeps investigating differences coming from participant type (i.e., operators vs. students) and simulator complexity (i.e., the Rancor Microworld vs. the CNS).

5. COMPARISON RESULTS

HRA data collected from Rancor can be directly compared with those from the full-scope training simulator based on TACOM scores. For example, Fig. 6 exemplifies the calculation of the TACOM score for a procedural step that belongs to one of the procedures used in the collection of HRA data from Rancor. In addition, neither EOO nor EOC were observed from operators and students who carried out the corresponding procedural step 10 and 9 times, respectively. In this way, a total of 187 data points were secured from Rancor. This implies that the HRA data gathered from Rancor can be directly compared with those of the full-scope simulator (refer to Figs. 7 and 8).

<table>
<tr><th>Task description</th><th colspan="2">Sub-measure</th></tr>
<tr><td rowspan="10">Verify Feedwater pumps are running
If FW A Pump is OFF, perform the following:
• Press the “Start” button of the FW A Pump
• Verify the FW A Pump is ON
If FW B Pump is OFF, perform the following:
• Press the “Start” button of the FW B Pump
• Verify the FW B Pump is ON
If both feedwater pumps are not ON
or flow has not been restored Go to STEP 3.</td><td>SIC</td><td>3.278</td></tr>
<tr><td>SLC</td><td>1.665</td></tr>
<tr><td>SSC</td><td>2.807</td></tr>
<tr><td>AHC</td><td>3.998</td></tr>
<tr><td>EDC</td><td>4.243</td></tr>
<tr><td>TS</td><td>3.144</td></tr>
<tr><td>TR</td><td>1.799</td></tr>
<tr><td>TU</td><td>4.243</td></tr>
<tr><td colspan="2">TACOM score</td></tr>
<tr><td colspan="2">3.071</td></tr>
</table>

Participant	Number of trial	EOO	EOC
Operator	10	0	0
Student	9	0	0

Figure 6: Example of TACOM score calculation

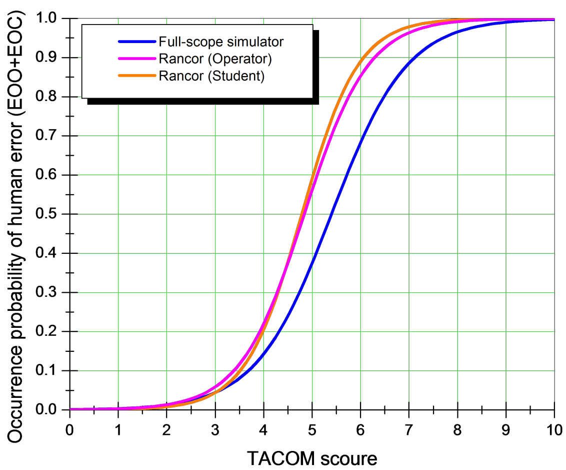

Figure 7: Comparing the occurrence probability of human errors obtained from the full-scope simulator and Rancor Microworld simulator – For all human errors

As can be seen from Fig. 7, it is interesting to point out that the changes of occurrence probabilities observed from different conditions are similar to each other. For example, when the TACOM score increased 4.0 to 5.0, then the chance of human error occurrence increased about 2.5 times and 3 times (i.e., 0.5/0.2 and 0.6/0.2) for the full-scope simulator and Rancor, respectively. Both students and operators showed almost identical trends of occurrence probabilities in terms of the change of TACOM scores.

