Importance Analysis for Uncertain Thermal-Hydraulics Transient Computations

Mohammad Pourgol-Mohammad*[a], Seyed Mohsen Hoseyni[b]

[a] Department of Mechanical Engineering, Sahand University of Technology, Tabriz, Iran

[b] Department of Basic Sciences, East Tehran Branch, Islamic Azad University, Tehran, Iran

Abstract: Results of the codes simulating transients and abnormal conditions in nuclear power plants are inevitably uncertain. In application to thermal-hydraulic calculations by thermal-hydraulics codes, uncertainty importance analysis can be used to quantitatively confirm the results of qualitative phenomena identification and ranking table (PIRT). Several methodologies have been developed to address uncertainty importance assessment. Existing uncertainty importance measures which are mainly devised for the PRA applications are not suitable for tedious calculations of the complex codes like RELAP. On the other hand, for the quantification of the degree of the contribution of each phenomenon to the total uncertainty of the output, a new uncertainty importance measure that needs affordable computational cost is very promising. A new uncertainty importance measure is introduced in this article to cope with the aforementioned deficiencies of the TH uncertainty importance analysis. Important parameters are identified qualitatively by the modified PIRT approach while their uncertainty importance is quantified by the proposed index. Application of the proposed methodology is demonstrated on LOFT-LB1 test facility.

Keywords: Uncertainty Importance, Uncertainty Analysis, IMTHUA, Thermal-Hydraulics.

1. INTRODUCTION

TH codes are tools for the calculation of the response of nuclear power plant to abnormal and accident conditions. The approach is to compare the figure of merit (as the code output) to the regulator's criteria. However, these predictions are uncertain due to significant sources of uncertainty in fully understanding of physical phenomena occurring during the accident, uncertainties in models due to simplification (including model form and parameter uncertainties), and computational numerical methods approximations. The first step in conducting uncertainty analysis is to identify these sources.

The previous article of the authors (reference [1]) demonstrated a hybrid qualitative/quantitative framework was proposed for the uncertainty analysis plus importance in severe accident calculations. The qualitative phase identifies, ranks and screens the important phenomena in the course of severe accident progression. The quantitative phase covers the contribution of the parameters obtained through the first phase to the total uncertainty of the output variable of interest. To overcome high computational cost in this phase, the code is emulated by using a metamodel of the code model. The obtained metamodel of the complex model could then be easily utilized for calculation of uncertainty importance measures.

However the RSM approach has some limitations. Drawbacks to RSM include:

- Difficulty of developing an appropriate experimental design
- Use of a limited number of values for each input variable
- Possible need for a large number of design points; Ineffective as the number of uncertain parameters increases requiring larger number of code executions
- Difficulties in detecting thresholds, discontinuities, and nonlinearities
- Difficulty in including correlations and restrictions between input variables

* pourgol-mohamadm2@asme.org

- Difficulty in constructing an appropriate response surface approximation to the model under consideration

The authors concluded in reference [1] that the extension of this area could be devising a new effective uncertainty importance measure that is more suitable for thermal-hydraulics and severe accident uncertainty analysis considering the large computational cost of the calculations. Consequently, the existing methodologies for uncertainty importance are not practical for thermal-hydraulic calculations (e.g., RELAP5 code calculations) due to required computational time and resources. The aim of the present paper is to devise a new effective uncertainty importance measure that is more suitable for TH uncertainty analysis considering the high cost of the calculations.

2. DESCRIPTION OF THE PROPOSED METHODOLOGY

Several methodologies have been developed to address uncertainty importance assessment in general. Existing methodologies for uncertainty importance are not efficient for TH applications which require significant amount of computational time and resources. Due to large uncertainty resources and time consuming nature of TH code calculation, TH uncertainty and sensitivity calculations require enormous number of code calculation and significant computational resources to estimate their uncertainty importance. An efficient uncertainty importance ranking method is developed here for comprehensive TH code uncertainty assessment [1-5]. The proposed uncertainty importance methodology is a hybrid two-phase qualitative/quantitative method. The first phase is qualitative step to identify and rank phenomena and processes based on their TH and uncertainty importance. The qualitative step, itself two stages, (so called modified PIRT) identifies, ranks and monitors the sources of uncertainties based on their impact and uncertainty importance. The second phase is a quantitative step to measure the effect of uncertainty sources on code output uncertainty distribution. The steps of the methodology are discussed in following sections. A flow chart of the hybrid methodology is shown in Figure 1.

