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A Combined Procedure of RSM and LHS for Uncertainty Analyses of *CsI* Release Fraction Under a Hypothetical Severe Accident Sequence of Station Blackout at Younggwang Nuclear Power Plant Using MAAP3.0B Code

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Abstract

Quantification of uncertainties in the source term estimations by a large computer code, such as MELCOR and MAAP, is an essential process of the current probabilistic safety assessment. The main objective of the present study is to investigate the applicability of a combined procedure of the response surface method (RSM) based on input determined from a statistical design and the Latin hypercube sampling (LHS) technique for the uncertainty analysis of *CsI* release fractions under a hypothetical severe accident sequence of a station blackout at Younggwang nuclear power plant using MAAP3. 0B code as a benchmark problem. On the basis of the results obtained in the present work, the RSM is recommended to be used as a principal tool for an overall uncertainty analysis in source term quantifications, while using the LHS in the calculations of standardized regression coefficients (SRC) and standardized rank regression coefficients (SRRC) to determine the subset of the most important input parameters in the final screening step and to check the cumulative distribution functions obtained by RSM. Verification of the response surface model for its sufficient accuracy is a prerequisite for the reliability of the final results that can be obtained by the combined procedure proposed in the present work.

1. Introduction

There are many uncertainties associated with the application of large computer codes, such as MELCOR [1] and MAAP [2] developed to represent accident progression, thermal-hydraulic phenomena, radionuclide behavior and transport, and environmental consequence analysis for severe reactor accident. Therefore, currently, the determination of the uncertainty in source term estimations calculated by MELCOR and MAAP has become an essential phase of the probabilistic safety assessment (PSA). The main reason for this is because the complex physical processes governing the phenomena that determine the radiological releases following severe reactor accidents are not completely understood yet. In the source term analysis, the phenomena during a hypothetical severe reactor accident are simulated by a mechanistic approach using large computer codes. The sources of uncertainties in mechanistic analyses arise mainly from imperfect modeling of phenomenology and/or from inaccuracy in physical parameters, which in a large code such as MAAP and MELCOR, usually appear in the form of input data [3]. The present work is mainly concerned with the treatment of the latter source of uncertainties associated with MAAP3. 0B code.

Many different techniques [3-18] have been proposed for performing uncertainty and sensitivity analyses on computer models for complex processes. Cox and Baybutt [5] conducted a survey and comparative evaluation of methods which have been developed for the determination of uncertainties in accident consequences and probabilities for use in probabilistic safety assessment (PSA). The methods included in their study are (1) analytic techniques, (2) Monte Carlo simulation, (3) response surface approaches, (4) differential sensitivity techniques, and (5) evaluation of classical statistical confidence bounds. According to their conclusion only the response surface and differential approaches are sufficiently general and flexible for use as overall methods of uncertainty analysis in PSA. The other methods considered, however, are very useful in particular problems : The Monte Carlo method, in particular, can be applied when output is not too expensive to evaluate, and partitioning of output uncertainty is not needed.

More recently, Iman and Helton [9] investigated the applicability of three widely used techniques to three computer models having large uncertainties and varying degrees of complexity in order to highlight some of the problem areas that must be addressed in actual applications. They considered the following three approaches to uncertainty and sensitivity analysis : (1) response surface methodology (RSM) based on input determined from a fractional factorial design ; (2) Latin hypercube sampling (LHS) with and without regression analysis ; and (3) differential analysis. They concluded that the technique using LHS and regression analysis had the best overall performance with respect to the following four criteria : (1) ease of implementation, (2) flexibility, (3) estimation of the cumulative distribution function of the output, and (4) adaptability to different methods of sensitivity analysis.

Kim et al. [10,11] suggested a statistical procedure using a RSM for analyzing the thermal margin of light water reactor core. They concluded that two level factorial design in RSM is a valuable method for investigating the sensitivities of input parameters. In their paper, three different methods are compared for the thermal margin of light water reactor core. But generally one should assess the reliability of uncertainty estimated by RSM for specific application problems, such as a severe accident analysis.

Kim et al. [10,12] proposed a technique based on the Fourier amplitude sensitivity test (FAST) and stepwise regression techniques (SRT) and applied to the thermal margin analysis of peak clad temperature for a loss of coolant accident. Kim et al. [10,12] pointed out that the FAST and SRT method needs a moderate number of sampling points compared to the crude Monte Carlo method. This method is applicable to perform a specific problem that is necessary for detailed information of uncertainties because it requires relatively large cost when it is used for an uncertainty analysis of large computer codes.

Park et al. [13] has developed a two-step tail area sampling technique which is effective for a long-tailed distribution such as a lognormal distribution. They recommanded that their method is more effective to perform a uncertainty analysis given inputs having long-tailed distributions.

Lee et al. [14] and Park et al. [15] proposed uncertainty analysis methods based on a Latin hypercube sampling technique. The essential feature of the methods proposed by Lee et al. [14] and Park et al. [15] is to determine the uncertainty distribution by performing the goodness-of-fit test for the result obtained by LHS. Park et al. [15] concluded that their method is useful to perform a large computer code uncertainty quantification problem with limited time and resources. However, the procedure to identify key contiributors of uncertainty has not been shown in the above papers.

Chun and Ahn [16] developed an alternative approach of uncertainty quantification using a fuzzy set theory as a complement or an alternative to the methods currently used in the risk assessment of nuclear power plants where experts opinion is a major means for quantifying some event probabilities and uncertainties. They concluded that the approach should be improved before it can easily be used for PSA purposes.

