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An Investigation of Time Distributions for Task Primitives to Support the HUNTER Dynamic Human Reliability Analysis

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ABSTRACT

As an effort to support data collection for dynamic human reliability analysis (HRA), this study investigates time distributions for task primitives defined in the Goals, Operators, Methods, and Selection rules (GOMS)–Human Reliability Analysis (HRA) method. GOMS-HRA was developed to provide cognition-based time and human error probability information for dynamic HRA calculation in the Human Unimodel for Nuclear Technology to Enhance Reliability (HUNTER) framework. HUNTER is a framework to support the dynamic modelling of human error in conjunction with other modelling tools. In this paper, we investigate time distributions using experimental data collected from the Simplified Human Error Experimental Program (SHEEP) study, which suggests an HRA data collection framework to complement full-scope simulator research as well as collect input data for dynamic HRA using simplified simulators such as the Rancor Microworld Simulator. In this study, time required for GOMS-HRA task primitives to satisfy thirteen statistical distributions is investigated. Then, the time distributions from student operators and professional operators are compared and discussed. As a result, this study identified several time distributions on five GOMS-HRA task primitives at a statistically significant level. According to analyses to date, a greater number of significant time distributions was found in abnormal or emergency operating procedures rather than standard operating procedures. In the future, it is expected that the result of this study can provide objective reference on elapsed time data for task primitives as well as help to realistically simulate scenarios within dynamic HRA.

Keywords: Dynamic human reliability analysis, Data collection, Time distribution

INTRODUCTION

Human reliability analysis (HRA) is an approach to evaluate human errors and quantify human error probabilities (HEPs) for application in probabilistic risk assessment (PRA) (Swain & Guttmann, 1983). The Risk-Informed System Analysis (RISA) pathway under the U.S. Department of Energy's Light Water Reactor Sustainability (LWRS) Program sponsors a number of

HRA-related projects that aim to create better tools to support industry risk assessment needs. One such tool is the Human Unimodel for Nuclear Technology to Enhance Reliability (HUNTER) project (Boring, et al., 2022). HUNTER is a framework to support the dynamic modeling of human error in conjunction with other modeling tools. HUNTER creates a virtual operator or, potentially, a human digital twin as a human operations counterpart to plant hardware modeling and simulation. The name HUNTER is meant as a counterpart to the various animal-named modeling tools developed at Idaho National Laboratory (INL), such as Risk Analysis Virtual Code ENvironment (RAVEN) and Multiphysics Object-Oriented Simulation Environment (MOOSE). These tool names playfully combine to become tools like RAVEN-HUNTER or MOOSE-HUNTER.

Our research team has developed an HRA data collection framework called the Simplified Human Error Experimental Program (SHEEP) to complement full-scope simulator studies as well as collect input data for dynamic HRA like HUNTER (Park, et al., 2022). The SHEEP framework aims to infer full-scope data based on experimental data collected from simplified simulators, specifically the Rancor Microworld Simulator (Rancor) and the Compact Nuclear Simulator (CNS). Within the SHEEP framework, our research team has experimentally collected the human reliability data from forty student operators and forty professional operators when they used CNS and Rancor. To date, human errors and performance measurements collected from experiments have been analyzed and discussed in the previous research (Park, et al., 2022; Park, et al., 2023).

From within the umbrella of the SHEEP framework, this study aims to investigate time distributions for task primitives defined in the Goals, Operators, Methods, and Selection rules (GOMS)-HRA method (Boring & Rasmussen, 2016). GOMS-HRA was developed to provide cognition-based time and HEP information for dynamic HRA calculation in the HUNTER framework. In this study, we investigated time distributions for GOMS-HRA task primitives using the SHEEP database, which includes experimental data when twenty student operators and twenty professional operators using Rancor. From the experimental data, time required for GOMS-HRA task primitives to satisfy thirteen statistical distributions was investigated. Then, the time distributions from student operators and professional operators are compared and discussed.

GOMS-HRA TASK PRIMITIVES

GOMS-HRA was developed to provide cognition-based time and HEP information for dynamic HRA calculation in the HUNTER framework. GOMS-HRA has been used to model proceduralized activities and evaluate user interactions with human-computer interfaces in human factors research. As a predictive method, GOMS-HRA is well-equipped to simulate human actions under specific circumstances in a scenario. The basic approach of GOMS-HRA consists of three steps: (1) breaking human actions into a series of task-level primitives, (2) allocating time and error values to each task-level primitive, then (3) predicting human actions or task durations.

