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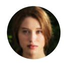
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DETERMINATION OF A GENERIC HUMAN ERROR PROBABILITY DISTRIBUTION, PART 2: A DYNAMIC SPAR-H EXAMPLE APPLICATION

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INTRODUCTION

Humans are an integral part of a nuclear power plant (NPP) from its construction, to its everyday maintenance and operation. In the nuclear industry there are many approaches to quantifying component reliability, which is called probability risk assessment (PRA). In PRA there are two considerations given to the quantification, static and dynamic. Static is quantified before or after an operation; and dynamic is time dependent, in that the probability changes as real time data are provided.

In PRA, the importance of the components is calculated, but what of the importance of the human component? There are several methods for human reliability analysis (HRA), which include but are not limited to: THERP, ATHEANA, CREAM, SPAR-H, ASEP, and SLIM [1] [2] [3] [4] [5]. Each of these methods aims to provide a more accurate and objective human error probability (HEP) quantification.

Of the methods listed above, ASEP, THERP, and SPAR-H are all inextricably linked. The Standardized Plant Analysis Risk-Human Reliability Analysis (SPAR-H) method was generated to better generalize the Technique for Human Error Rate Prediction (THERP) and Accident Sequence Precursor (ASEP) [6]. THERP is mapped to specific scenario templates, and ASEP is a simplified screening method, while SPAR-H employs generalizations to describe the spectrum of human behavior while maintaining the same theoretical underpinnings.

SPAR-H is a well-known and accepted HRA method that uses performance shaping factors (PSFs) to classify inputs to the human component [4]. PSFs capture a wide variety of input data, including plant status, crew dynamics, task description, and psychological aspects of the human operator.

Current efforts have been focused to further generalize SPAR-H in to a dynamic framework [7] [8] [9]. These methods can fit into dynamic NPP simulations such as RAVEN / RELAP-7 [10]. In order to do this, a dynamic methodology is applied to model the human as would be applied to the components. This method is applied in part one in the accompanying paper [9].

SPAR-H

In SPAR-H the quantification of the HEP is based upon eight PSFs. The eight PSFs defined by SPAR-H are Available Time, Stress/Stressors, Complexity, Experience/Training, Procedures, Ergonomics/ Human Machine Interface, Fitness for Duty, and Work Processes. Each PSF has a differing number of levels that are associated with multipliers as per Table 1.

Table 1. The SAPR-H available time PSF with its associated action and diagnosis multipliers.

PSF	PSF Levels	Diagnosis Multiplier	Action Multiplier
Available Time	Inadequate Time	P(Fail)=1	P(Fail)=1
	Available Time = Time Required	10	10
	Nominal Time	1	1
	Time Available > 5x the Time Required	0.1	0.1
	Time Available > 50x the Time Required	0.01	0.01
	Insufficient Information	1	1

For example, a PSF level from Table 1 for Available Time is selected based on the task, with the associated multiplier substituted into equation (1). This is completed for each of the eight PSFs—defining a level and substituting in a multiplier. These PSF multipliers have their product taken and are multiplied by a nominal HEP (NHEP). The NHEP differs for action and diagnosis, 1E-3 and 1E-2 respectively.

$$\begin{aligned} HEP = NHEP * \ & Available\ Time * Stress \\ & * Complexity * Expertise \\ & * Procedures * Ergonomics \\ & * Fitness\ for\ Duty \\ & * Work\ Process \end{aligned} \tag{1}$$

The calculation of the HEP in SPAR-H does have several abnormalities. These are events where multipliers produce HEPs greater than one. This is corrected by applying an adjustment; however, even with the correction there are occurrences where HEP is greater than 1. In these events, it is assumed that the HEP maximum value is 1. This is an integral point when applying a dynamic framework to SPAR-H.

DYNAMIC SPAR-H

To transition into a dynamic SPAR-H framework the multipliers associated with the PSF levels are fit with a continuous distribution, as outlined in [9]. The continuous distributions allow Monte Carlo simulations to be implemented, and subsequently scenarios can be further theoretically explored. Other approaches to dynamicizing SPAR-H are possible, and the continuous distributions provided here can serve to bound the range of outputs produced by such models. All of the distributions were identified as log-normal with parameter 1 (P1) as a log-mean, and parameter 2 (P2) as log-standard deviation. This information is provided in Table 2.

Table 2. All SPAR-H action PSFs fit to a continuous distribution [9].

PSF	P1	P2	S.E. P1	S.E. P2
Available Time	0.034	0.712	0.031	0.022
Complexity	0.049	0.2	0.009	0.006
Ergonomics / Human Machine Interface	0.152	0.601	0.026	0.018
Experience / Training	0.088	0.327	0.014	0.01
Fitness for Duty	0.025	0.2	0.009	0.006
Procedure	0.229	0.693	0.029	0.021
Stress / Stressors	0.112	0.265	0.011	0.008
Work Processes	0.282	0.649	0.026	0.018

The distributions defined in Table 2 are simulated using Monte Carlo for 10,000 observations. This approach uses the law of large numbers to produce reliable HEP values. The HEP is then calculated following equation (1). Consideration of other methods of calculating HEPs should be given, which may include dynamic Bayesian belief networks, Markov random field or other acyclic graphical approaches. Scenario specific results can be achieved by truncating, applying mixed models, or Bayesian updating the PSF distributions for level specific distributions; however this is not implemented. Application of equation (1), with Monte Carlo simulation and the distributions in Table 2 produces a simulation of 10,000 HEP values for a maximum likelihood estimate (MLE) algorithm, to fit several distributions. The distribution for the PSFs in Table 2, are limited to only action tasks, as this is was the aspect in which the scenarios were scored. The 10,000 simulated values for action HEP represent normal operations at a NPP, and do not encompass extreme scenarios.

