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A New Dynamic HRA Method and Its Application

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새로운 동적인간신뢰도 방법론과 적용

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Abstract

This paper presents a new dynamic HRA (Human Reliability Analysis) method and its application for quantifying the human error probabilities in implementing an accident management action. For comparisons of current HRA methods with the new method, the characteristics of THERP, HCR, and SLIM-MAUD, which are most frequently used methods in PSAs, are discussed. The action associated with the implementation of the cavity flooding during a station blackout sequence is considered for its application. This method is based on the concepts of the quantified correlation between the performance requirement and performance achievement. The MAAP 3.0B code and Latin Hypercube sampling technique are used to determine the uncertainty of the performance achievement parameter. Meanwhile, the value of the performance requirement parameter is obtained from interviews. Based on these stochastic distributions obtained, human error probabilities are calculated with respect to the various means and variances of the timings. It is shown that this method is very flexible in that it can be applied to any kind of the operator actions, including the actions associated with the implementation of accident management strategies.

요 약

이 논문은 새로운 동적 인간신뢰도 분석방법을 제시하였고, 사고관리 방안의 수행시 인간오류확률의 계산에 이 방법을 적용하였다. 기존의 다른 방법과 비교하기 위하여 PSA의 HRA수행시 가장 많이 사용되는 THERP, HCR, 및 SLIM-MAUD 방법론들의 특징을 논의하였다. 정전사고시 공동범람시키는 방안을 예제로 사용하였다. 이 방법은 Requirement와 Achievement의 연관개념에 기초하고 있다. Achievement 변수의 불확정성은 MAAP 전산코드와 Latin Hypercube Sampling 방법을 이용하여 결정하였고 Requirement 변수값은 운전원과의 면담을 통하여 얻었다. 이렇게 얻어진 변수들의 분포를 가지고 여러가지 시간값의 평균과 분산에 대하여 인간오류 확률값을 계산하였다. 이 방법은 매우 유연하여 사고관리 전략수행과 관련한 행위를 포함한 어떤 종류의 운전원 행위에도 적용가능 함을 보여주었다.

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1. Introduction

In typical PSAs (probabilistic safety assessments), the human errors are considered in the development of fault trees as well as event trees for some special cases. They have been identified as important contributors to plant risk in many PSAs. Nevertheless, there is no one HRA (human reliability analysis) method universally accepted for quantifying the human error probability (HEP). The HRA methods are thus still being refined and developed.

This paper presents a new dynamic method for assessing the human error probabilities and its application for quantifying the human error probability. The action associated with the implementation of the cavity flooding during a station blackout sequence is used as an example.

This proposed method is based on the concepts of the quantified correlation between the performance requirement and performance achievement. The MAAP 3. 0B code for the sensitivity and screening analysis and Latin Hypercube sampling technique are used to determine the uncertainty of the performance achievement parameter. The value of the performance requirement parameter can be obtained from plant simulator training records and/or interviews.

Most frequently used methods among about 18 published methods involve THERP, HCR, and SLIM-MAUD [1-3]. These three methods are discussed for comparisons with the new dynamic HRA method in the following Section. And the new method is described in detail, and finally applied to the practical problem.

2. Human Reliability Analysis Methods

2.1. THERP

THERP (Technique for Human Error Rate Prediction), generally called "HRA handbook", is the most commonly used method in PSAs [1]. This method treats the operator as one of the system components, and thus human reliability is assessed in the same manner as that of components. The concept of this method is that the human operator's activities are decomposed down to the levels where basic HEP can be found in the 27 tables of the handbook.

Operator action trees, which treat only both correct and incorrect cases, are used to accomplish the decomposition processes, and each branch represents one of the binary choices. The assigning probability to each branch is obtained from the corresponding human error probabilities in the handbook tables and then modified by multiplying the appropriate values associated with performance shaping factors (PSFs) to reflect the real situation where the human error occurs.

The PSFs are classified into three categories in this method. They are: a) external PSFs which are related to the environmental working conditions such as noise/humidity and control room design, b) internal PSFs such as skills and ability of the operators, training, and attitude, and c) physical (e.g., fatigue and hunger) and psychological factors associated with stress (e.g., fear and suddenness).

In this method, each operator is assumed to have the same failure probability in executing a specified task, and only dependencies between two consecutive tasks are considered. There are five levels of dependencies which are ZD (zero dependency), LD (low dependency), MD (medium dependency), HD (high dependency), and CD (completely dependency). The mathematical formula of each dependency level are used to calculate the failure probability of the crew [1].

This method has the sufficient database for modeling executional errors. But it has some drawbacks in addressing the causes and intention formation processes of the errors, and in treating dependencies among PSFs appropriately.