Table 1 shows the GOMS-HRA task primitives. GOMS-HRA originally suggested twelve task primitives performed in control rooms and in the field. However, in this study, we only concentrate on the five task primitives (i.e., A_C, C_C, R_C, S_C, and D_P) highlighted as grey color in the table. Actually, the SHEEP experiment has focused on control room data when a single operator runs a simulator using procedures. Accordingly, task primitives regarding field operations (i.e., A_F, C_F, R_F, and S_F), actions regarding decision-making without procedures (i.e., D_W), and communication between operators (i.e., I_P, and I_R) were excluded in this study.

Table 1. GOMS-HRA task primitives.

Task Primitives	Description
A_C	Performing required physical actions on the control boards
A_F	Performing required physical actions in the field
C_C	Looking for required information on the control boards
C_F	Looking for required information in the field
R_C	Obtaining required information on the control boards
R_F	Obtaining required information in the field
I_P	Producing verbal or written instructions
I_R	Receiving verbal or written instructions
S_C	Selecting or setting a value on the control boards
S_F	Selecting or setting a value in the field
D_P	Making a decision based on procedures
D_W	Making a decision without available procedures

THE SHEEP EXPERIMENT DATA

The SHEEP data have been collected from twenty student operators and twenty professional operators when they used Rancor. Most of the professional operators were licensed reactor operators currently employed at nuclear power plants (NPPs). They were all operators on shift (i.e., a shift supervisor, shift technical advisor, reactor operator, or turbine operator) or instructors at the training center. As for the student operators, they were all undergraduate seniors or graduate students from the Department of Nuclear Engineering at Chosun University. They were knowledgeable about NPP systems and operations, having completed a significant portion of their coursework, which included courses such as “Introduction to Nuclear Engineering,” “Reactor Theory,” “Reactor Control,” and “Simulator Operation.”

This study investigated time distributions of the GOMS-HRA task primitives depending on procedures. Basically, procedures used in NPPs have different goals. For example, operating procedures (OP) aim to stably reach different operating modes such as startup or hot standby, while emergency operating procedures (EOPs) are mainly composed of instructions for rapidly cooling down reactors. Accordingly, this study distinguished seven different procedure sets as shown in Table 2. For OP-03 and OP-04, and OP-05 and OP-06, these are combined as a procedure set respectively because these are used in a scenario for achieving a goal. Specifically, OP-04 and OP-06 are parts of OP-03 and OP-05. In this paper, the result of time distribution analysis on EOP-01 is mainly introduced in the next session.

Table 2. Procedure information used in the SHEEP experiment.

Procedure Set No.	Procedures Included	Description	Related Scenario
1	OP-01	This procedure describes how to start up and operate Rancor in auto mode.	Scenario #1 (fully auto start-up)
2	OP-02	This procedure describes the process to shut-down Rancor.	Scenario #2 (shutdown)
3	OP-03 & OP-04	This procedure describes how to start up and operate Rancor in control rod manual operation mode.	Scenario #3 (manual rod control during start-up)
4	OP-05 & OP-06	This procedure describes how to start up and operate Rancor in feedwater manual operation mode.	Scenario #4 (manual feedwater flow control during start-up)
5	AOP-01	This procedure shuts down the plant in an expedient manner.	Scenario #5~#10 (failure of a reactor coolant pump, failure of a control rod, failure of a feedwater pump, turbine failure, steam generator tube rupture, and loss of feedwater)
6	EOP-01	This procedure provides actions to minimize leakage of reactor coolant into the secondary system following a steam generator tube rupture.	Scenario #9 (steam generator tube rupture)
7	EOP-02	This procedure provides actions to diagnose and mitigate a loss of feedwater.	Scenario #10 (loss of feedwater)

TIME DISTRIBUTION ANALYSIS RESULT: EOP-01

Tables 3 and 4 show the number of tasks used for time distribution analysis and the result of goodness-of-fit test for thirteen statistical distributions on elapsed time of the five GOMS-HRA task primitives in the EOP-01 procedure depending on participant type, i.e., student operators, and professional operators. There were 490 total tasks counted when twenty student operators and twenty professional operators manipulate Rancor using the EOP-01 procedure. The number of tasks for student operators (248) was slightly higher than for professional operators (242). The differences on the number of tasks per participant type rely on cases that a participant additionally performs instructions that can be omitted within a procedure context, or a participant cannot continue a scenario because the reactor has abnormally tripped during the scenario.

Table 3. The number of tasks used for time distribution analysis (EOP-01).

Participant Type	GOMS-HRA Task Primitive					The Number of Tasks per Participant Type	The Total Number of Tasks
	A_C	C_C	R_C	S_C	D_P		
Student operators	59	80	49	10	50	248	490
Professional operators	57	78	49	10	48	242	

Table 4. Time distribution analysis on the five GOMS-HRA task primitives in the EOP-01 procedure depending on participant type (student vs. operator).