In the previous work [17,18], two methods of uncertainty quantification, i.e., the response surface method (RSM) and the Latin hypercube sampling (LHS) method have been assessed for applications to the source term uncertainty analysis of the Younggwang nuclear power plant using the MAAP 3.0B code. The results show that the RSM is difficult to generate an accurate response surface whereas the LHS method is difficult to treat the key contributors of uncertainty when both methods are used alone independently. In the source term analysis, the RSM has relative advantages in the analysis of importance and sensitivity: An important qualitative information about the relation between the inputs and outputs can be obtained. However, this advantage of the RSM does not outweigh the loss in accuracy when the approximate model used is not adequate. The LHS method is more readily executable without any prior procedure to obtain an approximate model to replace the large computer code.

The main feature of the present combined procedure for uncertainty analysis in source term quantifications is to use the Latin hypercube sampling (LHS) method in the calculation of standardized regression coefficients (SRC) and standardized rank regression coefficients (SRRC) to determine the subset of the most important input parameters in the final screening step. Another key idea is the suggestion to use the RSM as a principal tool for overall uncertainty analysis in source term quantification, while using the LHS method in checking the empirical distribution functions obtained by RSM. The main purpose of the present work is to present a combined procedure using RSM and LHS for uncertainty analysis of *CsI* release fractions under a hypothetical severe accident sequence of station blackout at Younggwang nuclear power plant using MAAP3.0B code as a benchmark problem for general applications in the source term uncertainty analyses.

2. Outlines of Two Uncertainty Analysis Methods Used for Computations and Checking

In the present work, the following often used two approaches to uncertainty analysis are selected to use together for actual computations and testing the result:

(1) Response surface method (RSM) based on input determined from an experimental design (more specifically, a foldover based on the Plackett-Burman design, augmented by center and star points).

(2) Latin hypercube sampling (Modified Monte Carlo).

The RSM is used here as a principal tool for overall uncertainty analysis in source term quantifications, whereas LHS method is used in the calculation of SRC and SRRC in the final screening step and testing of the response surface model obtained by RSM in the final stage. Since this study is not intended to be a detailed investigation of RSM and LHS, only key features of these methods are summarized here for convenience in discussions.

2.1. Response Surface Method of Uncertainty Analysis

Response surface methods of uncertainty analysis were developed to overcome the disadvantages of the Monte Carlo approach [5].

In the present work, the response surface equation obtained in a least-squares fitting procedure is a second-order polynomial in the input parameters [6-12]:

$$\hat{Y} = a_0 + \sum_{j=1}^{k} a_j X_j + \sum_{j=1}^{k} \sum_{l=j+1}^{k} a_{jl} X_j X_l + \sum_{j=1}^{k} a_{jj} X_j^2 \quad (1)$$

where $\tilde{Y}$ is the estimate of the response from the response surface equation, and a_0, a_i, a_{ii}, and a_{ij} are numerical coefficients estimated by least-squares fitting. A response surface replacement for a computer model is based on using an experimental design to select a set of specific values and pairings of the input variables X_1, X_2, $\cdots$, X_k that are used in making N runs of the computer model. The model output $\tilde{Y}_i (i=1, 2, \cdots, N)$ and input X_1, X_2, $\cdots$, X_k are used to estimate the numerical coefficients of Eq. (1). The estimated model is known as a fitted response surface, and it is this response surface that is used as a replacement for the computer model [9]. All inferences with respect to uncertainty analysis for the computer model are then derived from this fitted model.

2.2. Latin Hypercube Sampling Method of Uncertainty Analysis

Latin hypercube sampling (LHS), a type of stratified Monte Carlo sampling, has recently been used in uncertainty and sensitivity analyses of various computer models [4,8,9,14,15,17,18]. Iman and Helton [9] have shown that LHS technique offers an effective alternative to the response surface replacement approach.

Because of the random pairing of intervals in the mixing process, there exists the possibility of inducing undesired pairwise correlations among some of the variables in a Latin hypercube sample. This is more likely to occur if sample size n is small [9]. The choice of the sample size n will be dominated by the cost of making a single computer run and the number of input parameters k. However, it is preferable that sample size n be greater than or equal to $(4/3)k$ [9]. A comprehensive list of references on the use of LHS in uncertainty and sensitivity analysis can be found in Ref. 9.

3. A Combined Procedure of RSM and LHS for Uncertainty Analyses of *CsI* Release Fraction Under a Severe Accident Sequence Using MAAP3.0B

The two uncertainty analysis methods described in the above are now applied to the uncertainty analysis associated with estimations of *CsI* release fraction to the environment under a hypothetical severe accident sequence of a station blackout (SBO) of Younggwang 3&4 nuclear power plant [19]. The SBO sequence is an accident to cause core damage due to the loss of all electric powers in the nuclear power plant. The Younggwang nuclear power reactors are 2,815 MWt, 2-loop type PWRs and each reactor is housed in a large dry containment.

Only the *CsI* group release fraction at 10 hours after the occurrence of containment failure under a given SBO accident sequence has been estimated here for source term uncertainty analyses using MAAP3.0B code, although this code can calculate the behavior of 12 source term groups.

The MAAP (Modular Accident Analysis Program) version 3.0B used in this work simulates the response of light water reactor (LWR) power plants during severe accident sequences. This code quantitatively predicts the evolution of a severe accident starting from full power conditions given a set of system faults and initiating events through events such as core melt, reactor vessel failure, and containment failure. A detailed information on MAAP3.0B is given in Ref. 2. An alternative code whose scope is similar to MAAP is MELCOR [1], but less experience has been accumulated with this code than with MAAP. This is especially true for PWRs.

