

An Uncertainty Analysis for the Plant-specific Reliability Data Application

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Abstract

In spite of the current general trends of reliability data analysis using Bayesian techniques, which have been applied in most Korean PSAs, it is also necessary to apply the plant-specific data alone in risk-informed applications, because it can give more plant-specific insights. Considering the application of effective plant-specific data evidence, we developed the simulation methods for uncertainty propagation. With the separation of two uncertainty categories of both lack of knowledge and stochastic features, we can propagate the parameter uncertainty using Monte Carlo simulation technique. From the example application for the consideration on the arbitrary plant-specific input parameters, it shows that more broad uncertainty bounds can be developed than the case of generic input parameters.

1. Introduction

Probabilistic safety assessment (PSA) has been applied to nuclear facilities to give the reasonable end points' estimates against the uncertain future states of hazard sources and the undesirable scenarios. For nuclear power plants, in order to assure the operational safety during life time, the end points' measures should be based on a reasonable reliability data estimation of various components and human performance. Generally speaking, as described in ASME PSA standard [1], the objectives of the data analysis in the PSA are to provide estimates of the parameters used to determine the probability of the basic events representing equipment failures and unavailability in such a way that (a) parameters, whether estimated on the basis of plant-specific or generic data, appropriately reflect that configuration and operation of the plant, and (b) uncertainties in the data are understood and appropriately accounted for.

The parameter estimates may be based on relevant industry (i.e. generic) or plant-specific

evidence. The past general trends were to investigate methods of combining generic and plant specific data - in particular, the possibility of using Bayesian techniques. Especially, in most Korean PSAs, the EPRI ALWR URD [2] has been utilized as a generic data which is based on the result of extraction from the available sources, and its value is selected based on judgment regarding applicability to the anticipated ALWR designs. This application, on the other hand, may give some unavoidable bias in the estimation of actual plant-specific reliability parameters. It is also noted that the uncertainties introduced due to the use of generic data may be greater than the statistical uncertainties of plant-specific data alone [3]. Therefore, where feasible, the parameter estimates by using acceptable plant-specific data is more desirable. It is, however, recommended to evaluate the hypothetical effect on the plant-specific historical data to determine to what extent the data can be used. The major factors influencing to the hypothetical effect on the variation of plant-specific data can be specified as; regulatory policy & principles, maintenance policy, organization & management practices, and quality control program, etc. These 'influence factors' can directly or indirectly affect to the change of pool of plant-specific data, e.g., parameters of random failure characteristics.

In addition, the degree of uncertainty in using plant-specific data depends upon our total state of knowledge; upon all the evidence, data, and experience with similar courses of action in the past [4]. Therefore, a number of another factors affect the uncertainty in risk information. Interpreting the significance of the results of a PSA in light of the uncertainties is very important if the PSA results are to be applied to making meaningful decisions about changes in future risk.

2. Calculation Model and Method

This study presents the uncertainty analysis methodology for the case of plant-specific data variations, because it is important to identify the changes in the risk that could occur if several component failure probabilities were changed plant-specifically. The calculation method is proposed in order to consider the influence factors on the variation of plant-specific data. Firstly, the separation of uncertainty categories, depending on the individual features' characteristic and state-of-knowledge, is made in order to explicitly propagate the uncertainty. Next, parameter distribution for each plant-specific data is estimated to simulate the effects of influence factors. Finally, Monte Carlo technique is used because it is particularly appropriate for analysis problems in which large uncertainties are associated with the input variables.

A. Separating Treatment of Uncertainty

In general, the potential risks to future evolution from both lack of knowledge (i.e.,

epistemic) and stochastic features have been subjected to complex uncertainty assessment studies to those who want to use PSA techniques. Therefore, most risk assessors now agree that all the variables, which are used in the evaluation models for risk, contain both (i) variability (randomness) and/or (ii) subjective uncertainty, because of their specific nature. There were diverse approaches for effectively categorizing the uncertainty during the last decade [5-7].

