Uncertainty Correlation in Stochastic Safety Analysis of Natural Circulation Decay Heat Removal of Liquid Metal Reactor

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ABSTRACT

Since various uncertainties of input variables are involved and nonlinearly-correlated in the Best Estimate (BE) plant dynamics code, it is of importance to evaluate the importance of input uncertainty to the computational results and to estimate the accuracy of the confidence level of the results. In order to estimate the importance and the accuracy, the authors have applied the stochastic safety analysis procedure using the Latin Hypercube sampling method to Liquid Metal Reactor (LMR) natural circulation Decay Heat Removal (DHR) phenomenon in the present paper. 17 input variables are chosen for the analyses and 5 influential variables, which affect the maximum coolant temperature at the core in a short period of time (several tens seconds), are selected to investigate the importance by comparing with the full-scope parametric analysis. As a result, it has been demonstrated that a comparative small number of samples is sufficient enough to estimate the dominant input variable and the confidence level. Furthermore, the influence of the sampling method on the accuracy of the upper tolerance limit (confidence level of 95%) has been examined based on the Wilks' formula.

KEYWORDS

Uncertainty analysis, Latin Hypercube sampling, Best Estimate analysis, Liquid Metal Fast Reactor, Decay Heat Removal

1. INTRODUCTION

A concept of Best Estimate (BE) method has been widely used especially in a safety assessment analysis of Light Water Reactor (LWR) since the United State Nuclear Regulatory Commission (USNRC) has developed the Code Scaling, Applicability and Uncertainty (CSAU) methodology that provides a systematic approach for the investigation of uncertainty of safety related variables [1].

In the BE method, a stochastic approach is introduced by taking into account an uncertainty of input variable. Hence the number of code runs will increase exponentially when the number of the reviewing variables increases. Furthermore, the input variables are nonlinearly correlated each other and affects the computational result because various equipments such as a core vessel, pump and heat exchanger are installed in a nuclear plant and are connected by piping system. Accordingly, it is important to investigate the uncertainty correlation of input variables and to choose influential input variables upon the computational output. For instance, the Phenomena Identification and Ranking Table (PIRT) process is introduced so as to select the influential input variables in the CSAU methodology.

The authors performed the stochastic safety analysis of the natural circulation Decay Heat Removal (DHR) of Liquid Metal Reactor (LMR) [2] using the variance of the conditional expectation and the correlation ratio based on the Latin Hypercube Sampling (LHS) proposed by McKay [3]. And it was demonstrated that the stochastic analysis in the LMR plant was effective to estimate the uncertainty correlation between the input variables.

In the present study, the investigation of the uncertainty correlation has been carried out in the natural circulation DHR of LMR and the influential input variables have been chosen from the viewpoint of the coolant temperature increase at the core in a short period of time. Furthermore, the influence of the number of computer runs on the uncertainty correlation has been investigated by comparing the full-scope parametric analyses. The accuracy of the upper tolerance limit that corresponds to the confidence level of 95% has also been investigated.

2. NATURAL CIRCULATION DECAY HEAT REMOVAL IN LMR

Figure 1 shows the schematic of a loop type LMR system. The system consists of the reactor vessel, the primary heat transport system and the secondary heat transport system. The primary and the secondary heat transport systems are connected by the intermediate heat exchanger (IHX). In the secondary heat transport system, the steam generator and the air cooler (Auxiliary Cooling System, ACS) are installed as in Fig. 1. After the reactor protection system is actuated, the coolant flow path is switched from the steam generator to the air cooler.