3.1. Screening of Effective Input Parameters and Selection of the Values of the Input Parameters

The first step (in the second stage) of the present uncertainty analysis is the screening of the input variables, leaving only those most affecting the calculated consequences. The general problem addressed by screening is one that is basic to most large, complex deterministic models and computer codes that solve large system of equations requiring a vast number of input parameters whose quantitative importance is not known. Screening sensitivity analysis is designed to determine the relative significance of each input parameters for which an extensive uncertainty analysis is needed [4].

In the present analysis, three techniques, (1) subjective method, (2) one-at-a-time design, and (3) standardized regression coefficient (SRC) and standardized rank regression coefficient (SRRC), are used in series as described in the following.

(1) Screening by Subjective Method :

MAAP3.0B code has a total of 77 phenomenological model parameters. MAAP's treatment of uncertain severe accident phenomena is controlled by these model parameters. Model parameters are used both as inputs to a given physical model and to select between alternative descriptions of a phenomenon. A best-estimate value and range for these parameters are given in the code documentation [20].

As a first cut at the 77 input model parameters of MAAP3.0B code, 39 model parameters are selected by subjective method based on selection criteria given in Ref. 20. These 39 parameters are used in the following step of sensitivity analysis to assess the relative significance of each input model parameters.

(2) Screening by One-At-A-Time Design :

The uncertainty of the input parameters can be quantified by treating the parameters as random variables with appropriate density functions (pdfs) or cumulative distribution functions (cdfs). The uncertainty ranges of each of the 39 parameters used in the present screening process are obtained from the full ranges of each input parameter given in MAAP 3.0B code manual [2]. A uniform distribution is assumed to be valid for most parameters, whereas a log-uniform distribution is assumed to be valid for those parameters whose uncertainty ranges exceed 10^2. Based on the magnitude of the sensitivity coefficient of each parameter, 22 parameters are selected to be assessed further in the following step (Table 1). The intermediate results along with all the necessary data used for this step can be found in Ref. 21.

(3) Screening by the Coefficients of SRC and SRRC :

In this final screening step to determine the subset of the most important input parameters, SRC and SRRC are first calculated for 22 input parameters using the Latin hypercube sampling (LHS) with a minimum sample size of 23. The 22 input parameters are then ranked according to the magnitudes of both SRC and SRRC of each input parameters. Based on the rank of SRC and SRRC of each parameter and the results obtained in the previous steps of screening, only 12 most important parameters are finally selected out of 22 parameters examined in this step (Table 1). Range and distribution functions assumed, along with a description of the 12 most important parameters, are given in Table 2. These variables are assumed to behave independently of one another.

3.2. Uncertainty Analyses by RSM and LHS

3.2.1. Uncertainty Analysis by RSM

The response surface method of uncertainty analysis consists of (1) screening to determine the subset of important parameters, (2) statistical design for an efficient empirical exploration of the response surface, (3) response surface modeling to obtain a proxy to the original code (MAAP3.0B in the present case), and (4) estimation of the output distribution function. Screening of the input parameters, however, has already been described in the above, because this step is common to both methods of RSM and LHS. The remaining 3 steps are described in the following.

(1) Statistical Design Selected for This Work :

With the RSM uncertainty analysis, the perturbations of the input parameters are carried out according to an experimental design that enables an efficient empirical exploration of the response surface. The choice of the experimental design depends on the number of inputs to be varied, but the basic approach is to implement a composite design in a sequential manner.

The statistical design selected for this work is a foldover based on the Plackett-Burman design, augmented by center and star points. This combination of design accounts for the linear and quadratic effects of the inputs as well as those of two-factor interactions between inputs, while requiring a

Table 1. Screening by One-at-a-time Design and by Coefficients of SRC and SRRC

Screening by One-at-a-time	Screening by SRC and SRCC	Model Parameters	Min.[1]	Max.[2]	PDF[3]	|SRC|[4]	|SRRC|[5]
√[6]	√	CSHAPE	1	15	Uniform	5.808E-03(22)[7]	8.696E-02(14)
√	×[8]	SCALH	0.5	10	Uniform	4.056E-01(2)	2.687E-01(5)
√	√	FRCOEF	0.001	0.1	Logunform	3.381E-01(4)	2.104E-01(8)
√	√	TDSTX	0	0.5	Uniform	3.009E-02(20)	1.997E-01(9)
√		TCNMP	1200	1950	Uniform	9.014E-02(17)	7.708E-02(15)
√	√	FAOX	1	2	Uniform	2.474E-01(11)	1.482E-01(13)
√		FCSIVP	−100	100	Uniform	3.599E-02(19)	1.581E-01(11)
√	√	ACFPR	0.01	10	Logunform	3.168E-01(5)	3.360E-02(20)
√	√	TEU	2400	3000	Uniform	2.170E-01(12)	1.719E-01(10)
√	√	LHEU	1	1E06	Logunform	1.571E-01(13)	1.383E-02(22)
√	√	TTENTR	0.1	10	Uniform	3.045E-01(7)	5.276E-01(2)
√		TTRX	30	1000	Uniform	4.331E-02(18)	2.628E-01(6)
√	×[9]	PCF	577000	1.5E06	Normal	6.415E-01(1)	7.559E-01(1)
√	√	HTCMCR	500	5000	Uniform	3.050E-01(6)	1.512E-01(12)
√	√	FFPREL	0.01	1	Logunform	2.848E-01(8)	3.112E-01(4)
√	√	XRSEED	1E-07	1E-06	Uniform	2.552E-01(10)	3.142E-01(3)
√		FENTR	0.2	100	Logunform	1.004E-02(21)	5.534E-02(17)
√		FPRAT	1	2	Flag	2.662E-01(9)	5.249E-02(18)
√		GSHAPE	1	10	Uniform	1.362E-01(14)	1.680E-02(21)
√		FCRBLK	0	1	Flag	1.029E-01(15)	3.926E-02(19)
√		FCHF	0.12	0.3	Uniform	9.513E-02(16)	7.312E-02(16)