Distribution	P-value of Goodness of Fit Test									
	Student					Operator				
	A_C	C_C	R_C	S_C	D_P	A_C	C_C	R_C	S_C	D_P
Normal	<0.005	<0.005	<0.005	0.014	<0.005	<0.005	<0.005	<0.005	0.237	<0.005
Normal (after Box-Cox transformation)	0.374	<0.005	0.010	0.653	0.070	0.340	<0.005	<0.005	0.237	0.041
Lognormal	0.374	<0.005	0.010	0.404	0.070	0.340	<0.005	<0.005	0.031	0.041
Exponential	0.023	<0.003	0.018	0.486	0.051	<0.003	<0.003	<0.003	0.021	<0.003
2-parameter exponential	0.083	<0.010	<0.010	>0.250	0.011	<0.010	<0.010	<0.010	0.012	0.034
Weibull	<0.010	<0.010	<0.010	0.189	<0.010	0.015	<0.010	<0.010	0.236	0.022
3-parameter Weibull	0.013	<0.005	<0.005	0.404	<0.005	0.084	<0.005	<0.005	0.254	0.006
Smallest extreme value	<0.010	<0.010	<0.010	<0.010	<0.010	<0.010	<0.010	<0.010	0.092	<0.010
Largest extreme value	<0.010	<0.010	<0.010	0.037	<0.010	0.088	<0.010	<0.010	0.227	0.016
Gamma	<0.005	<0.005	0.007	0.208	0.006	0.167	<0.005	<0.005	0.182	0.047
Logistic	<0.005	<0.005	<0.005	0.016	<0.005	<0.005	<0.005	<0.005	0.235	<0.005
Loglogistic	>0.250	<0.005	<0.005	>0.250	0.032	0.233	<0.005	<0.005	0.104	0.017
Normal (after Johnson transformation)	0.563	N/A	N/A	0.763	N/A	0.364	N/A	N/A	N/A	N/A

Among student operators' task primitives, elapsed time for A_C was statistically significant on normal distribution after Box-Cox transformation, lognormal distribution, 2-parameter exponential distribution, loglogistic distribution, and normal distribution after Johnson transformation. The statistical significance for elapsed time means that the data set are distributed within confidence intervals in each statistical distribution. For elapsed time for S_C, the task primitive satisfied statistical significance level on normal distribution after Box-Cox transformation, lognormal distribution, exponential distribution, 2-parameter exponential distribution, Weibull distribution, 3-parameter Weibull distribution, gamma distribution, loglogistic distribution, and normal distribution after Johnson transformation. In addition, elapsed time for D_P was statistically significant on normal distribution after Box-Cox transformation, lognormal distribution, and exponential distribution. On the other hand, elapsed time for A_C from professional operators' data showed statistically significant result on normal distribution after Box-Cox transformation, lognormal distribution, 3-parameter Weibull distribution, largest extreme value distribution, loglogistic distribution, and normal distribution after Johnson transformation. For elapsed time for S_C, the task primitive satisfied statistical significance level on normal distribution, normal distribution after Box-Cox transformation, Weibull distribution, 3-parameter Weibull distribution, smallest extreme value distribution, largest extreme value distribution, gamma distribution, logistic distribution, and loglogistic distribution.

Figures 1–5 summarize the most optimal time distributions representing the highest p-value among time distributions per each task primitive. Figure 1, Figure 2, and Figure 3 include normal distributions (after Johnson transformation) of A_C and S_C, and lognormal distribution of D_P for student operators' tasks in the EOP-01 procedure. The average elapsed time from the time distributions are 11.92 seconds for A_C, 9.80 seconds for S_C, and 6.14 seconds for D_P. Figure 4 and Figure 5 show normal distributions (after Johnson transformation) of A_C and 3-parameter Weibull distribution of S_C for professional operators' tasks in the EOP procedure, respectively. The average elapsed time from these time distributions are 7.21 seconds for A_C and 5.30 seconds for S_C.

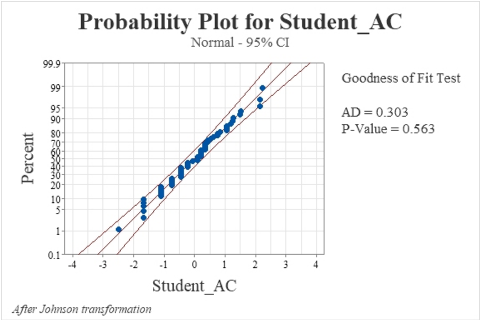

Figure 1: Normal distribution (after Johnson transformation) of A_C for student operators' tasks in the EOP-01 procedure.

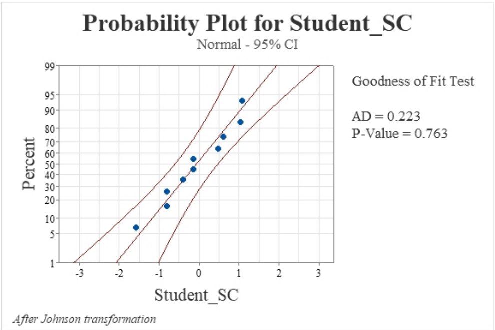

Figure 2: Normal distribution (after Johnson transformation) of SC for student operators' tasks in the EOP-01 procedure.