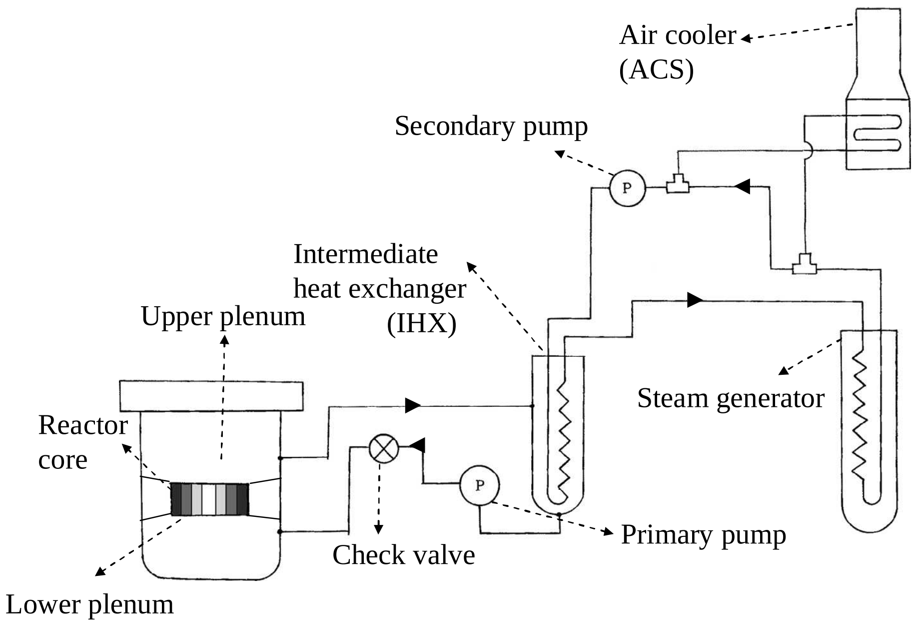
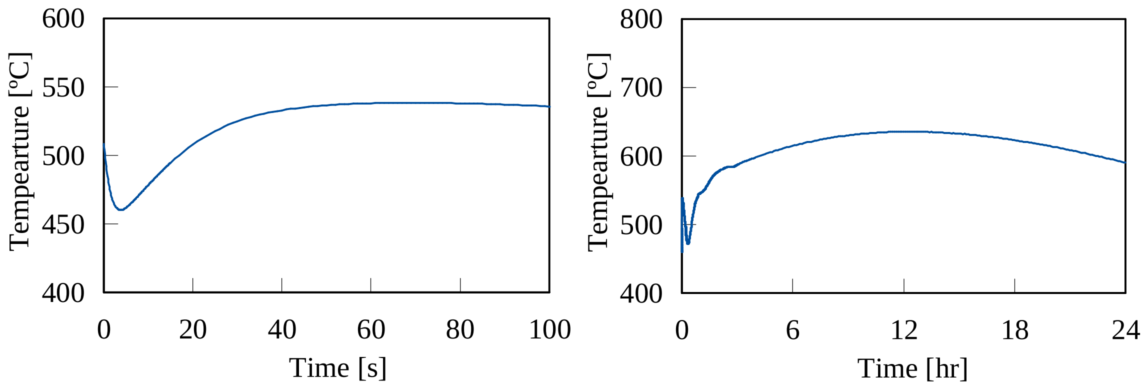


Fig. 1 Schematic of LMR system

Since the location of the IHX is higher than the reactor core and ACS is higher than the secondary heat transport system, the natural circulation DHR can be achieved. The decay heat of the reactor core is removed at the air cooler via the primary system, the IHX and the secondary system.

Typical transients of the coolant temperature, in which the most appropriate input values are selected, at the core in a short period of time and at the upper plenum in a long period of time are shown in Fig. 2. From the safety viewpoint, the cladding temperature of the fuel and the structure temperature of the primary coolant boundary are of importance. Hence, the core coolant temperature and the upper plenum temperature are chosen as a code output for the structural integrity of the fuel and the primary coolant boundary, respectively.

When the reactor protection system is actuated, the heat generation decreases rapidly because of the insert of the control rod resulting in the rapid decrease of the coolant temperature as shown in the left side viewgraph of Fig. 2. At the same time, the pumps are also shut down and the coolant flow rates both of the primary and secondary systems decrease. Hence the coolant temperature increases after several seconds. As the natural circulation develops, the local maximum appears after several tens seconds due to heat removal by the natural circulation. On the other hand, the plant system is large and a huge amount of coolant exists in the plant so that it takes several or more hours to achieve the total DHR through the whole system as seen in the right side of Fig. 2. It is noted that the total heat removal is affected strongly by the heat removal capacity of the ACS. In the present study, a comparatively small capacity of the ACS is assumed resulting in the existence of the maximum temperature at approximately 12hr after the protection system is actuated.



Short period (0-100s) at core **Long period (0-24hr) at upper plenum**

Fig.2 Typical transient of coolant temperature

3. METHODOLOGY OF STOCHASTIC SAFETY ANALYSIS

3.1. Variance of Conditional Expectation and Correlation ratio

In Mckay [2], the variance of code output (y) can be divided into two portions as:

$$\mathrm{V}[y] = \mathrm{V}[\mathrm{E}(y \mid \mathbf{x}_S)] + \mathrm{E}(\mathrm{V}[y \mid \mathbf{x}_S]), \tag{1}$$

here, V[·] and E(·) denotes the variance and the expected value respectively. $\mathbf{x}$ is the input variables vector. V[y|$\mathbf{x}_S$] and E(y|$\mathbf{x}_S$) mean the variance and the expectation on condition that a subset $\mathbf{x}_S$ of the input vector is fixed. The input variables vector $\mathbf{x}$ is expressed as the uniform of $\mathbf{x}_S$ and the complementary subset $\mathbf{x}_{\bar{S}}$ as:

$$\mathbf{x} = \mathbf{x} \cup \mathbf{x}_{\bar{S}}. \tag{2}$$

The first term in the right hand side of Eq. (1) is the Variance of Conditional Expectation (VCE). The VCE indicates the magnitude of the correlation of the input parameter $\mathbf{x}_S$ and the code output (y) and is defined as:

$$\mathrm{V}[\mathrm{E}(y\,|\,\mathbf{x}_\mathrm{S})] = \int (\mathrm{E}(y\,|\,\mathbf{x}_\mathrm{S}) - \mathrm{E}(y))^2 f_{\mathbf{x}_\mathrm{S}}(\mathbf{x}_\mathrm{S}) d\mathbf{x}_\mathrm{S}\,. \tag{3}$$