1) Min. : minimum value.
2) Max. : maximum value.
3) PDF : probability density function.
4) |SRC| : absolute value of SRC.
5) |SRRC| : absolute value of SRRC.
6) √ : selected parameter by the screening.
7) ( ) : ranking of parameter.
8) unselected parameter bacause some values of SCALH can drive anunstable code run.
9) unselected parameter bacause some values of PCF can result in a long time to containment failure (>48hr), which is unreasonable to calculate the *CsI* release fraction at 10 hours after the occurrence of containment failure.

Table 2. Minimum and Maximum Values and Distribution Functions Assumed for 12 Most Important Model Parameters

Model Parameter	Description of the Parameter	Minimum Values	Maximum values	Distribution Functions Assumed	Random Variable
FRCOEF	Friction coefficient used to compute heat transfer coefficient in vessel failure	0.001	0.1	Loguniform	$X_1 = \log_{10} x_1$
ACFPR	Containment failure area (m^2)	0.005	10.0	Loguniform	$X_2 = \log_{10} x_2$
FAOX	Clad surface multiplier	1.0	2.0	Uniform	$X_3 = x_3$
TDSTX	Time delay between debris contact with floor and initiation of steam explosion (sec)	0.0	0.5	Uniform	$X_4 = x_4$
FFPREL	Multiplier for in-vessel fission product release rates	0.01	1.0	Loguniform	$X_5 = \log_{10} x_5$
HTCMCR	Heat transfer coefficient between corium pool and frozen crust (W/m-K)	500.0	5000	Uniform	$X_6 = x_6$
FCMDCH	Debris fragmentation fraction	0.0	1.0	Uniform	$X_7 = x_7$
TTENTR	Time constant for debris transport (sec)	0.1	10.0	Loguniform	$X_8 = \log_{10} x_8$
CSHAPE	Shape factor for aerosol settling velocity	1.0	15.0	Uniform	$X_9 = x_9$
LHEU	Latent heat of U-Zr-O eutectic (J)	1.0	1.0×10^{6}	Loguniform	$X_{10} = \log_{10} x_{10}$
XRSEED	Seed radius of hygroscopic aerosol (m)	1.0×10^{-7}	1.0×10^{-6}	Uniform	$X_{11} = x_{11}$
TEU	Eutectic melting temperature (K)	2400.0	3000.0	Uniform	$X_{12} = x_{12}$

small number of computer runs [3]. As a special case of the resolution Ⅲ design, the Plackett-Burman design does not meet the requirement of Eq. (1), for the main effects, although independent of each other, are confounded with two-factor interaction effects, and the latter with each other. To eliminate confounding between the main effects and the two-factor interaction effects, a foldover design can be constructed by adding to the Plackett-Burman design, a duplicated design with reversed signs [3].

The foldover design based on the Plackett-Burman design doubles the number of runs in the resolution Ⅲ design but allows one more factor to be studied by association of that factor with the identity-column in the resolution III design. This design requires 24 observations ($N=24$) to study 12 parameters and accounts for the linear effects and two-input interaction effects. To account for the quadratic effects, one center point and 24 star points are added to the foldover design.

In the present analysis, all input variables are normalized as follows :

$$\alpha_{ij} = \frac{(x_{ij} - \mu_j)}{\sigma_j} \tag{2}$$

where $i=1, 2, \cdots, N$ (number of code runs), and $j=1, 2, \cdots, k$ (number of input parameters). In Eq. (2), α_{ij} = i'th dimensionless value of j'th input, x_{ij} = i'th value of j'th perturbed input, μ_j = mean value of j'th input, and σ_j = standard deviation of uncertainty distribution of j'th input. Then α_{ij} is equal to ± 1, implying a variation of $\pm\sigma_j$ about the nominal value μ_j.

In summary, the statistical design selected for this work requires a total of 49 observations for 12 input parameters as shown in Table 3. This design accounts for the linear effects, the quadratic effects of each input parameter, and the effects of two-input interactions. The linear and quadratic effects are in-

Table 3. Plackett-Burman Design for N=12, k=11 Obtained by Foldover Augmented by Center and Star Points