Variability represents the heterogeneity in a well-characterized and/or known population, and is usually not reducible through further investigation or study. It has also been referred to as Type A uncertainty, inherent uncertainty, stochastic uncertainty, as well as aleatory uncertainty. On the other hand, subjective uncertainty represents our ignorance about a poorly-characterized phenomenon or models, and may be reducible through further measurement or study. It has also been referred to as Type B uncertainty, cognitive uncertainty, as well as epistemic uncertainty. The term of aleatory/epistemic uncertainty is mainly used in this study. Anyway, in addressing the critical parameters in a model, we should consider the ‘non-deterministic’ specific nature originating from a very broad range of aleatory and epistemic uncertainties, in addition to inaccuracy due to modeling and simulation error, as explained by Oberkampf, et al. [8]. Inaccuracy due to modeling and simulation error is not concerned in this study.

B. Uncertainty Propagation

Recently, some remarkable researches were made for the uncertainty propagation, with emphasis on the separation principle for both uncertainty types in each variable, so called ‘divide and conquer’, where are referred on Hoffman [9], Hofer [10], and Helton [11]. Also, the priority work is required to determine quantitatively how and in what way safety-related parameters contribute to risk. Therefore, it is essential to determine quantitatively how and in what way dominating uncertain variables contribute to risk, relating with diverse complex operating environment. The uncertainties arisen from different operating environments should be adequately propagated throughout the analysis. Also, in general, as the probability distribution well represents an expression of the quantitative, predicted values, it should be considered in the estimation of the end points’ measures. Probability distributions representing the uncertainties of plant-specific reliability data are used with some reasonable assumptions, which may simplify the given problem.

3. An Application

A. An Example Accident Sequence

To develop a probability distribution of parameters, reported available data must be interpreted in light of the use of the input variables in the model. It is well acknowledged that

uncertainties in a variable are treated in PSAs as being aleatory when the variable is assumed to be the result of a random process. Combined with the epistemic uncertainty of their parameters, we can imagine a variable status with ‘true but unknown’ distributions, as shown in Fig. 1. The assessment of distribution representing the variable uncertainty will follow the selection basis of Hattis [12]. In this study, as used in most PSAs, the lognormal distribution is assumed for aleatory uncertainty of all related parameters. For the case of epistemic uncertainty, the triangular distribution is assumed. As an example, station-blackout-induced core damage sequence from Ulchin 3&4 PSA [13] is selected, thus one minimal cutset is provided for the application as follows:

$$\text{MCS\#2 (of LOOP-26)} = \text{ILOOP} * \text{AFTPW01B2A} * \text{EGDGK01ABET} \\ * \text{NR-AC6HR}$$

Where,

ILOOP = Initiating event (loss of offsite power, frequency = $6.15e-2/\text{yr}$),

EGDGK01ABET = 1E DG-01A & 01B & AAC DG-01E CCF fail to run ($\beta\gamma\lambda T_m$),

AFTPW01B2A = CCF (demand failure) of AFW TDP 01B & 02A (2/2) (βQ),

NR-AC6HR = Non-recovery action probability of AC power within 6 hours (0.14).

B. Parameter Estimation Process

Table 1 shows the information of the related failure rates, demand probability, and common cause failure (CCF) factors of emergency DG and AFW TDP, which were used in Ulchin 3&4 PSA. Table 2 shows the reliability database of both generic and plant-specific evidence from the currently available database sources, especially for two major components denoted in above minimal cutset, where probability distribution of initiating event frequency is not specified because we desire to get any available insights only regarding component reliability data. In other words, in order to simplify the uncertainty problem, initiating event frequency, human action probability, and common cause failure factor are not concerned, but random failure probabilities are investigated. The plant-specific data for KSNP (YGN 3&4 and UCN 3&4) collected and analyzed by Han [14] was also utilized to give another evidence for plant-specific data. With the arithmetic evaluation of plant-specific values given in Table 2, the basic event parameters of exemplified accident sequence chosen in this study were derived for arbitrary plant-specific epistemic distributions. It is assumed, also, that all components used in various plant-specific data have similar characteristics, and have essentially enough operating experiences (i.e., component population times operating years), in order to reduce a sampling standard error.

C. Uncertainty Propagation Results

To propagate the parameter uncertainty, Monte Carlo simulation technique is used. Because simple random sampling is preferred when sufficiently large samples are possible, on the other hand, because Latin hypercube sampling is used when large samples are not computationally practicable, we decided to establish an application principle for Monte Carlo sampling; (1) to use simple random sampling technique for aleatory uncertainty propagation, and (2) to apply Latin hypercube sampling technique for epistemic uncertainty propagation. Desirable features of Latin hypercube sampling are to give unbiased estimates for parameters across the range of sample variable [15].