Where $f(\cdot)$ denotes the Probability Density Function (PDF) of the variable. The second term in the right hand side of Eq. (1) is the within-group variance or the residual expressed as:

$$\mathrm{E}(\mathrm{V}[y\,|\,\mathbf{x}_\mathrm{S}]) = \iint (y - \mathrm{E}(y\,|\,\mathbf{x}_\mathrm{S}))^2 f_{y|\mathbf{x}_\mathrm{S}}(y) f_{\mathbf{x}_\mathrm{S}}(\mathbf{x}_\mathrm{S}) dy d\mathbf{x}_\mathrm{S}\,. \tag{4}$$

The residual reflects the variation of the individual data within the group from the group-mean value and thus it has nothing to do with $\mathbf{x}_\mathrm{S}$. Accordingly, one can consider that Eq. (4) reveals the residual with respect to the uncertainty of $\mathbf{x}_\mathrm{S}$.

The relative importance of uncertainty of the input parameter with respect to the output uncertainty is defined by the correlation ratio as:

$$\eta_{\mathbf{x}_\mathrm{S}} = \frac{\mathrm{V}[\mathrm{E}(y\,|\,\mathbf{x}_\mathrm{S})]}{\mathrm{V}[y]}. \tag{5}$$

3.2. Sampling Method

In each stochastic analysis, the code runs are planed based on the design matrix ($n \times s$) and its replicates. Here, s is the number of the input variables. The Latin Hypercube Sampling (LHS) method is applied to the design matrix and the replicates. In the LHS, the PDF of each input variables $\mathbf{x}_\mathrm{S}$ is divided into n strata of equal marginal probability (=1/n). Next, a random sampling is done once from each stratum. Then, the design matrix and its replicate are generated based on the Latin square design so that the cumulative stratum between the input variables does not appear in a same code run.

When one focuses on the input variable x_i, the sample average of the output (y) for $x_i = x_{ij}$ is expressed as:

$$\bar{y}_j = \frac{1}{r}\sum_{k=1}^{r} y_{jk}\,. \tag{6}$$

Where, r is the number of the replicates. The expected value of the variance of $\bar{y}_j$ is obtained in the following.

$$\mathrm{E}(\mathrm{V}[\bar{y}_j\,|\,x_i]) = \frac{1}{n}\sum_{j=1}^{n} (\bar{y}_j - \bar{y})^2\,. \tag{7}$$

Here, $\bar{y}$ is the total average of the output. Eq. (7) is also written as:

$$\begin{aligned}\mathrm{E}(\mathrm{V}[\bar{y}_j\,|\,x_i]) &\simeq \mathrm{V}[\mathrm{E}(\bar{y}_j\,|\,x_i)] + \mathrm{E}(\mathrm{V}[\bar{y}_j\,|\,x_i]) \\ &= \mathrm{V}[\mathrm{E}(y\,|\,x_i)] + \frac{1}{r}\mathrm{E}(\mathrm{V}[y\,|\,x_i]) = \mathrm{VCE}(x_i) + \frac{1}{r}\mathrm{E}(\mathrm{V}[y\,|\,x_i]).\end{aligned} \tag{8}$$

The expected value of the variance of y for which $x_i = x_{ij}$ ($\mathrm{E}(\mathrm{V}[y \mid x_i])$) is calculated as:

$$\mathrm{E}(\mathrm{V}[y \mid x_i]) = \frac{1}{nr}\sum_{j=1}^{n}\sum_{k=1}^{r}(y_{jk} - \overline{y}_j)^2 . \tag{9}$$

Substituting Eqs. (7) and (9) into Eq. (8), the VCE for the input variable x_i is expressed in the following.

$$\mathrm{VCE}(x_i) = \frac{1}{n}\sum_{j=1}^{n}(\overline{y}_j - \overline{y})^2 - \frac{1}{nr^2}\sum_{j=1}^{n}\sum_{k=1}^{r}(y_{jk} - \overline{y}_j)^2 . \tag{10}$$

The variance of the output is obtained as:

$$\mathrm{V}[y] = \frac{1}{nr}\sum_{j=1}^{n}\sum_{k=1}^{r}(y_{jk} - \overline{y})^2 . \tag{11}$$

Finally, the correlation ratio is calculated from Eq. (5).

In the present study, the center of each PDF stratum is selected as an input variable instead of the random sampling for simplicity. This method is called Midpoint Latin Hypercube Sampling (MLHS) or centered LHS [4].

In the following stochastic analyses, the number of sample (n) that corresponds to the number of stratum in each input variable is set to 10 at each replicate considering the number of code run in the full-scope analysis. As concerns the s and r, parametric study has been carried out. It is noted that the total number of code runs (= $n \times r$) is independent of the number of the input variables (s). This is one of the great advantages of the LHS method.