	A	B	C	D	E	F	G	H	I	J	K	Id.
Plackett-Burman Design for 11 Factors	+[a]	−[a]	+	−	−	−	+	+	+	−	+	+
	+	+	−	+	−	−	−	+	+	+	−	+
	−	+	+	−	+	−	−	−	+	+	+	+
	+	−	+	+	−	+	−	−	−	+	+	+
	+	+	−	+	+	−	+	−	−	−	+	+
	+	+	+	−	+	+	−	+	−	−	−	+
	−	+	+	+	−	+	+	−	+	−	−	+
	−	−	+	+	+	−	+	+	−	+	−	+
	−	−	−	+	+	+	−	+	+	−	+	+
	+	−	−	−	+	+	+	−	+	+	−	+
	−	+	−	−	−	+	+	+	−	+	+	+
	−	−	−	−	−	−	−	−	−	−	−	+
Foldover (Sign Reversed Plackett-Burman)	−	+	−	+	+	+	−	−	−	+	−	−
	−	−	+	−	+	+	+	−	−	−	+	−
	+	−	−	+	−	+	+	+	−	−	−	−
	−	+	−	−	+	−	+	+	+	−	−	−
	−	−	+	−	−	+	−	+	+	+	−	−
	−	−	−	+	−	−	+	−	+	+	+	−
	+	−	−	−	+	−	−	+	−	+	+	−
	+	+	−	−	−	+	−	−	+	−	+	−
	+	+	+	−	−	−	+	−	−	+	−	−
	−	+	+	+	−	−	−	+	−	−	+	−
	+	−	+	+	+	−	−	−	+	−	−	−
	+	+	+	+	+	+	+	+	+	+	+	−
Cemter Point	0[b]	0	0	0	0	0	0	0	0	0	0	0
Star Points	+2[c]	0	0	0	0	0	0	0	0	0	0	0
	−2[c]	0	0	0	0	0	0	0	0	0	0	0
	0	+2	0	0	0	0	0	0	0	0	0	0
	0	−2	0	0	0	0	0	0	0	0	0	0
	0	0	+2	0	0	0	0	0	0	0	0	0
	0	0	−2	0	0	0	0	0	0	0	0	0
	0	0	0	+2	0	0	0	0	0	0	0	0
	0	0	0	−2	0	0	0	0	0	0	0	0
	0	0	0	0	+2	0	0	0	0	0	0	0
	0	0	0	0	−2	0	0	0	0	0	0	0
	0	0	0	0	0	+2	0	0	0	0	0	0
	0	0	0	0	0	−2	0	0	0	0	0	0
	0	0	0	0	0	0	+2	0	0	0	0	0
	0	0	0	0	0	0	−2	0	0	0	0	0
	0	0	0	0	0	0	0	+2	0	0	0	0
	0	0	0	0	0	0	0	−2	0	0	0	0
	0	0	0	0	0	0	0	0	+2	0	0	0
	0	0	0	0	0	0	0	0	−2	0	0	0
	0	0	0	0	0	0	0	0	0	+2	0	0
	0	0	0	0	0	0	0	0	0	−2	0	0
	0	0	0	0	0	0	0	0	0	0	+2	0
	0	0	0	0	0	0	0	0	0	0	−2	0
	0	0	0	0	0	0	0	0	0	0	0	+2
	0	0	0	0	0	0	0	0	0	0	0	−2

[a] ± = ±0.856(±25%).
[b] 0 = ±0.000 (mean).
[c] ±2 = ±1.386(±45%).

dependent of each other and from two-factor interactions, but the latter are confounded with each other. Higher order interactions between three or more input factors are not accounted for, but normally they are negligible [3].

(2) Response Surface Modeling :

The statistical design described above, when used in connection with a computer code, generates a set of calculated values (observations) for the consequence of interest. From these observations, a linear regression technique constructs the multivariable function Y of the calculated consequence. That is, using the statistical design described above, 49 responses (*CsI* release fractions at 10 hours after the occurrence of containment failure) have been calculated by MAAP3.0B. These 49 responses are then used in a least-squares fitting procedure to estimate the numerical coefficients a_0, a_j, a_{jl}, and a_{jj} in Eq. (1). These coefficients are chosen in the least-squares sense to minimize the standard error of the fit. The resulting multivariate function $\tilde{Y}_{CsI}$ representing the log *CsI* release fraction (transformed into logarithmic values) at 10 hours after the occurrence of containment failure under a station blackout accident sequence is as follows :

$$\begin{aligned}
\tilde{Y}_{CsI} = & \log_{10} \tilde{y}_{CsI} \\
= & - 1.01226 + 0.02434X_1 + 0.24005X_2 - 0.02153X_3 + 0.05670X_4 \\
& + 0.04138X_5 - 0.01547X_7 - 0.09064X_8 + 0.03068X_9 + 0.04505X_{10} \\
& - 0.07454X_{11} + 0.08451X_{12} \\
& + 0.10957X_1X_8 - 0.05955X_1X_{12} + 0.07465X_2X_3 + 0.11925X_2X_8 \\
& - 0.11116X_2X_{10} - 0.09440X_3X_4 - 0.04404X_3X_5 - 0.06014X_3X_{11} \\
& - 0.05155X_4X_5 - 0.07112X_{4X_{12}} + 0.02895X_5X_{10} - 0.06200X_5X_{12} \\
& + 0.16722X_{11}X_{12} \\
& - 0.11357X_1^2 - 0.06022X_2^2 - 0.05629X_5^2 - 0.11337X_8^2 \\
& - 0.04698X_9^2 - 0.19005X_{10}^2 - 0.03811X_{11}^2 - 0.05172X_{12}^2 . \qquad (3)
\end{aligned}$$

Now it is necessary to verify the ability of Eq. (3) to reproduce the calculations of MAAP3.0B with sufficient accuracy. A direct comparison between the predictions of Eq. (3) and MAAP3.0B calculations shows that the agreement is very close as can be seen in Fig. 1. In addition, as shown in Table 4 the R^2 statistic is 0.9956 which indicates that Eq. (3) is an excellent fit. The statistics of stepwise regression