2.1 Qualitative Phase (Modified PIRT)

With many physical phenomena involved, TH analyses deal with various sources of uncertainties. While ideally all sources of uncertainties should be considered in the analysis explicitly [4], it is neither practical nor necessary to evaluate all processes and components in detail. The original PIRT process aims to identify and rank phenomena and processes based on their safety importance only. For the purpose of uncertainty analysis, this step is necessary but not adequate. The phenomena may be important from the TH as well as in respect to uncertainty importance. The degree of knowledge about phenomena and credibility of models must be characterized, and when possible quantified. This paper suggests a methodology for involving level of knowledge of each phenomenon into the problem for more effective uncertainty assessment.

The proposed two-step PIRT methodology here called “modified PIRT” provides a process for more precise uncertainty analysis. The process identifies and ranks phenomena based on TH importance as well as uncertainty importance. Experience with TH phenomena shows that phenomena with TH and uncertainty importance contribute more significantly to output uncertainty than those based on either TH importance or uncertainty importance alone. The analytical hierarchical process (AHP) has been used as a formal approach for TH identification and ranking. AHP [6] is a powerful tool for ranking of alternatives and attributes of a decision, especially when limited experts are available. A formal uncertainty importance technique is used to estimate the degree of credibility of the TH model(s) for the important phenomena. This part uses subjective assessment on the basis of evaluating available information and data from experiments on code predictions. The idea is shown in Figure 1a.

Figure 1b shows several phenomena with their TH and uncertainty importance. By uncertainty importance, we mean the level of contribution of the phenomena to the uncertainty in the code prediction (for a given figure of merit). For example, decay heat power is considered high in its TH importance due to its impact on PCT itself. The phenomenon is well known, and correlations to predict it are well developed. Therefore, low uncertainty is assigned to it, indicating a high confidence in the phenomena model used in TH codes. Loosely speaking, TH importance impacts the output’s mean value, while uncertainty importance affects its variance. There are different qualitative and quantitative approaches to assigning ranks to phenomena. Rankings of high, medium, and low are used in some studies, while others use ranking on scale of 1 to 9, where 9 means the highest importance and 1 is the lowest. A detailed description of the modified PIRT is provided in [1-5].

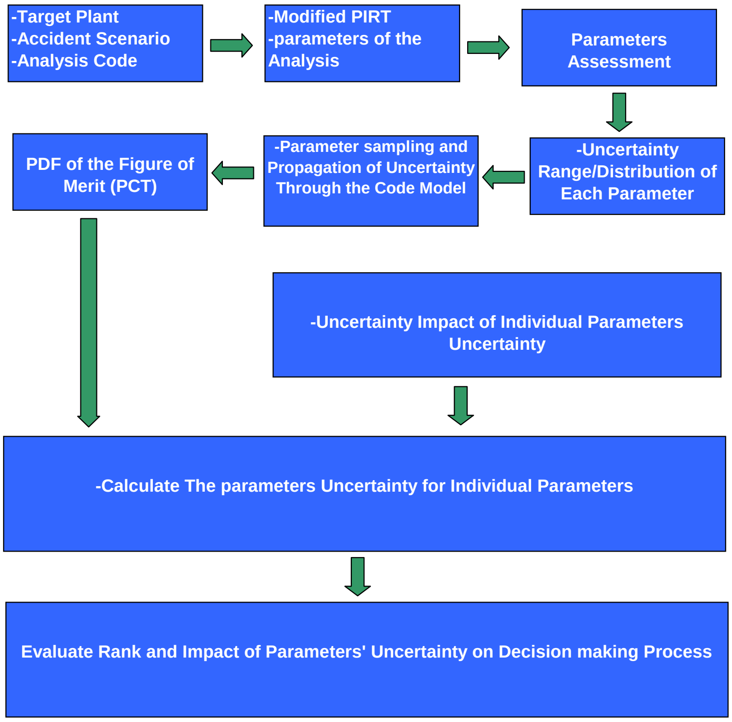
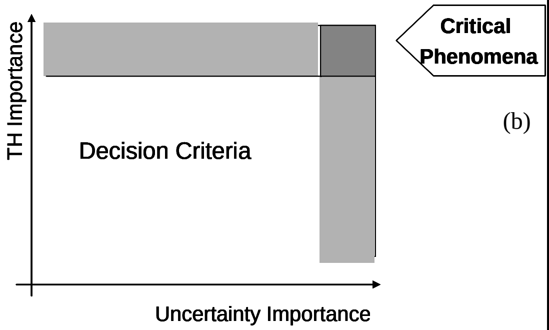