2.2. HCR

The HCR (human cognitive reliability) model is an empirical model based on data collected from simulators. It is used to quantify the non-response probability of the crew using some parameters [2]. The non-response denotes "non-successful" in performing a specified task, where no action is taken within the time available. Three key parameters required to evaluate the non-response probability are determined for the cognitive types of skill, rule, knowledge based behavior [4], median response time of the crew, and PSFs (e.g., skill, stress level, and quality of control room design), respectively. In order to identify the types of cognitive behavior, an event tree, which consists of asking whether it is a routine operating and whether it is covered by any written procedure, etc. , is used. The median non-response time to perform the required task is determined from simulator data, expert judgments, and interviews. This method provides criteria for judging the levels of three PSFs and their corresponding K coefficient, where K_1 represents the level of the operator's skill, K_2 the stress level, and K_3 the quality of the control room design. Based on the median response time and coefficients identified, the adjusted median response time is determined. This time is then used to match the corresponding curve which is characterized by three parameter Weibull distributions.

A major assumption of this method is that cognitive behavior can be exactly classified into one of three types. Recent benchmark study shows that crew responses do not fall exactly into any one of the three behavior types [5]. Another assumption is that PSFs can only affect the non-response time, i.e., they are assumed to be independent to each other. This may not be true, because, under high level of stress, an operator may forget the rules previously stored in his mind and therefore turn from the rule-based behavior into knowledge based one.

2.3. SLIM

The SLIM (success likelihood index methodology) is a structured, expert judgment based technique which can be used to assess the human error probabilities [3]. It takes 5 steps.

1. Selection of those tasks with the same PSFs.
2. Assignment of relative importance to each PSF.
3. Assignment of rating scale from 1 to 9 to each PSF in every task.
4. Manipulation of the rating and relative weights to obtain the success likelihood index (SLI) for each task.
5. Conversion of SLI into human error probabilities.

Typical PSFs used in this method are design quality, meaningfulness of procedures, stress, time pressure, seriousness of consequence, task complexity, motivation, and quality of teamwork. After a group of tasks with the same PSFs are chosen, the experts are asked to assign the relative importance to each PSF, where it is later normalized. They then assign the rating scale to each PSF in every task. A scale of range from 1 to 9 which represents the level of the PSF is given to each task. After these are done, rescaling is executed by measuring the difference between the assigned rating and the ideal rating of each PSF. The SLI for each task is just the sum of the products of rescaled rating and the relative importance of each PSF. HEP for each task is then calculated by the following formula: $\log(HEP) = a^* SLI + b$, where the coefficients, a and b, can be obtained from the anchor points, which are known probabilities of two tasks. These known probabilities can be provided by simulators or other available data sources. When the elicitation of the expert judgment is carried out using a computer program, it is called SLIM-MAUD (multiattribute utility decomposition).

This method also has some drawbacks. The dependencies among PSFs, a sequence of tasks, and control room operators are not treated appropriately.

There are other issues such as variability in experts and inappropriate treatment of time available for a task. Another imperfection of this method is the huge sensitivity in withdrawing or adding a task from the selected group of tasks.

2.4. Dynamic HRA Methods

The assessment of human reliability depends on the determination of both the required performance distribution and the achieved performance distribution. These two concepts of requirement and achievement are presented in Ref. [6, 7]. The quantified correlation between requirement and achievement represents a comparison between two competing variables. The method for the competition of two processes in time (growth time and suppression time by plant personnel) has also been used in fire risk analysis [8]. In the same manner, the success of the operators is governed by the time available for action (achievement) and the time required by the operators to diagnose the situation and act accordingly (requirement). Since both times are uncertain variables, the human error probability, HEP, is simply the fraction of times that the required time, T_1 (operational time) exceeds the available time, T_2 (phenomenological time).

Then,

$$HEP = P(T_1 > T_2) = \sum_t \text{Prob}[(T_1 > t) \text{ and } (T_2 = t)] = \sum_t P[(T_1 > t) * (T_2 = t)] = \int_0^\infty (1 - F_{T1}(t)) f_{T2}(t)\, dt \quad (1)$$

, where $F_{T1}(t)$ is the cumulative distribution of the operational time, T_1 and $f_{T2}(t)$ is the probability density function (pdf) of the time, T_2 (phenomenological time).

This method takes 3 steps.

1. Assessment of a stochastic distribution for T_1.
2. Assessment of a stochastic distribution for T_2.
3. Evaluation of these distributions as shown in Eq. (1).

The following Section describes an application of this method for quantifying the human error probabilities for an accident management action.