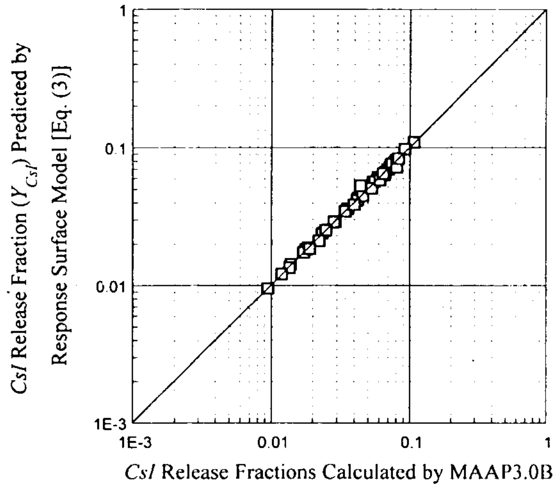

Fig. 1. A Direct Comparison of *CsI* Release Fractions Between Those Calculated by Response Surface Model [Eq. (3)] and Those by MAAP3.0B.

are also summarized in Table 4.

(3) Estimation of the Output Distribution Function :

Knowing that Eq. (3) is a satisfactory response surface to approximate the output, it can be used to approximate the probability density function (pdf) of output Y. There are two major methods of estimating the pdf of Y using the response surface model [6,7] : (1) the moment matching technique and (2) the crude Monte Carlo technique. In the present analysis, the response surface model obtained in the above, Eq. (3), is used as a proxy for the original code and 1000 crude Monte Carlo simulations have been performed to obtain an approximate density function (df) of the output. The 12 input parameters used in this crude Monte Carlo simulation with Eq.

Table 4. Statistics of Stepwise Regression

	Analysis of Variance		
	Degree of Freedom	Sum of Squares	Mean Square
Regression	32	3.47902088	0.1087194
Error	16	0.01535008	0.00095938
Total	48	3.49437097	
F=113.32	Prob.>F 0.0001		R^2=0.9956072

Parameters in the Regression Equation

Parameters	Parameters Estimate	Standard Error	Type II Sum of Squares	F	Prob.>F
Intercept	−1.0122607	0.0274712	1.3026303	1357.78	0.0001
X_1	0.0243356	0.0069245	0.0118494	12.35	0.0029
X_2	0.2400493	0.0071721	1.0747321	1120.24	0.0001
X_3	−0.0215325	0.0071153	0.0087860	9.16	0.008
X_4	0.0566947	0.0072014	0.0594618	61.98	0.0001
X_5	0.0413823	0.0072265	0.0314603	32.79	0.0001
X_7	−0.0154732	0.0067171	0.0050908	5.31	0.035
X_8	−0.0906409	0.0070526	0.1584690	165.18	0.0001
X_9	0.0306790	0.0067043	0.0200893	20.94	0.0003
X_{10}	0.0450541	0.0067369	0.0429079	44.72	0.0001
X_{11}	−0.0745438	0.0066666	0.1199502	125.03	0.0001
X_{12}	0.0845123	0.0069827	0.1405335	146.48	0.0001
X_1^2	−0.1135715	0.0143257	0.0602972	62.85	0.0001
X_1X_8	0.1095713	0.0196061	0.0299640	31.23	0.0001
X_1X_{12}	−0.0595487	0.0215782	0.0073064	7.62	0.014
X_2^2	−0.0602181	0.0185529	0.0101073	10.54	0.0051
X_2X_3	0.0746456	0.0178673	0.0167448	17.45	0.0007
X_2X_8	0.1192513	0.0178630	0.0427092	44.52	0.0001
X_2X_{10}	−0.1111593	0.0115204	0.0893198	93.10	0.0001
X_3X_4	−0.0943973	0.0205297	0.0202835	21.14	0.0003
X_3X_5	−0.0440445	0.0156598	0.0075892	7.91	0.0125
X_3X_{11}	0.0601409	0.0196037	0.0090292	9.41	0.0074
X_4X_{10}	−0.0515546	0.0137888	0.0134114	13.98	0.0018
X_4X_{12}	−0.0711245	0.0234898	0.0087956	9.17	0.008
X_5^2	−0.0562863	0.0144372	0.0145824	15.20	0.0013
X_5X_{10}	0.0289498	0.0129467	0.0047968	5.00	0.0399
X_5X_{12}	−0.0620049	0.0152972	0.0157622	16.43	0.0009
X_8^2	−0.1133706	0.0144629	0.0589499	61.45	0.0001
X_9^2	−0.0469802	0.0111082	0.0171605	17.89	0.0006
X_{10}^2	−0.1900478	0.0202112	0.0848268	88.42	0.0001
X_{11}^2	−0.0381095	0.0109806	0.0115559	12.05	0.0032
$X_{11}X_{12}$	0.1672172	0.0161561	0.1027731	107.12	0.0001
X_{12}^2	−0.0517249	0.0111324	0.0207116	21.59	0.0003

Table 5. Major Statistical Parameters of RSM and LHS($\tilde{Y}_{CsI} = \log_{10} \tilde{y}_{CsI}$)

	Mean	Median	5%	95%	Standard Deviation
RSM	−1.6496	−1.5348	−2.5387	−0.9642	0.4907
LHS	−1.6031	−1.4814	−2.2832	−0.9298	0.5347