Figure 1: The Methodology Flow Chart

(a)



(b)

Uncertainty / TH	High	Medium	Low
High	Spacer Grid Rewetting and Droplet Breakup	Rewet	Decay Heat Power
Medium	Time of Burst	Rod-to-Spacer Grid Local Heat Transfer	Cladding Phase Change
Low	Rod-to-Rod Mechanical Interaction	Cladding Oxidation	Fuel Relocation

Figure 2: TH Importance vs. Uncertainty Importance in Chosen Criteria b) Some Phenomena with their TH and Uncertainty Ranks

2.2 Quantitative Phase (Uncertainty importance Calculation)

Every model of interest, Thermo-hydraulics code here, can be represented as a function of the form: $y = f(x)$, where $x=[x_1, x_2, \ldots, x_n]$ is a vector of uncertain analysis inputs and $y=[y_1, y_2, \ldots, y_n]$ is a vector of analysis results.

The proposed uncertainty importance measure is defined in multiples of standard deviation ($x\sigma$, $x=\ldots,-2,-1,0,1,2,\ldots$) changes in a given input parameter over the change in the output (Figure of Merit) as shown in Figure 3. For example, x is the number of σ's in the FOM (e.g., ΔPCT) resulting from running the code for +1σ and -1σ change in the input parameter nominal values. An average of 2, 4, or 6σ importance measure can also be used for the analysis but this should be applied uniformly for all uncertainty parameters. The measure can be defined as ratio of standard deviations.

$$IM = \frac{Uncertainty of Parameter i}{Uncertainty of the Output} = \frac{\rho_{Pi}}{\rho_{out}} \tag{1}$$

The term ρ is defined as:

$$\rho = \frac{\sigma}{\mu} \tag{2}$$

where μ and σ are variable's mean and standard deviation.
IM is the importance measure, ρ_{Pi} is the given parameter coefficient of variation, and σ_{out} is the coefficient of variation of the obtained distribution from uncertainty propagation and assessment [3]. The uncertainty measure can also be defined the ratio of parameter standard deviation (σ_{P_i}) to overall FOM standard deviation (σ_{out}).

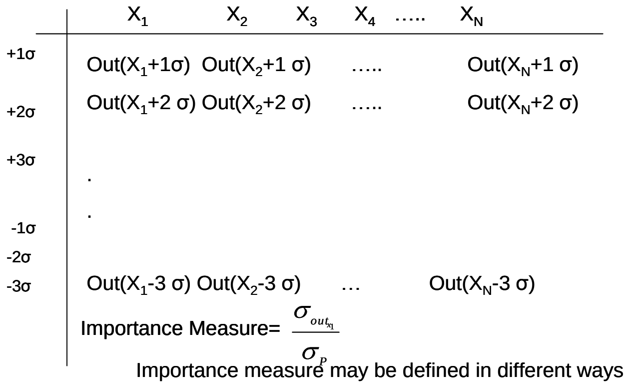


Figure 3: Perturbation of the input parameters for uncertainty importance assessment

The total uncertainty range resulted from propagation of uncertainties is obtained from the input-based uncertainty calculation of the integrated methodology IMTHUA [4-5], developed by the author or any other available methodologies e.g., CSAU [7], GRS [7], UMAE [7]. There are some difficulties in assessment of non-linearity of some input changes vs. variations in the output variables, which require special treatment. For more precise study of parameter uncertainty importance, the method proposed by Iman [8] furnishes more accurate results. Different levels of input change (multiples of standard variation) are devised for accurate ranking of uncertainty contributors. Comparing the output change as a fraction of the overall uncertainty range will result in a ranking index to show the contribution of each uncertainty source.

3. Application on LOFT LB-1 Experiment

A schematic view of LOFT test facility is shown in Figure 4. Components used in LOFT are similar in design to those of a PWR. Because of scaling and component design, the LOFT is expected to closely model a PWR LOCA. The facility is designed and scaled to represent a 1/60-scale model of a typical 1000-MWe commercial four-loop PWR. Three PWR primary-coolant loops are simulated by a single intact loop in LOFT scaled to have the same volume-to-power ratio. A broken loop in LOFT simulates the fourth PWR primary-coolant loop where a break may be postulated to occur. The facility includes most of components in a typical 4-loop nuclear power plant consisting of five major systems of: 1) Primary Coolant System, 2) The Reactor System with 1.68m nuclear core, 3) Blowdown Suppression System, 4) Emergency Core Cooling System, and 5) Secondary Coolant System.