3. Application of the Dynamic HRA Method

The present method is applied to an operator action of flooding the cavity in a station blackout sequence before the core slumps. The time to core slumping is used because if the water reaches the vessel lower head after a significant amount of debris has relocated there, a film boiling situation will exist and the heat transfer will not be sufficient to cool the vessel enough to prevent melting and failure. Since the current EOPs do not contain specific instructions for initiating the flooding of the reactor cavity in the station blackout sequence, it is assumed that the current EOPs would be modified so that the procedures necessary to allow this strategy would be provided, and that the actions would be initiated at the time of core uncovery.

Based on the facts that the station would be blacked out, but the core exit thermocouples that might help in detecting core uncovery would be available, the failure of the plant operators to correctly initiate the strategy would be governed by two uncertain variables. The diagnosis and decision time (T_d) is the time available for the operators to initiate flooding of the reactor cavity. The auxiliary operators outside the control room are assumed to be available to operate the fire pump system.

It might take the operators time (T_a) to detect core uncovery, to dispatch an auxiliary operator to the emergency fire pump, and to start the fire pumps [9]. The major uncertainty is associated with the critical time determined by the phenomena occurring during the melt progression. Since the water must reach the top of the vessel lower head before the core slumps, the critical time, T_c, is $T_{cs} - T_{cu}$ (the time from core uncovery (T_{cu}) to core slumping (T_{cs})). Another relevant parameter is the time required to fill the reactor cavity up to the required level, T_f. This parameter is known and is a function of the reactor cavity volume [624 m^3 (164,830 gal)] of the reference plant and the fire pump capacity (2140 gpm), and is calculated to be 77 min [10].

Using T_{cu} as the reference time, the human error probability associated with the probability that t $(T_a+T_d+T_f)$ exceeds T_c $(T_{cs}-T_{cu})$ can be derived from Eq. (1) as follows:

$$HEP = P_r\,(t > T_{cs} - T_{cu})$$

$$= \int_0^{\infty} [1 - F_t(t)]\, f_{T_c}(t)dt, \qquad (2)$$

where

$f_{T_c}(t)$ = probability density function (pdf) of the critical time, $T_{cs}-T_{cu}$,

$F_t(t)$ = cumulative distribution function of the time required by the operators to complete the strategy.

By obtaining the two distributions, $F_t(t)$ and $f_{T_c}(t)$ in Eq. (2), a human error probability, which denote the likelihood of failure in performing a particular task within the time available, can be quantified. It should be noted that the numerous potential human performance shaping factors (PSFs) are incorporated in the distribution, $F_t(t)$.

The processes of determining the distributions of the uncertain variables are presented in the following Section.

3.1. Distribution of the Time to Core Slumping

3.1.1. Variable Screening for MAAP Parameters

Sensitivity analysis investigates the effect of changes in input variables on output predictions. MAAP sensitivity analysis has been performed by changing model parameters associated with the event timing of core slumping for the reference plant [10]. The core support plate failure time in the MAAP output corresponds to the core slumping time. The MAAP parameters that may highly affect the time to core slumping are selected according to the suggestion from the report [11] and they are listed in Table 1. Table 1 also lists the changes in the variables and the changes in the time to core slumping determined by the MAAP 3.0B code [12]. For example, the variation 0-2.0) in the initial FAOUT shows by how much it may vary due to insufficient knowledge.

In order to eliminate unimportant variables, the values of the variables given in Table 1 are used as the base values. Each variable is changed by an estimated amount and the MAAP code is run to determine the change in the time to core slumping due to the change in that variable. The change in the value of a variable may result from plant-to-plant variations, statistical uncertainty, or state-of-knowledge uncertainty. Although the variation of each variable is not the maximum possible variation, it is at least a large percentage of the maximum possible variation. The values in the last column (Δt) of Table 1 are used as criteria to eliminate unimportant variables. Only 8 variables caused changes that were larger than three minutes. They are listed in Table 2.

3.1.2. Latin Hypercube Sampling

There are several methods developed for the propagation of uncertainty; the method employed here is Latin Hypercube technique [13]. A sample size of 100 was used to propagate the uncertainty for the key variables through the MAAP 3.0B code. How each variable is sampled is determined by what kind of uncertainty is associated with it. Deterministic variables are sampled zero-one. This means that every sample observation contains either the value of 0.0 or the discrete variables (X1, X8). For variables with stochastic characteristics (X2-X7), the continuous distributions are sampled. The MAAP code is run for every member of Latin Hypercube samples and results in a point value for the time to core slumping for each member. The distribution of the time to core slumping ($f_{T_c}(t)$ in Eq. (2)) is found through the MAAP 3.0B calculation using a set of input data produced by Latin Hypercube sampling. The cumulative distribution of the time to core slumping is shown in Figure 1.