The goodness of fit for the distributions is defined via the lowest Akaike information criterion (AIC) value [11]. The resulting fit of the distributions is provided in Table 3, with only standardized distributions considered.

Table 3. The fitting of HEP with a continuous distribution.

Distribution	P1	P2	S.E. P1	S.E. P2
Beta	0.31	27.54	0.01	0.57
Log Normal	-5.98	1.84	0.02	0.01
Weibull	0.51	0.01	0.003	0
Gamma	0.33	17.27	0.004	0.36
Exponential	51.82	NA	0.52	NA
Normal	0.02	0.09	0.001	0.001

In Table 3, P1 and P2 refer to the standard parameterization of their respective distributions; S.E. P1 and S.E. P2 refer to the standard error surrounding parameter 1 and 2 respectively. It is generally understood that no model can ever fit data perfectly, so there is uncertainty in the parameter values defined. As indicated by the lowest AIC value the beta distribution fits the HEP the best. This is very conventional as the beta distribution is a probability distribution bounded between 0 and 1. The beta distribution selected in Table 3 is graphed in Figure 1.

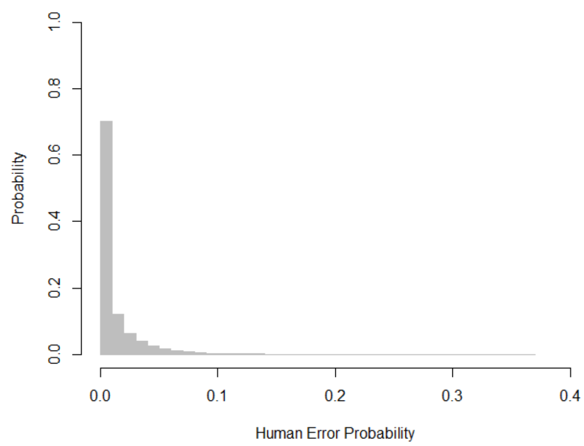

Figure 1. Beta distribution fit by MLE algorithm to represent HEP.

NUCLEAR SPAR-H SCORE

Application of the defined HEP beta distribution to a specific previously scored SPAR-H scenario can be achieved through several methods. These methods include distribution truncation, mixed models, or Bayesian updating to represent each PSF level, however this is not employed. The scenario considered herein is provided in the primary publication of SPAR-H in Appendix E and is the scored human action of dry cask storage operations for spent commercial reactor fuel [4]. This task is considered a diagnosis and an action, thus the two SPAR-H HEPs are added together. Due to the limitations of the provided data, only the action HEP value is considered here. Excerpts from the published document can be found in Table 4.

Table 4. SPAR-H Action PSF scoring for dry cask storage.

PSF	Level	Action Multiplier
Available Time	Nominal	1
Complexity	Moderately Complex	2
Ergonomics / Human Machine Interface	Poor	10
Experience / Training	Nominal	1
Fitness for Duty	Nominal	1
Procedure	Nominal	1
Stress / Stressors	Nominal	1
Work Processes	Nominal	1
HEP		0.02

Most of the PSF levels are nominal; specifically, available time, experience/training, procedures, fitness for duty, and work processes have no impact on the HEP value. The scoring sheet defines stress as 'insufficient information,' as there is no information provided about stress. The complexity is considered moderate, as there are multiple assemblies with specific placements in the canister. This task has poor ergonomics / HMI, as it needs to be completed by remote control, underwater, using a camera. This results in an action HEP of 1E-3 x 20 = 0.02. Leveraging the beta distribution defined in Table 3, an action HEP of 0.02 is very common with a majority of HEP action values occurring at or below this level. An action HEP of 0.5 for a normal operation task such as dry cast storage would be very unlikely. The beta distribution utilized maxes out at an HEP of 0.4 and applies to normal operation. As such, the specific distributions would need refinement, based upon recorded data, to be applied to events outside of normal operation.

Further methods to apply SPAR-H in a dynamic framework may use regression, stochastic models, or truncation of distributions to define the PSFs. This would allow for refinement of the PSF multiplier based upon internal and external stimuli to the human. This would therefore allow for the propagation of uncertainty around the HEP and produce more advanced models.

CONCLUSION

There are many methods to quantify the HEP; one of the most well-known is SPAR-H. This method relies on PSFs, which are quantitatively represented as multipliers and can be described as continuous distributions. Using these distributions in a Monte Carlo simulation, a normal operation HEP can be calculated and a beta distribution fitted. The beta distribution can inform uncertainty around the HEP so that risk can be more accurately managed.

When considering a previously published SPAR-H scoring, the resulting HEP beta distribution appears to be in line with expert intuition. Further progression of the method is encouraged, with possible application of stochastic models, regressions, truncated distributions, mixed models, dynamic belief networks, and other methods.

DISCLAIMER

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