The plots obtained from the program running of uncertainty propagation are presented with the probability distributions of sampled accident sequence, as shown in Fig. 2 and Fig. 3. As an end points' measure, specific risk criteria, e.g., conditional core damage probability (CCDP) given LOOP event in this case, is used. Fig. 2 shows the traditional propagation results using generic data, as a form of cumulative density function, which results in a mean value of $5.46e-5$ and the error factor of 28.4. Fig. 3 shows the summarized propagation results using arbitrary plant-specific data, as a form of resultant family of probability density functions. The distributions shown in Fig. 3 provide the variability in the outcome that varies with different percentile levels of uncertainty. From all the curves in Fig. 2 and Fig. 3, one can conclude that under Monte Carlo simulation, more broad uncertainty ranges in application of plant-specific reliability data than generic data may be developed. The range of true uncertainty can be also obtained by determining the width of the confidence interval about a specified confidence bound (such as 95th) of all the variability curves.

4. Concluding Remarks

The results in the application of arbitrary plant-specific data evidence give us some insights for the applicability of risk information. For example, the confidence range considering the parameter uncertainty can be varied according to the specific application problems. It is also noted that more specified plant-specific data considering various influence factors can greatly reduce the uncertainty bounds in the actual problem. The effects of influence factors to the plant-specific component reliability behavior should be more researched with the methodology development.

We can easily imagine that the overall uncertainty consideration on the plant-specific evidence of other input variables in PSA, such as initiating event frequency, human error probability, and common cause failures, as well as random failure probabilities, will give more

plant-specific insights in the risk-informed decision making.

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Table 1. The values used in Ulchin 3&4 PSA

Components	Point Estimate (Q)	Error Factor (EF) of Point Estimate	CCF β	CCF γ	CCF EF
AFW TDP (AFTP)	1.5e-2/d	3.6	0.797	-	10.
EDG	2.4e-3/hr * 24 hr	3.2	0.0883	0.9423	10.

Table 2. Reliability database in various sources

Data Category	Data Sources ([Ref.])	AFTP Fail to Start (FTS, /demand)	EF of AFTP FTS	EDG Fail to Run (FTR, /hr)	EF of EDG FTR
Generic	EPRI ALWR URD [2]	1.5e-2	3.6	2.4e-3	3.2
	EUR, Rev. B [16]	7.0e-3	10.	3.0e-3	5.0
Plant-specific	KSNP [14]	1.71e-2		2.54e-2	
	Oconee NPP [2]	5.3e-2		-	
	Zion NPP [2]	2.6e-2		4.5e-3	
	Indian Point NPP [2]	5.8e-3		8.2e-4	
	Millstone NPP [2]	-		9.8e-4	

Table 3. The parameter values adopted for the application

Parameters\Components		AFTP		EDG	
Type A	Dist.	Log-Normal		Log-Normal	
		Median	CCF EF (Note)	Median	CCF EF (Note)
Type B	Dist.	Tri.	Tri.	Tri.	Tri.
	Min.	5.8e-3	10 - α	8.2e-4	10 - α'
	Mode	2.5e-2	10.	7.9e-3	10.
	Max.	5.3e-2	10+ α	2.5e-2	10 + α'

(Note) Epistemic distribution of error factors depends on the complexity of the study. In this case, we assume that these distributions are very narrow. Therefore, single small value is given to the alpha.