Table 1. Sensitivity Parameters And Their Values

Parameters	Definition	Typical Ranges	Base Case Value	$\|\Delta t^*\|$ Time (s)
FCRBLK	Flag to select use of channel blockage model	0-1	0	147
TEU	Eutectic melting temperature	2100-2800	2500 (K)	873
LHEU	Latent heat of fusion of eutectic mixture	1.0E5-4.E5	2.5E5[J/Kg]	1432
FAOX	Zircaloy oxidation area multiplier	1.0-2.0	1.0	952
TCLMAX	Clad rupture temperature	1200-2100	4502 [K]	105
VFSEP	Void fraction at which the primary system natural circulation stops	0.25-0.6	0.35	1268
FFRICR	Friction factor for axial flow in core	0.05-0.2	0.1	124
FFRICX	Friction factor for cross flow in core	.25-.45	.25	100
NSAMP	Coeff. to smooth numerical oscillation in core natural circulation	1-20	10	0
HTSTAG	Heat transfer coefficient between NC water and SG tube	100-5000	850 [J/sec/M2/K]	253
FAOUT	Fraction of SG tube carrying 'out' flow	0.1-0.5	0.5	257
FWHL	Flow coefficient for hot leg counter-current flow	0.09-0.115	0.115	12
IEVENT	Event code to clear RCP suction volume	0 or 1	0	3109

* The maximum difference between the result of base calculation (1033 sec) and that of the bound calculation for the core slumping timing.

Table 2. Eight variables Selected Via Screening Analysis

Variables	Base Case Value	Typical Range	Distribution Type
X1 : FCRBLK	1	0/1	Discrete
X2 : TEU	2500	2100.-2800. [K]	Uniform
X3 : LHEU	2.5E5	1.E5-4.E5 [J/Kg]	Uniform
X4 : FAOX	1.0	1.0-2.0	Uniform
X5 : VFSEP	0.35	0.25-0.6	Uniform
X6 : HTSTAG	850.0	100.-5000. [J/sec/m^2/K]	Uniform
X7 : FAOUT	0.5	0.1-0.5	Uniform
X8 : IEVENT	0	0/1	Discrete

3.2. Distribution of the Required Time by the Operators

Given the sampled timing data for the action time, maximum likelihood or moment estimators will result in the values of the parameters of the distributions. One type of distribution that has been extensively used for the operational (action time) is the two-parameter Weibull distribution. Using moment estimators, the values of λ and β can be obtained.

It is required to find $fr_a(t)$. Since the current EOPs of the reference plant are not developed for initiating the cavity flooding, the timing for historical events is not applicable. Instead, the simulator records col-

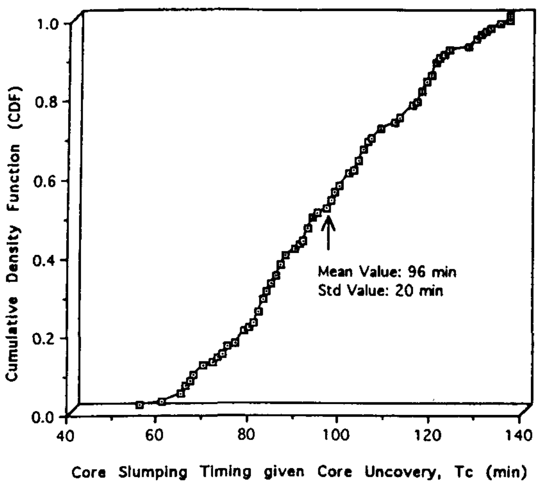

Fig. 1. Core Slumping Timing Produced from MAAP 3.0B Calculations with 100 LH Sample Sets of Inputs

lected for this analysis can be used. Nevertheless, no actual data were currently available for our use, so we were forced to assume a reasonable distribution for $f_{T_a}(t)$. There is a reason to believe that initiation of flooding the cavity might be delayed for several minutes past the time when the core uncovers. Contributors to this delay including stress, fear of adverse effects, and extreme environment might exist. After all, the performance shaping factors (PSFs) should be reflected to determining the distribution $f_{T_a}(t)$.

By interviewing the operators in the reference plant, it is assumed that the time required to fill the cavity is 15 ± 10 min. Then the values of the parameters of the Weibull distribution related to the mean and the variance can be solved numerically by one of the parameter estimation methods like the moment method, the curve fitting, the bayesian estimator, or the maximum likelihood estimator. Since all actions will have their own curve, a distribution will be determined.