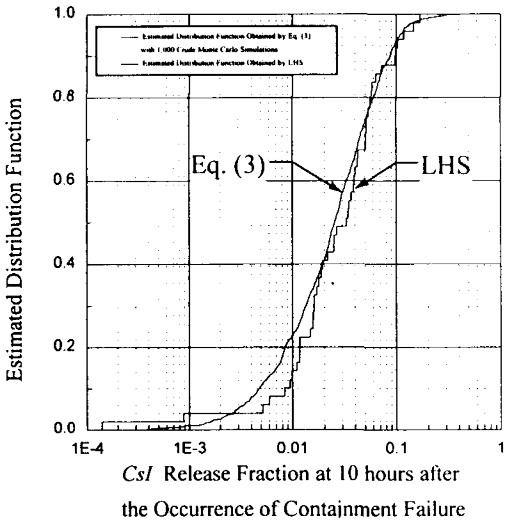

Fig. 2. A Comparison of Cumulative Distribution Function for *CsI* Release Fractions between That Obtained by RSM and That by LHS Using Equal Amount of Information.

(3) are shown in Table 2, whereas the major statistical parameters of *CsI* release fraction are given in Table 5. The cumulative distribution obtained by the 1000 crude Monte Carlo simulations, on the other hand, is shown in Fig. 2.

3.2.2. Uncertainty Analysis by LHS

Now, it is necessary to prove the validity of the empirical distribution function of *CsI* release fraction obtained by RSM (i.e., Eq. (3)). The best method is to compare the cumulative distribution function (cdf) *generated* by RSM (shown in Fig. 2) directly with actual empirical data or exact solutions when they are available. In the absence of this information at present, however, the next choice is to estimate the cdf by some other simple and reliable method and compare with the results of RSM. For this purpose, LHS seems to be the best choice based on the four criteria described in the introduction.

Therefore, an additional uncertainty analysis has been performed by LHS method to check the results obtained by RSM. The present analysis is performed with a Latin hypercube sampling of size 49 using the 12 input parameters given in Table 2. This sample size is identical to the number of observations used to fit the response surface model and is selected to make a fair comparison between the two methods of uncertainty analysis. The main concern here is that the cumulative distribution obtained and major statistical parameters estimated from each technique should be based on equal amount of information.

To estimate the MAAP3.0B predictions by LHS method, a computer program that can generate the Latin hypercube sample has been developed. The restricted pairing procedure of Iman and Conover [8] with a slight modification to simplify the program was built into the computer program to preclude spurious correlations within the sample. The correlation matrix for the LHS input parameters had a variance inflation factor (VIF) of 1.32, indicating negligible pairwise correlations within the sample.

In uncertainty analysis associated with LHS, it is desired to estimate the distribution function and the variance for the particular output variable(s) *Y* under consideration. Since LHS is based on a probabilistic input selection technique, an estimate of the cdf is obtained directly when an output variable is graphed as an empirical cumulative frequency distribution [9]. In Fig. 2, the empirical distribution for the *CsI* release fraction obtained by LHS method is compared with the results obtained by RSM technique. In addition, major statistical parameters estimated by LHS and RSM are shown in Table 5.

4. Discussion of Results

To verify the ability of the response surface model obtained (Eq. (3)) to reproduce the calculations of MAAP3.0B with sufficient accuracy, *CsI* release fractions predicted by Eq. (3) are compared directly with those values calculated by MAAP3.0B in Fig. 1. The results in Fig. 1, as well as the R^2 statistic given in Table 4, show that these two results are in good agreement.

As a method of checking the result obtained from RSM by a different technique, the cumulative distribution functions of the *CsI* release fractions to the environment evaluated by RSM and LHS are compared in Fig. 2. This figure shows that the agreement between the two cdfs is very close except for the lower percentile regions. Also, the result of a statistical test of the hypothesis that two distributions are the same by Kolmogorov-Smirov two-sample test shows that there is no evidence of a difference between the two distributions at 5% significance level.

To further examine the accuracy of the response surface model (Eq. (3)), the MAAP3.0B code has been run 49 times using the Latin hypercube sampling with 12 input parameters shown in Table 2. These 49 data points are then compared with predictions made by Eq. (3) using the same input values used in the LHS as shown in Fig. 3. Those points that lie on the diagonal in Fig. 3 indicate that the *CsI* release fractions predicted by the response surface model (Eq. (3)) perfectly agrees with the values obtained by MAAP3.0B using LHS. Figure 3 shows that about 20% of the data points predicted by Eq. (3) is quite different from the values obtained by MAAP3.0B with LHS even though the two cdfs obtained by two methods agree very closely as shown in Fig. 2.

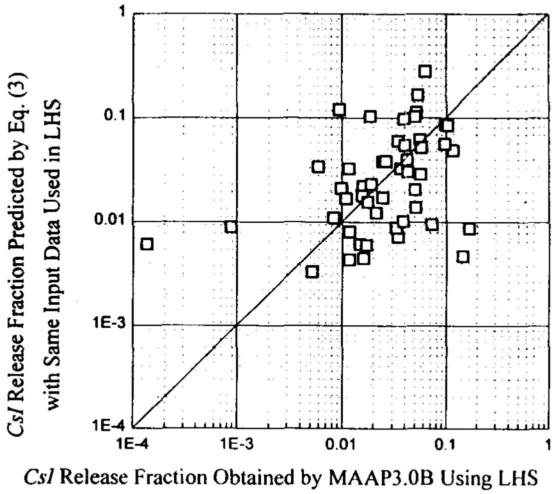

Fig. 3. Comparison between the *CsI* Release Fractions Data Obtained by MAAP3.0B Using LHS and Those by Response Surface Eq.(3)

From the results shown in Fig. 1 and Fig. 2, it can be inferred that the LHS technique does not reproduce the calculations of MAAP3.0B with as much accuracy as the RSM which is represented by Eq. (3) in the present case.