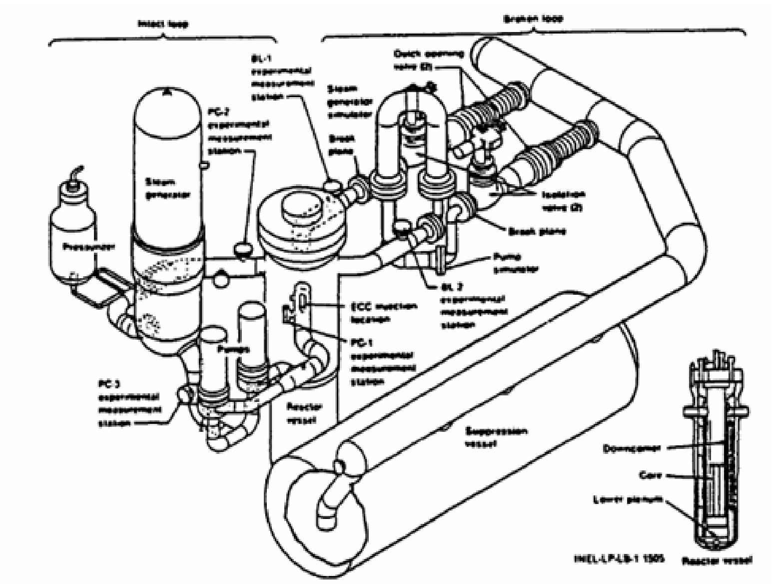


Figure 4: The LOFT Test Facility [14]

With recognition of the differences in commercial PWR designs and inherent distortions in reduced scale systems, the design objective for the LOFT facility was to produce the significant thermal-hydraulics phenomena that would occur in commercial PWR systems in the same sequence and with approximately the same frames and magnitudes [15].

3.1 Parametric Uncertainty Quantification

The input uncertainty quantification is focused on the identification of uncertainties in code structure (including model and parameters). These uncertainties are propagated through code calculations to arrive at a distribution of output uncertainty on specified figures of merit. Sources of uncertainty in "input" include values of model parameters, boundary/initial conditions, and uncertainties in structure of sub-models (sub-model uncertainty).
In the first step of uncertainty propagation, for each of the identified sources of uncertainty from the previous steps, a probability distribution is assigned. Figure 5 schematically illustrates the process of uncertainty propagation.

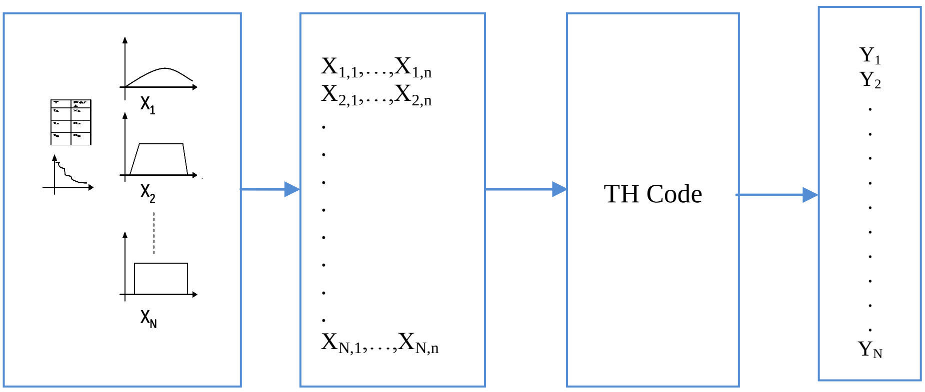


Figure 5 Sampling and Propagation of Uncertainties in Order Statistics Based Frameworks

3.2 Distribution Assignment for Uncertain Input Parameters

By input, models form and parameters are meant in this research. The main calculation for uncertainty assessment is performed in this stage of the work. In the first step of uncertainty propagation, for each of the identified sources of uncertainty from the previous steps [5-6], a probability distribution is assigned. For any parameter of interest, the range and the form of the distribution is determined. This range is used for the sampling in the next stages of the work and is one of the major steps in the quantification of uncertainties. Based on our information and the available data and knowledge on the phenomena or model or parameter the range of uncertainty is identified. If the available data and information is little then the uncertainty range will be large in opposite to the case of information abundance about the phenomena which results in the smaller uncertainty range.