4. Results

To solve the Eq. (2), the distributions of two random variables, the critical time (T_c) and the action time (T_a), should be obtained. A two-parameter Weibull distribution, represented as Weibull (λ, β), is considered here; however, the present method will work for other distributions as well. The density functions associated with T_c and Ta will be denoted by $f_{T_c}(t)$ and $f\ T_a(t)$, respectively, and its functional form is as follow:

$$f_c(t) = \frac{\beta}{\lambda}\left(\frac{t}{\lambda}\right)^{\beta-1}\exp\left\{-\left(\frac{t}{\lambda}\right)^{\beta}\right\},\ \lambda>0 \text{ and } \beta>0 \text{ for } t>0 \quad (3)$$

$$\mu = \lambda\,\Gamma\left(\frac{1+\beta}{\beta}\right) \quad (4)$$

$$\sigma^2 = \lambda^2\left[\Gamma\left(\frac{2+\beta}{\beta}\right) - \Gamma^2\left(\frac{1+\beta}{\beta}\right)\right] \quad (5)$$

, where Γ, λ and β are a gamma function, the scale factor and the shape factor, respectively.

Eq. (4) and (5) are used to estimate λ and β. The mean, m, is set to be the sample mean of 96.4 min and the variance, σ^2, is the sample variance of 20.2 min, based on the results (Figure 1). Then, Eq. (4) and (5) are solved numerically to find $\lambda=104.4$ and $\beta=5.5$. Using the distributions obtained by the approach given in the previous Section, the Eq. (2) becomes as follows:

$$\text{HEP} = \int_0^{\infty}\left[1-\exp\left\{-\left(\frac{t}{\lambda'}\right)^{\beta'}\right\}\right]\left[\frac{\beta}{\lambda}\left(\frac{t}{\lambda}\right)^{\beta-1}\exp\left\{-\left(\frac{t}{\lambda}\right)^{\beta}\right\}\right]dt \quad (6)$$

, where λ' and β' are the scale factor and the shape factor, respectively, associated with the time (μ', σ') taken by the operators in initiating water injection into the cavity via the emergency fire system.

By the Eq. (6), the HEP is calculated to be a value of 0.39. If the distribution of the critical time is so close to that of the time required by the operators to implement the cavity flooding strategy, the calculated HEP can significantly increase. The calculation results for various cases with different means and variances for the required time by the operators are shown in Table 3.a. Table 3.b shows the results for the case that the parameter T_f, the time required to fill the reactor cavity up to the required level, is almost zero.

Table 3. Dynamic Human Error Rates for the Time (T_f) Required to Fill the Reactor Cavity up to the Required Level with Respect to the Various Mean and Variance.

a)

μ' \ σ'	5	10	15
10	0.312	0.324	0.325
15	0.396	0.3921	0.378
20	0.479	0.450	0.424
30	0.541	0.517	0.490

b)

μ' \ σ'	5	10	15	20
15	6.13E-05	5.32E-04[1]	4.15E-03	1.09E-02
30	1.35E-03	2.79E-03	7.33E-03	1.86E-02
60	4.92E-02	5.97E-02	7.79E-02	1.01E-01

[1] The human error rate based on the values obtained by interviewing the operators in the reference plant.

This case may happen when the action of flooding the cavity initiates much earlier before core uncovery.

5. Conclusions

In this paper, a new dynamic HRA method has been presented for quantifying the human error probabilities and subsequently applied to a practical problem. The present method is very flexible in that it can be applied to any kind of the operator actions, including the actions associated with the implementation of accident management strategies.

Though the numerical calculations given here are only for illustrative purposes, assuming that steps to implement accident management actions could be taken and the hardware available, the information gained from using the method would be beneficial. The method may contribute to assessing the feasibility of the candidate strategies in advance and then developing accident management procedures.

The common features on all the existing HRA methods, including the dynamic HRA method, are that they only deal with the observable human errors, and that the dependencies of performance shaping factors (PSFs) are not treated appropriately. For the results of HRA to be realistic, first, PSFs need to be considered dependent each other, while they are assumed to be independent in the existing methods. Second, the causes and intention formation processes of the observable human errors need to be modeled and incorporated into human error assessments.

According to such recognition, recent researches have been focused on modeling how human intentions are formed and how they are executed. These developing cognitive models include CES (cognitive environmental simulation) model, GEMS (generic error modeling system) model, INTEROPS (integrated reactor operator/system) model, and COSIMO (Cognitive Simulation Model) [14 – 17]. To develop better cognitive models, psychology and cognitive science will be necessary tools in future.

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