4. STOCHASTIC SAFETY ANALYSES OF DHR IN LMR

In the stochastic safety analyses of the DHR in LMR, effective input variables are investigated based on the correlation ratio (Eq.(5)), firstly. Then the prediction accuracy of the correlation ratio is evaluated by comparing the full-scope parametric analysis. The upper tolerance limit of 95% confidence level has been also investigated based on the Wilks' formula. With regard to the plant dynamics analyses, the LEDHER [5] code has been used.

4.1. Investigation of Correlation Ratio

In the investigation of the correlation ratio, 17 input variables are chosen tentatively so as to estimate the propagation of input uncertainty to the output. Table 1 shows the input variables selected in the present study.

In a stochastic analysis, a coefficient of variance (COV), which is defined as a standard deviation divided by its mean value, is one of the most important issues and there is a little information about it. In the present study, the following three categories are assumed by an engineering judgment.

It is known that a comparative large uncertainty is included in an empirical correlation such as a pressure drop coefficient and a heat transfer coefficient when they are determined based on a fundamental experiment. Hence, the COV of 30% is assumed in the input variables that consist of the empirical correlations.

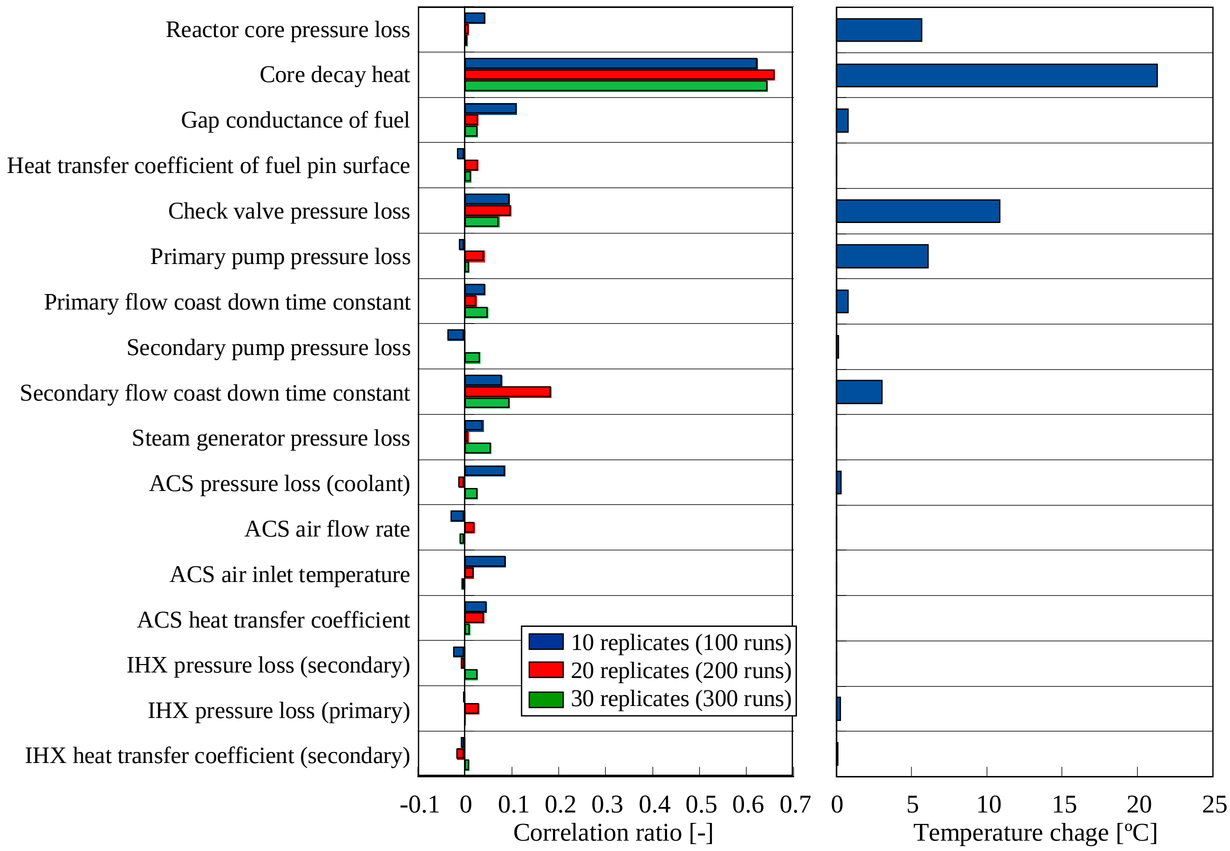
Table 1. Statistical properties of input variables