It may be noted here that the more accurate response surface equation could be constructed if one increases both the number of code runs and the number of input parameters. For this purpose, however, a considerable amount of time and additional effort might be needed. To obtain just one data point of the *CsI* release fraction (shown in Fig. 3) with MAAP3.0B, for example, the CPU time of the SUN SPARC 10 workstation used in the present work varied from 50 to 150 minutes depending on the values of input parameters.

5. Summary and Conclusions

An outline of the present combined procedure of RSM and LHS for uncertainty analyses of source term quantifications with MAAP3.0B has been summarized in Table 6. It should be noted here that

Table 6. Summary of Combined Procedure of RSM and LHS for Uncertainty Analyses of Source Term Quantifications with MAAP3.0B

Three Stages		Subject of Major Steps	Items to Be Treated
1st Stage "Summary of Given Conditions for Analysis"	1	– Collection of Data and Research to Obtain the Important Characteristics of the Given Nuclear Power Plant for Severe Accident Analysis	– Containment Performance Data – Important Design Characteristics – Plant Response Under Severe Accident Conditions
	2	– MAAP3.0B Code Characteristics – Review and Analysis of Model Parameters – Plant Specific Parameters	– Structure of the Code – Important Physical Parameters – Important Input Parameters
	3	– Accident Scenario Selection	– Selection of Scenarios – Analysis of Scenarios
2nd Stage "Uncertainty Analysis"	4	– Screening of Input Parameters (Selection of Effective Input Parameters) – Estimation of Input Uncertainties (Ranges of Values of Input Parameters to Be Used in the Analysis)	– 3-Step Screening : (1) Subjective, (2) One-at-a-time, (3) SRC & SRRC – Summary of Important Phenomena and Important Models – Uncertainty Estimations of the Screened Input Parameters (e.g., Probability Density Functions and Ranges)
	5	– Propagation of Uncertainty	– RSM : (1) Experimental Design, (2) Response Surface Modeling by Least-square Fitting, (3) Estimation of Output Distribution Function – Checking Cdf Obtained by RSM with LHS : (1) Sampling, (2) Estimation of Output Distribution Function – Statistical Test (for the Results of RSM and LHS) – Estimation of Output Uncertainty (e.g., CDF and/or PDF ; their Ranges)
	6	– Assessment of the Relationships Between the Input Parameters and Response Surface Model Output by Regression Techniques	– Rank of the Important Input Parameters – Information on the Relative Contribution of Input Uncertainties to the Output Uncertainties
3rd Stage "Interpretation of Uncertainty Analysis Results"	7	– Uncertainty Estimation of Key Output Parameters	– Containment Failure Time, Amount of Each Source Term Group Released to the Environment, etc.
	8	– Results of Uncertainty Analysis for Physical and Phenomenological Models	– Results of Quantitative Analysis
	9	– Interpretations of Overall Uncertainty Analysis Results	– Integration of All the Scenarios – Explanations and Conclusions of Major Findings

the present work is mainly concerned with an overall procedure for an application to the second stage shown in Table 6.

On the basis of the results presented in this paper, a combined procedure of RSM based on input determined from a statistical design and LHS is recommended to be used as a principal tool for an overall uncertainty analysis in source term quantifications, while using the LHS in the calculations of SRC and SRRC to determine the subset of the most important input parameters in the final screening step and to check the cdfs obtained by RSM. The accuracy of the response surface equation is a prerequisite for the reliability of the uncertainty analysis results obtained by the present combined RSM and LHS. Therefore, verification of the response surface model for its sufficient accuracy by either a direct comparison (as shown in Fig. 1) or by comparing with the results obtained by LHS method (as shown in Fig. 2) should be performed prior to the generation of cumulative distribution functions.

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Acronyms

cdf	Cumulative Distribution Function
CsI	Cesium Iodide
df	Density Function
LHS	Latin Hypercube Sampling
pdf	Probability Density Function
PSA	Probabilistic Safety Assessment
PWR	Pressurized Water Reactor
RSM	Response Surface Method
SBO	Station Blackout
SRC	Standardized Regression Coefficients
SRRC	Standardized Rank Regression Coefficients
VIF	Variance Inflation Factor

Nomenclature

a_0	Regression Coefficients (Intercept)
a_j	Regression Coefficients (1st Order Terms)
a_{jl}	Regression Coefficients (Interactive Terms)
a_{jj}	Regression Coefficients (2nd Order Terms)
k	Number of Input Parameters
n	Sample of Size
N	Number of Code Runs
R^2	Multiple Correlation Coefficient Squared
x_{ij}	i'th Value of j'th Perturbed Input
X_j	Input Parameters
Y	Output Parameter
$\tilde{Y}_i$	Prediction of Response Surface
$\tilde{y}_{CsI}$	*CsI* Release Fraction
$\tilde{Y}_{CsI}$	Log Transformed *CsI* Release Fraction
α_{ij}	i'th Dimensionless Value of j'th Input Value
μ_j	Mean Value of j'th Input
σ_j	Standard Deviation of Uncertainty Distribution of j'th Input

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