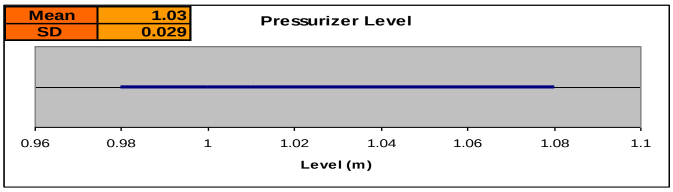


Figure 6: Uncertainty Range for Pressurizer Level in LOFT Test Facility with μ= 1.03 m and σ=0.029 m

3.3 Sampling from Uncertain Parameters

Total of 100 samples are generated for propagation of uncertainty parameters to the output. Figure 7 demonstrates how the samples are generated from the assigned distribution of the parameter. Pair-wise dependency between parameters is not considered in generating the samples in this stage of the research. If there was a significant dependency between parameters, it is included in obtaining the samples. Data-informed dependency calculation is the most common way to calculate dependency in domain of complex code calculation.
Table 1 lists all LOFT-LB1 uncertain parameters with their uncertainty characteristics.

Table 1: Uncertain Parameters for LOFT LB-1 Experiment

Parameter Name	Distribution Type	Nominal Value	Lower Bound	Higher Bound	Mean Value	Standard Deviation
Pressurizer Level (m)	Uniform	1.04	0.98	1.08	1.03	0.03
Pressurizer Pressure (MPa)	Uniform	14.92	14.81	15.03	14.92	0.06
Initial Core Power (MWt)	Uniform	49.3	48.1	50.5	49.3	0.61
Accumulator Level (m)	Uniform	2.362	2.337	2.387	2.362	0.01
Accumulator Pressure (MPa)	Uniform	4.22	4.05	4.39	4.22	0.09
Safety Injection Temperature (°K)	Uniform	302	296	308	302	3.06
Break discharge coefficient	Uniform	1.0 (default)	RC x 0.70	RC x 1.15	1.0	0.13
Peaking factor	Normal Multiplier	1.0	0.95	1.05		0.0255
Gap size	Normal Multiplier	1.0	0.8	1.2		0.102
UO2 conductivity	Normal Multiplier [0.9, 1.1] (Tfuel <2000 K) [0.8,1.2] (Tfuel >2000 K)	1.0	0.9	1.1		0.051 for (Tfuel <2000 K) 0.102 for (Tfuel >2000 K)

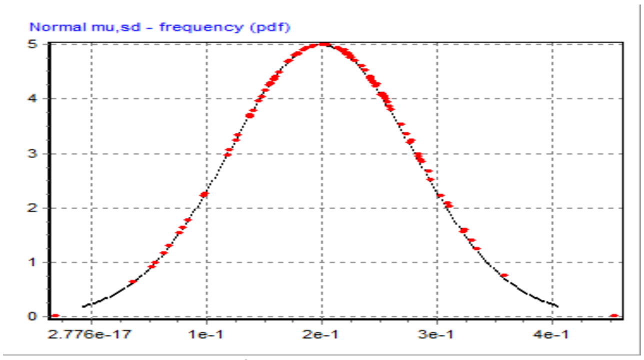


Figure 7 100 Samples from Normal distribution; an example

3.4 Uncertainty Propagation

In this application, we start with the results of the “input phase uncertainty propagation,” developed in detail in reference [4]. In that exercise, the RELAP5 code structure and parameter uncertainties were explicitly propagated to obtain uncertainty scatters for the hottest fuel rod at 0.66m height in the active core. Figure 8 illustrates peak clad temperature (PCT) profile and compares the results of 100 code runs for different values of uncertain parameters and sub models.