Input variable	PDF	COV (%)
Reactor core pressure loss	Normal	30
Core decay heat	Normal	10
Gap conductance of fuel	Normal	30
Heat transfer coefficient of fuel pin surface	Normal	30
Check valve pressure loss	Normal	30
Primary pump pressure loss	Normal	30
Primary flow coast down time constant	Normal	20
Secondary pump pressure loss	Normal	30
Secondary flow coast down time constant	Normal	20
Steam generator pressure loss	Normal	30
ACS pressure loss (coolant side)	Normal	30
ACS air flow rate	Normal	10
ACS air inlet temperature	Normal	10
ACS heat transfer coefficient	Normal	30
IHX pressure loss (secondary side)	Normal	30
IHX pressure loss (primary side)	Normal	30
IHX heat transfer coefficient (secondary side)	Normal	30

In case of the flow coast down time constant, one may obtain an exact prediction based on a mock-up test of pump. However, it is strongly affected by pressure drop of connected piping system. Therefore, a middle COV range (20%) is applied to the time constant.

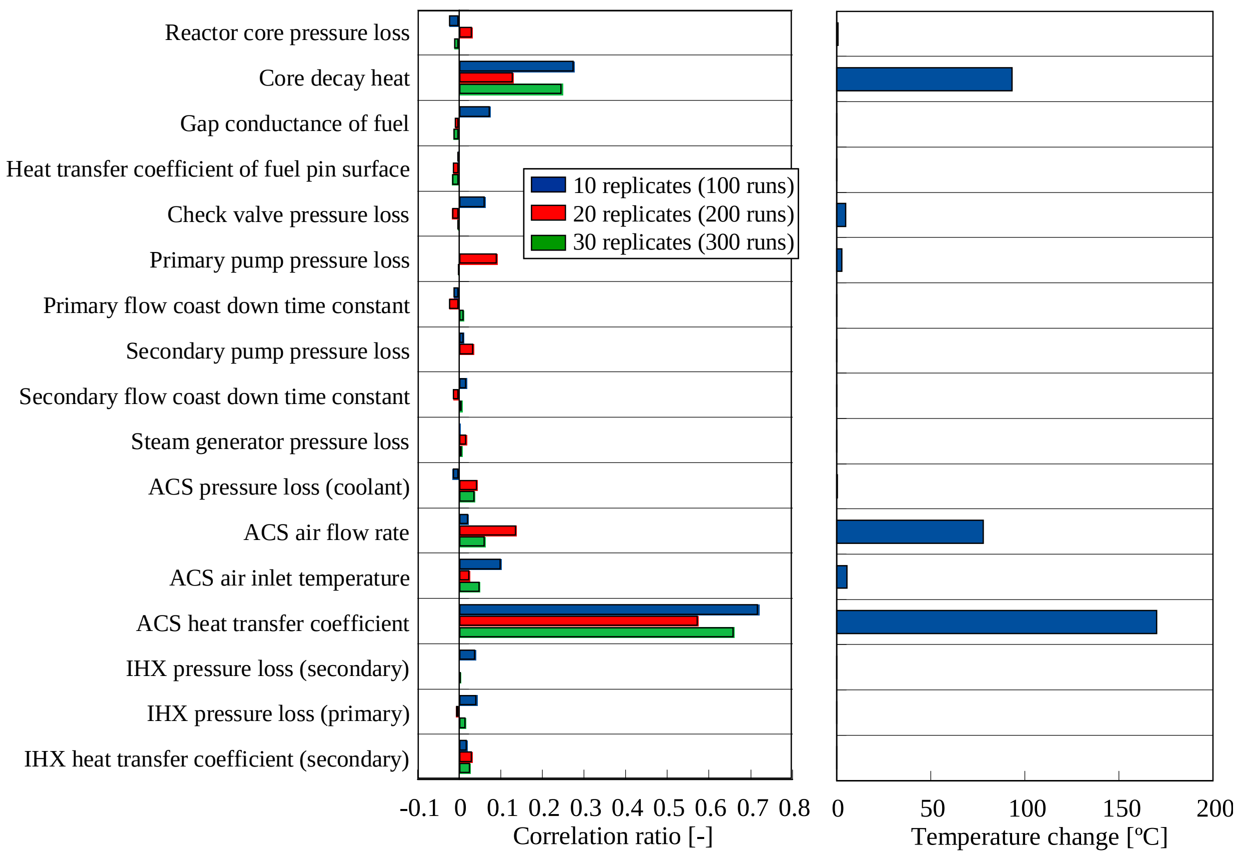
With regard to the core decay heat, it is well-investigated and appropriate value is recommended [6]. Therefore, the COV of the core decay heat is assumed to be 10%. The COV of 10% is also assigned in the ACS air flow rate and the air inlet temperature tentatively. In the present study, each input variable has a most probable value and its uncertainty. Hence a normal distribution is applied as the PDF. The statistical properties (PDF and COV) are also summarized in Table. 1.

In the analyses, the number of the replicates (r) is chosen as a parameter and is set to 10, 20 and 30 which mean the code runs ($n \times r$) of 100, 200 and 300 respectively. As an output, the maximum coolant temperatures at the core for short period transient and at the upper plenum for long period transient are selected (see Fig.2). The sensitivity analysis of each variable are also carried out as a reference where each input varies from the lowest to the highest COVs independently and the maximum temperature change is evaluated.