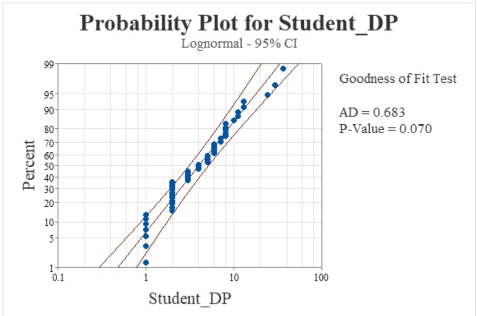

Figure 3: Lognormal distribution of dp for student operators' tasks in the EOP-01 procedure.

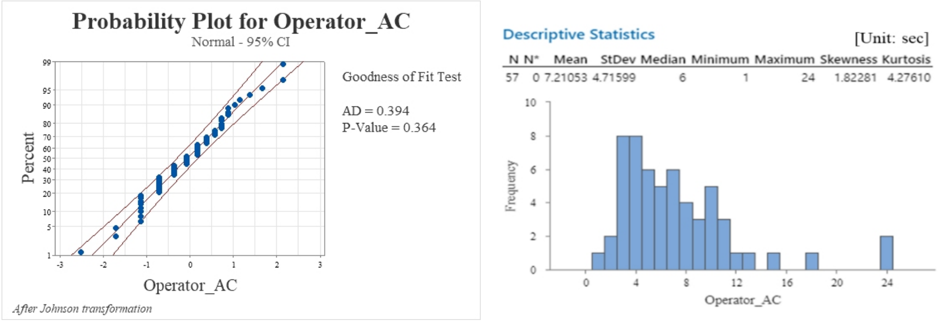

Figure 4: Normal distribution (after Johnson transformation) of AC for professional operators' tasks in the EOP-01 procedure.

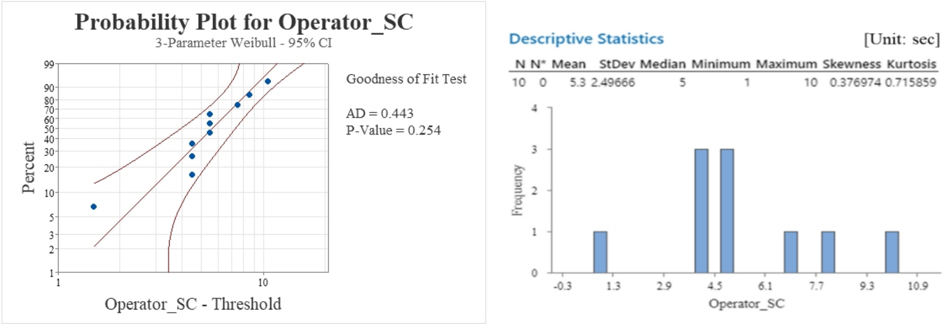

Figure 5: 3-parameter weibull distribution of SC for professional operators' tasks in the EOP-01 procedure.

CONCLUSION

This study investigated time distributions for five GOMS-HRA task primitives from the seven different sets of procedures having different goals and comparing the time distributions depending on participant type. In this paper, time distributions for the five GOMS-HRA task primitives in the EOP-01 procedure are introduced. As a result, several time distributions on the five GOMS-HRA task primitives were found at statistically significant level. Specifically, the greater number of time distributions were found in abnormal operating procedure (AOP)-01, EOP-01 and EOP-02 when compared to the OP procedures. Manipulation-related task primitives, i.e., A_C (Performing required physical actions on the control boards) and S_C (Selecting or setting a value on the control boards), satisfied relatively many statistical distributions with high confidence levels in comparison with other task primitives.

A relatively smaller number of time distributions satisfied statistically significant levels in the OP procedures. Actually, some tasks in the OP procedures include elapsed time for plant parameters to reach certain values. These may make it difficult to get time distributions with statistical significance level. Also, no time distributions have been found on R_C (Obtaining required information on the control boards) regardless of participant type. In the SHEEP experiment, each participant carried out six scenarios at one setting. Accordingly, there may be learning effects for participants to obtain any information from the Rancor interface. The learning effect may interfere with satisfying time distributions.

Our research team continues analyzing the experimental data. Further analyses will be performed to clarify these issues and arrive at better time distributions applicable to dynamic HRA in the future. Already, these data show the possibility of using GOMS-HRA task level primitives to arrive at time distributions. Such time distributions may eventually prove as useful as outright HEP estimations in future HRA applications.

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