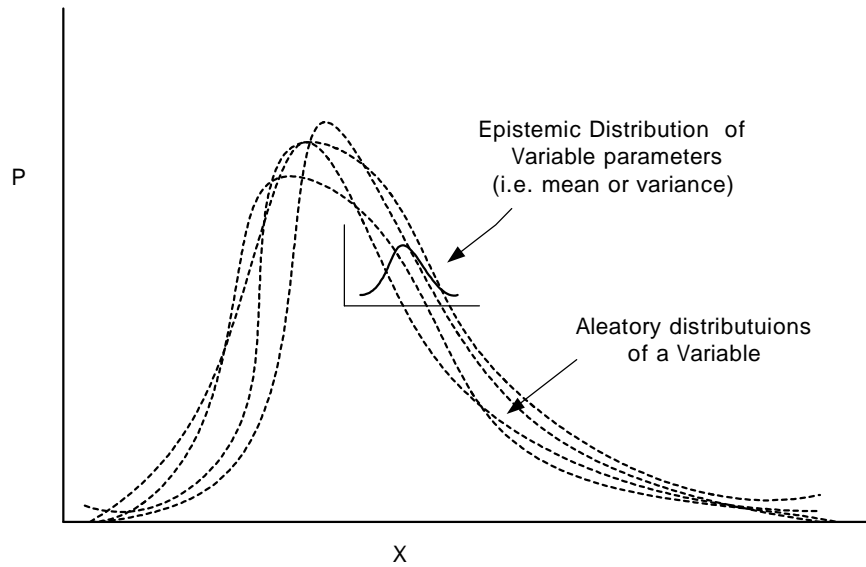


Fig. 1. Conceptual representation of 'True but unknown' distributions. The large 4 distributions shows a example for aleatory uncertainty of given variable. The actual profile of aleatory uncertainty is not shown in this figure. Imaginatively, the small distribution shows epistemic uncertainty in a parameter of given variable.

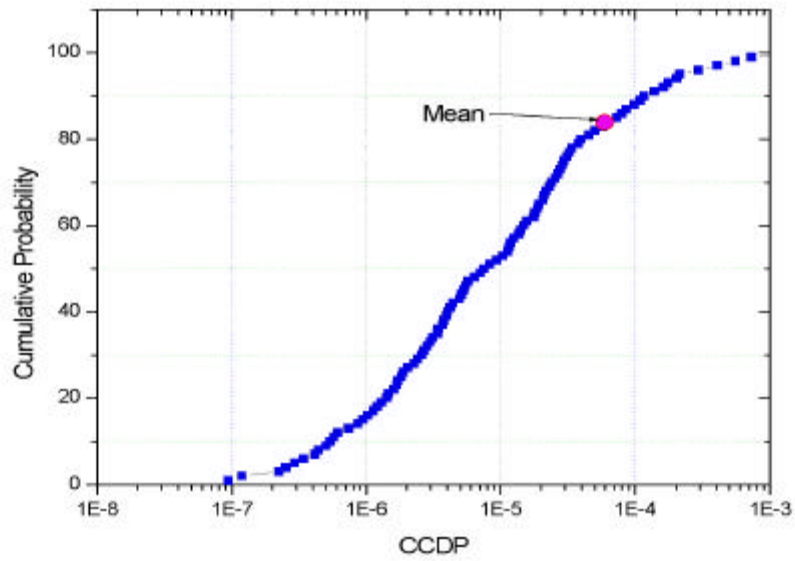


Fig. 2 End points' measure representation #1 by the Monte Carlo simulation – Use of generic data for parameter estimation

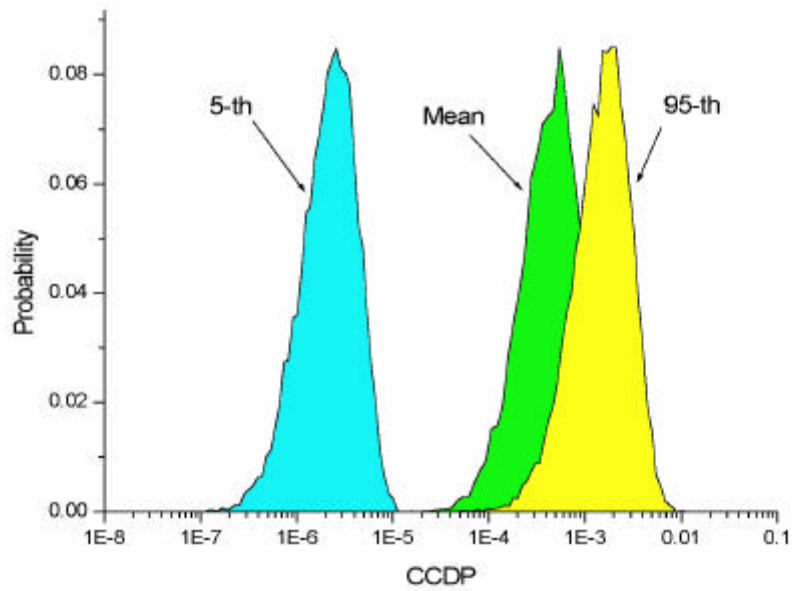


Fig. 3 End points' measure representation #2 by the Monte Carlo simulation – Use of arbitrary plant-specific evidence for parameter estimation