(Stochastic analysis) (Sensitivity analysis)

Fig. 3 Correlation ratio in short period transient (core coolant temperature)



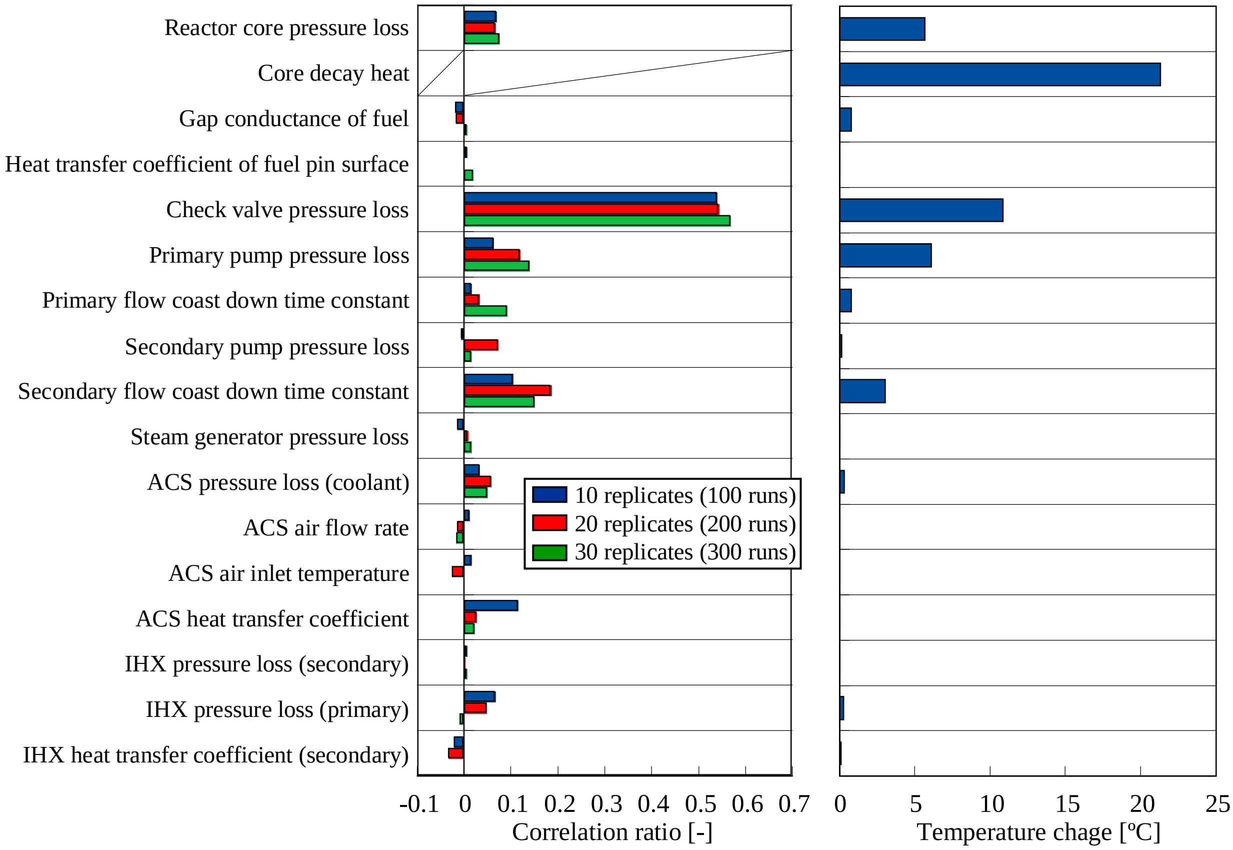
(Stochastic analysis) (Sensitivity analysis)

Fig. 4 Correlation ratio in long period transient (coolant temperature of upper plenum)

The correlation ratio in the short and long transients and the comparison with the sensitivity analysis (the change of maximum temperature) are shown in Figs. 3 and 4. As seen in Fig. 3, the core decay heat is the most influential input variable to the short transient of the core coolant temperature both in the stochastic and sensitivity analyses. Since the quite large magnitude of the correlation ratio is estimated in the core decay heat regardless of the number of replicates, the weight of the other correlation ratios on the core coolant temperature seems obscure comparing with the sensitivity analysis and is affected by the number of replicates.

In case of the upper plenum temperature (Fig. 4), the input variables of the ACS heat transfer coefficient and the core decay heat are obtained as the first two influential inputs that also correspond to the sensitivity analysis. It would be said that almost the same tendency of the influence of the input variables are investigated both in the stochastic and sensitivity analyses as seen in Fig. 4. This might be attributed to the fact that no discontinuity or outlying responses have been investigated in the DHR of LMR because it is a single-phase thermal-hydraulics phenomenon [2].