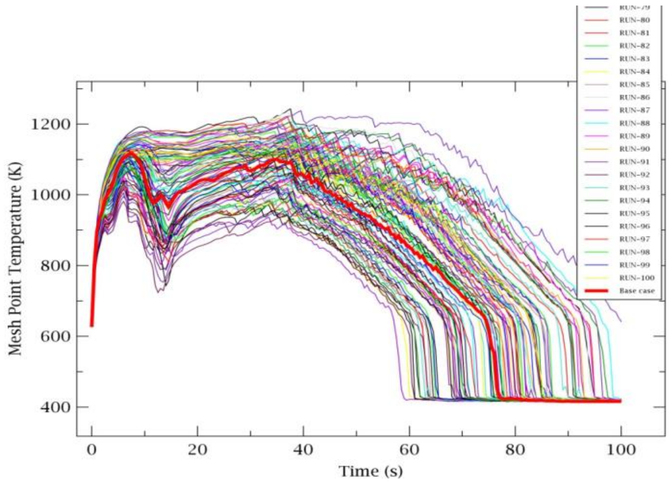


Figure 8: Uncertainty Propagation Results from Input Phase vs. Experimental Data

Figure 9 shows scatter plots for data obtained from RELAP5 uncertainty calculation. The scatter points are used to develop an “input phase” uncertainty distribution of PCT.

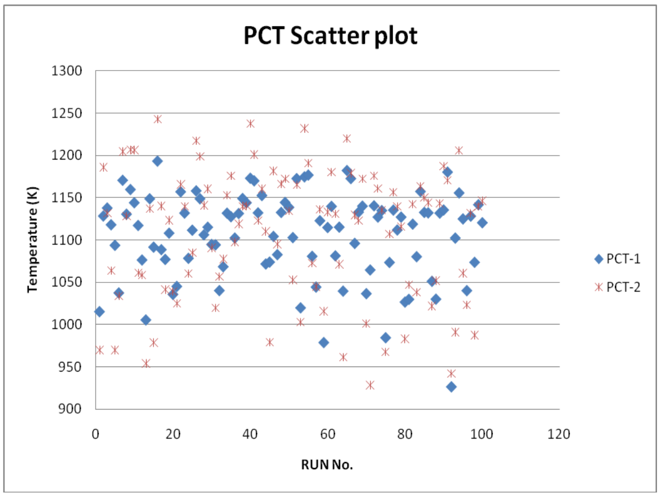


Figure 9: Scatter Plot for Peak Clad Temperature

Figure 10 shows the results of fitting truncated normal distributions separately to the RELAP5 code data. Two methods can be used to fit a parametric distribution to the code calculations:

I. A distribution shape that best fits the data is assumed (e.g., normal or lognormal distribution). With the distribution considered, we estimate parameters from the data. The range of the distribution from tolerance interval is assigned to distribution quantiles based on coverage (e.g. the smallest used as 2.5% and the largest as 97.5%, see Figure 4). The parameters of distributions are obtained from these quantiles. By doing so we are trying to preserve the information from order statistics based tolerance limit.

$$\frac{x_{0.95}-\mu}{\sigma}=1.96$$
$$\frac{x_{0.05}-\mu}{\sigma}=-1.96 \tag{3}$$

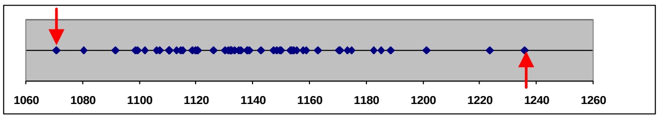


Figure 10: RELAP5 Calculated PCT (°K)

II. After a distribution shape is assumed for the data, Bayes' theorem is used to estimate the distributions of the parameters of the distribution based on the code-calculated date points. This is formally expressed as

$$\pi(\mu,\sigma \mid T_1,T_2,\dots,T_N)=\frac{L(T_1,T_2,\dots,T_N \mid \mu,\sigma)\pi_0(\mu,\sigma)}{\iint_{\mu,\sigma} L(T_1,T_2,\dots,T_N)\pi_0(\mu,\sigma)} \tag{4}$$

Where μ and σ are parameters of the assumed distribution, N is number of code runs, L is likelihood function of data and $\pi_0(\mu,\sigma)$ is the prior distribution of the parameters. The Bayes fit is then obtained through

$$\pi(T \mid T_1,T_2,\dots,T_N)=\iint_{\mu,\sigma}\pi(T \mid \mu,\sigma)\pi(\mu,\sigma \mid T_1,T_2,\dots,T_N) \tag{5}$$

Table 2: Statistical parameters in LOFT LB1 Uncertainty Analysis

Statistical Parameter	PCT1	PCT2
Sigma	50.62	76.44
Mean	1105.89	1106.75
Min	926.16	928.37
Max	1192.76	1242.69
Ref.	1116.27	1101.45