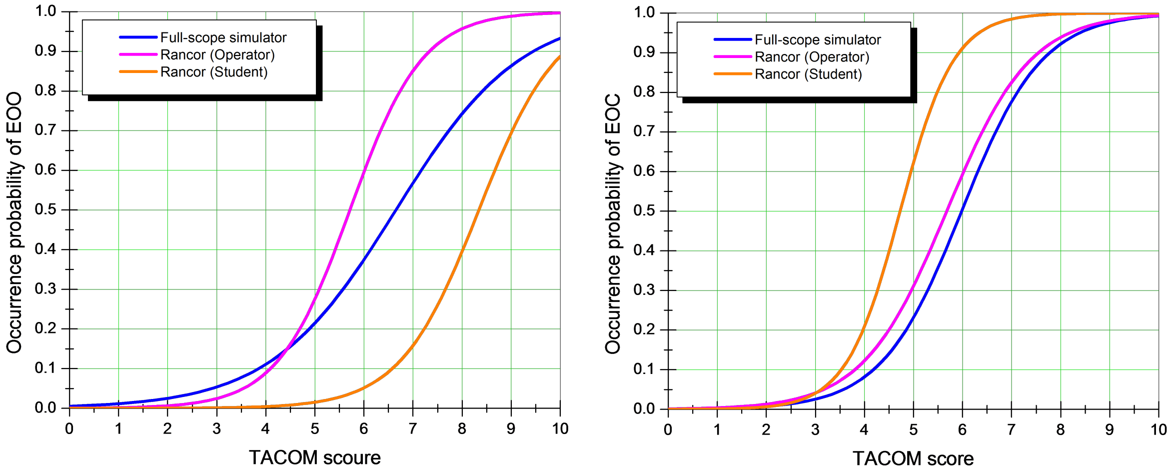

Figure 8: Comparing the occurrence probability of human errors obtained from the full-scope simulator and Rancor microworld simulator – EOO and EOC

In contrast, if we focus on the types of human error (i.e., EOO and EOC) shown in Fig. 8, the chance of human error occurrence varies with respect to a specific setting. For example, in the case of EOC, the logistic regression result of the full-scope simulator is similar to that of operators in the Rancor microworld simulator. In addition, it appears that the logistic regression result of the full-scope simulator and that of students in Rancor quite resemble each other. This implies that, to some extent, insights from Rancor are meaningful for understanding the nature of EOCs.

In contrast, in terms of EOOs, some caution must be observed because the differences of logistic regression results become significant (refer to the left of Fig. 8). That is, the effects of TACOM scores on the changes of occurrence probabilities are not homogeneous with respect to who carried out the required tasks. This alludes to the fact that the characteristics of EOOs would be different from those of EOCs.

6. DISCUSSION AND CONCLUSION

In terms of enhancing the safety of NPPs, one of the important considerations is to enhance the performance of human operators who are responsible for their operation. This means that the identification of significant contexts that directly cause human errors (e.g., error forcing contexts) is the crucial step for enhancing safety. In this regard, since the HRA process can be used for specifying when and why human errors occur, it is very important to collect credible information for supporting the HRA process which can be gathered from diverse sources including a full-scope simulator or a simplified simulator. In order to soundly accomplish this goal, it is necessary to clarify how to properly integrate different kinds of information obtained from the diverse information sources. For this reason, in this paper, human performance data observed from Randor and those from the full-scope simulator are directly compared based on the complexity scores of proceduralized tasks. As a result, it is observed that the complexity of a proceduralized task (i.e., TACOM score) seems to be dominant factor for the occurrence of human errors. In other words, regardless of EOOs and EOCs, Fig. 7 reveals that TACOM scores are significant in explaining the occurrence probabilities of human errors. If so, it is possible to expect that the TACOM measure can be used as a baseline to scrutinize the characteristics of human performance data observed from diverse information sources.

For example, as can be seen from Fig. 7, the occurrence probabilities of human errors observed from the students and operators of the Rancor microworld simulator are almost identical while those of the full-scope simulator are slightly different. Here, since the environment of Rancor is different from that of the full-scope simulator, a couple of remarkable PSFs that could result in this difference can be suggested (e.g., level of experience, the amount of domain knowledge possessed by the students and/or operators, type of HMIs and scenario difficulties). If we continuously accumulate human performance data obtained from other experiments that might have different settings and TACOM scores, it is anticipated to clarify the effect of each PSF on the occurrence probability of human errors. Indeed, this idea is already included in the SHEEP framework (refer to Steps #2 and #3 in Fig. 5). The results of this study would be a good starting point to complete the implementation of the SHEEP framework.

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