In order to investigate the influence of the other input variables on the short transient of the core coolant temperature, additional stochastic analyses are carried out in which the number of the input variables is changed from 17 to 16 (eliminating the core decay heat). The analytical result is indicated in Fig. 5. As shown in Fig.5, the influential variables are found to be almost the same with those in the sensitivity analysis.



(Stochastic analysis) (Sensitivity analysis)

Fig. 5 Correlation ratio in short period transient (eliminate influence of core decay heat)

Let us discuss the influence of the code runs. As seen in Figs. 3 to 5, the similar value of the correlation ratio is achieved regard less of the runs when its magnitude is comparatively large. On the contrary, it varies widely in case of the low correlation ratio. In some variables, a negative value is investigated especially under the case of 100 code runs (10 replicates). As shown in Eq. (3), the value of VCE should be positive theoretically. On the other hand, the negative value could be calculated in the descritized sampling manner (Eq. (10)) when the number of the samples is insufficient for prediction. It can be said that the magnitude of the negative value will be an indicator of the correlation ratio accuracy.

4.2. Prediction Accuracy of Correlation Ratio

In order to investigate the prediction accuracy of the correlation ratio in the limited number of code runs, the full-scope parametric analysis has been carried out. For this purpose, the short transient assessment and five input variables of the reactor core pressure loss, the core decay heat, the check valve pressure loss, the primary pump pressure loss and the secondary flow coast down time constant are selected taking into account the result of the sensitivity analysis (Fig. 3).

The same number of the samples (n=10) is assigned and thus 100,000 code runs are done in the full-scope analysis. With regard to the stochastic analyses with LHS method, the number of replicates (r) is set to 10, 20, 30 and 50.

Table 2 summarizes the average value of the maximum core coolant temperature and its sample variance. The cumulative frequency of the maximum coolant temperature at the core is shown in Fig. 6 and the comparison of the correlation ratio is pictured in Fig. 7. In Fig. 6, the cumulative normal distribution function in which the analytical average and the variance are used is also indicated.

As shown in Fig. 6, the cumulative distribution in the full-scope analysis agrees so well with the cumulative normal distribution function. It is again concluded that the stochastic analysis is preferable for the DHR phenomena in LMR as mentioned in the previous work [2].

With regard to the average value of the maximum temperature, almost the same value is investigated between the full-scope analysis and the stochastic analyses. Since the sample of input variable is chosen from each strata of equal marginal probability and every sample is used once in one replicate in the LHS method, almost the same average value is investigated regardless of the code run as in Table 2. On the other hand, the variance in case of stochastic analyses is a little bit underestimated rather than that in the full-scope analysis though the variation between the code runs is small.

Table 2. Comparison of average value and variance

Case	Average [ºC]	Sample variance
Full-scope	537.77	48.51
10 replicates	537.87	42.16
20 replicates	537.86	41.94
30 replicates	537.86	42.59
50 replicates	537.86	39.66

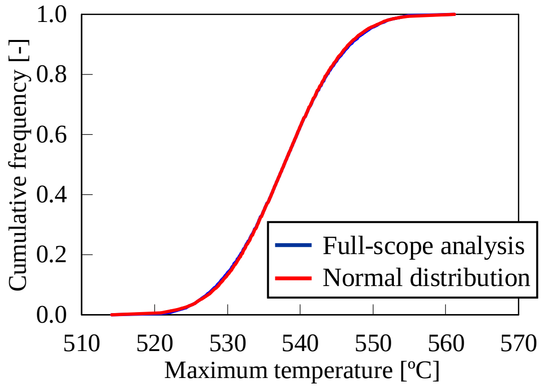


Fig. 6 Cumulative frequency of full-scope analysis

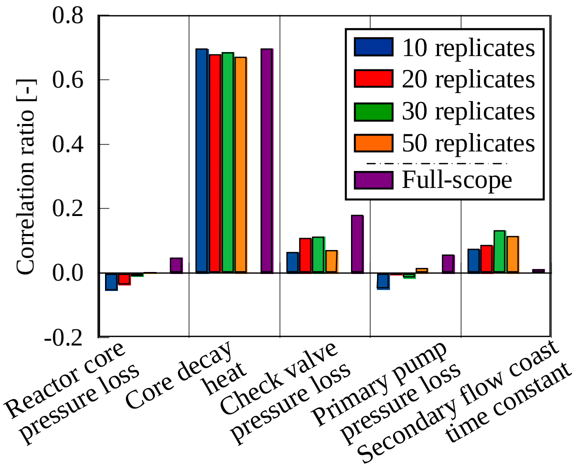


Fig. 7 Comparison of correlation ratio

As concerns the correlation ratio, no obvious differences are investigated in the stochastic analyses under 10 to 50 replicates (100 to 500 code runs) as in Fig. 7. The highest correlation ratio of stochastic analyses is in accordance with that in the full-scope analysis. However, the prediction accuracy of low correlation ratio seems to be not good. It will be concluded that a comparative small number of the code runs is sufficient enough to investigate the dominant propagation of input variables to the output. At the same time, one will need a mature investigation of the sampling number and the sampling method to obtain more detailed distribution of the ratio.