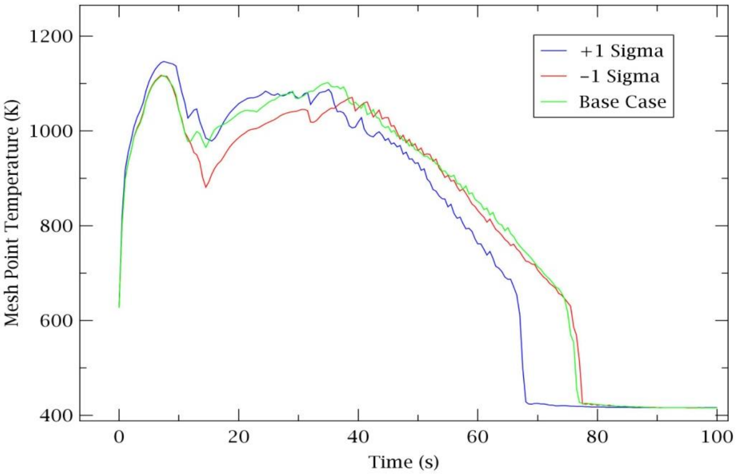


Figure 11: Axial PPF Effect on PCT

The approach is to use smallest and biggest value in the ordered sample as 5th and 95th percentiles as shown in equation (1), where μ and σ are two parameters of the normal distribution.
The results for axial power peaking factor parameter uncertainty importance analysis are given in Figure 11 which shows the uncertainty range introduced by this parameter. Table 3 lists the calculations of the effects of the changes in each input parameter on "PCT1", "PCT2" and "end of quench time" as the code calculated outputs. Here the proposed uncertainty importance measure is only applied on the PCT as the figure of merit of the problem.
Each parameter was perturbed 2 times in multiples of standard deviation values and the resulting changes in the PCT1 and PCT2 were recorded. With total uncertainty range for PCT from uncertainty quantification, uncertainty is calculated for the parameter.

Table 3: Effect of each parameter on different FOMs

	-1 Sigma			+1 Sigma		
Parameter	**PCT1 (K)**	**PCT2 (K)**	**End of Quench (s)**	**PCT1 (K)**	**PCT2 (K)**	**End of Quench (s)**
Pressurizer Level (m)	1116.2	1068.8	68.0	1115.5	1106.5	77.5
Pressurizer Pressure (MPa)	1118.7	1116.79	79.5	1116.03	1073.46	69.02
Initial Core Power (MWt)	1109.7	1095.5	72.5	1120.7	1136.89	77.0
Accumulator Level (m)	1116.27	1109.8	76.0	1116.27	1098.79	77.0
Accumulator Pressure (MPa)	1116.27	1107.8	77.0	1116.27	1111.58	78.0
Safety Injection Temperature (°K)	1116.27	1105.14	76.0	1116.27	1108.25	76.0
Break discharge coefficient	1117.5	1102.27	69.0	1112.43	1123.87	85.5
Peaking factor	1117.25	1070.36	77.5	1146.10	1087.13	68.0
Gap size	1098.37	1030.02	67.0	1130.71	1100.43	77.0
UO2 conductivity	1120.71	1088.52	69.5	1104.95	1040.58	67.5

4. DISCUSSION ON THE OBTAINED RESULTS

Importance of each parameter could be calculated in multiples of 2, 4, 6 sigma. The average value is calculated for uncertainty importance of the parameter. Each single value can also be used as the importance measure. The values for importance measure are relative (importance measure value for a parameter is compared with the importance of other components). Non-linearity of the TH code is another reason for calculation in different level of variation. In some cases non-proportionality of variation level in parameter with output variation was experienced.
Calculated uncertainty importance values are summarized in Table 4. We well know from LBLOCA phenomenology that PCT1 is during blow down phase while PCT2 occurs in refill phase of the accident. With this physical representation, accumulator parameters are not affecting PCT1 that is confirmed by the uncertainty importance measure. The highest value of uncertainty importance is for gap size meaning that if we need to invest in uncertainty reduction, gap size parameter should be a higher priority than others.
There are some difficulties in assessment of non-linearity of some input changes vs. variations in the output variables, which require special treatment. We believe that although the MC based approaches could furnish more accurate results but because of their large calculation cost are not applicable for TH applications unless the surrogate model of the complex model is used that it could be itself as an another uncertainty source in some cases. The proposed uncertainty importance measure calculates locally the effect of each parameter and gives promising results in TH application.

Table 4: Calculated uncertainty importance measure values

Parameter	PCT1 Importance %	PCT2 Importance %
Pressurizer Level	0.73	12.67
Pressurizer Pressure	2.76	14.467
Initial Core Power	11.46	13.557
Accumulator Level	0	3.64
Accumulator Pressure	0	1.25
Safety Injection Temperature	0	1.03
Break discharge coefficient	5.28	7.09
Peaking factor	29.61	5.68
Gap size	33.70	24.16
UO2 conductivity	16.45	16.46

5. CONCLUDING REMARKS

This paper summarizes a new framework for the quantification of the effect of uncertainty sources on the code output distribution. It was discussed that for uncertainty analysis plus importance in TH problems, the existing uncertainty importance measures are not computationally affordable. A new uncertainty importance measure is proposed here to overcome this limitation with minimal computational burden. Successful application of the proposed framework is demonstrated for LOFT LB1 large LOCA experiment. The extension of this work could be development of the mathematical proof of the proposed measure.

6. NOMENCLATURE

CSAU	Code Scaling, Applicability and
FOM	Figure of Merit
IMTHUA	Integrated Methodology on TH
LWR	Light Water Reactor
LOCA	Loss of Coolant Accident
LOFT	Loss of Flow test
MPIRT	Modified Phenomena Identification and
MC	Monte Carlo
NPP	Nuclear Power Plant
PCT	Peak Clad Temperature
PEC	Primary Evaluation Criteria
PIRT	Phenomena Identification and ranking
PSA	Probabilistic Safety Assessment
PWR	Pressurized Water Reactor
RSM	Response Surface Methodology
TH	Thermal-Hydraulics
USNRC	United States Nuclear Regulatory Commission

References

[1] Hoseyni S.M., Pourgol-Mohammad M., Abbaspour Tehranifard A. Yousefpour F.. “A systematic framework for effective uncertainty assessment of severe accident calculations; Hybrid qualitative and quantitative Methodology”, Reliability Engineering and System Safety 125 (2014) 22-35, Special issue of selected articles from ESREL 2012.

[2] Hosseini S.M., Pourgol-Mohamad M., Abbaspour Tehranifard A., Yousefpour F. "Phenomena Identification and Ranking for Severe Accident Uncertainty Assessment; a Systematic, Two-Dimensional Approach." PSAM11, ESREL2012. 2012.

[3] Pourgol-Mohamad M., et. al. "Modified Phenomena Identification and Ranking Table (PIRT) for Uncertainty Analysis." *14th Int. Conf. Nuclear Engineering (ICONE 14).* 2006.

[4] Pourgol-Mohamad, M. *Integrated Methodology on Thermal Hydraulics Uncertainty Analysis (IMTHUA).* PhD Thesis, University of Maryland, 2007.

[5] Pourgol-Mohamad, M. "Integrated Methodology for Thermal-Hydraulic Code Uncertainty Analysis with Application." *Nuclear Technology* 165 (2007): 333-359.

[6] Saaty TL. Models, methods, concepts & applications of the analytic hierarchy process. Boston: Kluwer Academic Publishers; 2001.

[7] Pourgol-Mohammad M., 2009, “Thermal–hydraulics system codes uncertainty assessment: A review of the methodologies”, Annals of Nuclear Energy 36 (2009) 1774–1786

[8] Iman, R.L., M.E. Johnson, and T.A. Schroeder. "Assessing hurricane effects. Part 2: Uncertainty analysis." *Reliability Engineering and System Safety* 78, no. 2 (2002): 145–153.

[9] OECD/NEA. "CSNI-R2006-2, BEMUSE Phase II Report", 2006.

[10] OECD/NEA. "CSNI-R2004-4, BEMUSE Phase III Report", 2004.

[11] OECD/NEA. "CSNI-R2008-6, BEMUSE Phase IV Report", 2008.

[12] OECD/NEA. "CSNI-R2009-13, BEMUSE Phase V Report", 2009.

[13] OECD/NEA. "CSNI-R2011-4, BEMUSE Phase VI Report", 2011.

[14] FZKA 6424, "Validation of the Reflood Model of RELAP5/MOD3.2 Gamma Using Experimental Data from the Integral Facility LOFT LP-LB-1"

[15] US-NRC, NUREG/IA-0089, "Post-Test-Analysis and Nodalization Studies of OECD LOFT Experiment LP-LB-1 With RELAP5/MOD2"