4.3. Upper Tolerance Limit of Maximum Temperature

According to Wilks [7], the minimum number of samples (N) in which the highest value of the output has a probability of a given one sided tolerance level (β) for a given confidenc level (γ) is determined in case of one sided tolerance limit as:

$$\beta = 1 - \gamma^N . \tag{12}$$

Guba [8] generalized the Wilks' method for multivariate condition as:

$$\beta = \sum_{j=0}^{N-p} \binom{N}{j} \gamma^j (1-\gamma)^{N-j} , \tag{13}$$

here, p is the number of output variables desired. The advantage of Eqs. (12) and (13) is an independency of the minimum number of samples on the number of input variables.

In this section, the influence of the sampling method on the upper tolerance level has been investigated based on the Wilks' formula. Two sampling methods are examined: one is the present LHS method and the other is a random sampling (Monte Carlo method). One sided tolerance limit (95%) is taken into account in condition of no multivariate and the confidence level of 95%. Hence, the number of minimum samples is 59 from Eq. (12).

Each stratum of input variable (n) is the same both in the sampling methods. In case of the random sampling, the design matrix is determined with the Monte Carlo method in which no restraint condition is considered mentioned in Sec. 3.2. and 590 code runs are done to obtain 10 upper tolerance limits. On the other hand, 60 replicates are designed in case of the LHS method and first 590 code runs are used.

In the analysis, the short transient DHR is calculated. Since the analytical result of the DHR in LMR is in accordance with a normal distribution function as mentioned above (see Fig. 6). The confidence level of 95% (one sided) can also be obtained from the normal distribution function as:

$$T_{conf}^{95\%} = \mu + 1.645\sigma , \tag{14}$$

here, μ and σ are the average and the standard deviation. The confidence level of the present stochastic analyses mentioned in Secs. 4.1. and 4.2. are also calculated using Eq. (14) as well as the result of the full-scope analysis.

The results of numerical examinations and the confidence level obtained by the full-scope analysis are summarized in Table 3. In case of the full-scope analysis, the confidence level is evaluated directly by counting the 94,999th value. As shown in Table 3, the upper tolerance limit is higher in both cases than the 95% confidence level obtained from the full-scope analysis even in case of μ - 1σ. The variance in the LHS is comparative small rather than that in the random sampling method. When a limited number of code runs is examined, the upper tolerance limit of the random sampling would be affected strongly by a quality of random digit. The upper tolerance limit based on the LHS seems to be more precise in that case.

Table 4 indicates the confidence level of 95% from Eq. (14) in case of the present stochastic analyses. As shown in Table 4, the number of input variables and the code runs has almost no influence on the confidence level in the present LHS method. It might be concluded that the investigation of the confidence level based on the assumption of normal distribution will be an alternative way in the DHR analysis of LMR.

Table 3. Comparison of upper tolerance limit value using Wilks' formula

	Average [ºC]	Unbiased variance
LHS	551.57	2.00
Random sampling	553.83	10.84
Full-scope	549.44 (95% confidence level)	

Table 4. 95% confidence level by assuming normal distribution

Num. of variables	Num. of replicates	Value [ºC]
17	10	548.11
17	20	548.21
17	30	548.21
5	10	548.55
5	20	548.51
5	30	548.59
5	50	548.22
Full-scope		549.23

5. CONCLUSIONS

The stochastic safety analysis using the Latin Hypercube sampling (LHS) method to Liquid Metal Reactor (LMR) natural circulation Decay Heat Removal (DHR) phenomenon has been carried out. In the stochastic analysis, the number of input variables (s) and the replicates (r) that correspond to the code runs are chosen as a parameter and are set to s = 5, 17 and r = 10-50. The full-scope parametric analysis has also been carried out so as to investigate the prediction accuracy of the correlation ratio for the specific application case. This ratio reveals the relative importance of uncertainty of the input variable. The full-scope analysis is also used to have a precise estimation of the confidence level of 95%.

In the investigation of the correlation ratio and its prediction accuracy, it is concluded that a comparative small number of the replicates (10 replicates which corresponds to 100 code runs) is sufficient enough to investigate the dominant influential input variables. On the other hand, one needs a mature consideration of the sampling method and the number of the samplings when more detailed distribution of the correlation ratio is required.

As a result of the comparison of the upper tolerance limit between the LHS method and the random sampling method, the LHS method would have superiority in terms of the smaller variance when a limited number of code runs is examined.

Since the DHR phenomenon in LMR is a single phase thermal-hydraulics, the output will be in accordance with a normal distribution function. Consequently, sensitivity analyses of each input variables seems to be useful for investigation of the relative importance of uncertainty. Furthermore, the assumption of the normal distribution in the output might be an alternative way of the investigation of the upper confidence level.

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