Uncertainty and Sensitivity Analyses for Postulated Severe Accidents of Reference PWRs and SMRs in the Frame of the IAEA CRP and Relevant Insights

Kwang-Il Ahn,[a*] Federico Mezio,[b] Shaukat Ali,[c] Xuewu Cao,[d] Yong Jin Cho,[e] Bassam Khuwaileh,[f] Victor Martinez-Quiroga,[g] Fulvio Mascari,[h] Fabrizio Gabrielli,[i] David Luxat,[j] and Tatjana Jevremovic[k]

[a]*KAERI, Daejeon, Republic of Korea*
[b]*CNEA, Buenos Aires, Argentina*
[c]*DNPER/PAEC, Islamabad, Pakistan*
[d]*Shanghai Jiao Tong University, Shanghai, China*
[e]*KINS, Daejeon, Republic of Korea*
[f]*University of Sharjah, Sharjah, United Arab Emirates*
[g]*ENSO, Madrid, Spain*
[h]*ENEA, Bologna, Italy*
[i]*Karlsruhe Institute of Technology, Karlsruhe, Germany*
[j]*Sandia National Laboratories, Albuquerque, New Mexico*
[k]*International Atomic Energy Agency, Vienna, Austria*

Abstract — *In 2019, the International Atomic Energy Agency (IAEA) launched the 5-year Cooperative Research Project (CRP) I31033 to advance the understanding and characterization of sources of uncertainty and to investigate their effects on the key figures of merit (FOMs: response parameters of interest) of the severe accident code predictions for water-cooled reactors. Twenty-two institutions from 18 member states participated in the CRP, and as a result, TECDOCs are being developed for the relevant benchmark exercises. The respective TECDOCs address a specific exercise and outline relevant research results pointing to best practices for the uncertainty and sensitivity analyses of the currently available severe accident codes.*

For the uncertainty analysis exercise, the CRP participants defined their own analysis scope and framework, including target plant, severe accident code, accident scenario, and relevant FOMs. According to each respective framework, participants independently carried out their own exercise, including plant modeling and nodalization, simulation of reference cases, and relevant uncertainty and sensitivity analyses.

Finally, general conclusions were made based on an analysis of the results in view of the best-practice application of the uncertainty and sensitivity methods. Among them, this paper summarizes the main results of the uncertainty and sensitivity exercise performed for both pressurized water reactors and integral light water small modular reactors in the frame of the IAEA CRP with relevant insights.

Keywords — *International Atomic Energy Agency Cooperative Research Project, water-cooled reactors, PWR and SMR, severe accident code, uncertainty and sensitivity.*

Note — *Some figures may be in color only in the electronic version.*

*E-mail: kiahn@kaeri.re.kr

I. INTRODUCTION

Currently available computational codes used for severe accident (SA) analysis of nuclear power plants (NPPs)[1] include numerous uncertainty models and parameters representing a wide range of physicochemical phenomena for a comprehensive plant simulation, consequently, making relevant uncertainty analysis a nontrivial task. Over a couple of decades, a variety of studies have been performed to understand the uncertainties addressed in relevant code analyses and to numerically capture their impacts,[2–8] including methodological aspects for uncertainty analysis.[9–13]

Due to the computational resources available at that time, most of these studies, which relied on sampling-based probabilistic and statistical approaches, were greatly burdensome when using a large number of samples. In recent times, however, as the robustness of the SA codes has greatly improved and the performance of computational platforms significantly increased, a larger number of samples have become available to obtain relevant uncertainty results than before.

Reflecting on the this situation, a few national and international projects, such as SOARCA (State-of-the-Art Reactor Consequence Analyses, United States) uncertainty studies,[14–16] MUSA (Management and Uncertainty of Severe Accidents, European Commission) project,[17] and the International Atomic Energy Agency (IAEA) Cooperative Research Project (CRP) I31033[18] have been conducted to quantify the uncertainty addressed in dedicated SA codes, identify relevant key contributors in a more realistic way, and to advance relevant methodologies. Among them, this paper highlights the results of the uncertainty and sensitivity analyses performed for pressurized water reactor (PWR) and small modular reactor (SMR) types[19] within the context of the IAEA CRP and relevant insights into the best-practice analysis and improvement in the sophistication and quality of SA analyses through various code simulations and modeling.

The 5-year IAEA CRP I31033 project, which launched in 2019,[18] was triggered to advance the understanding and characterization of sources of uncertainties and their effects on the predictions of key figures of merit (FOMs: response parameters of interest) in SA codes for water-cooled reactors (WCRs) and to improve the capabilities and expertise of member states to perform state-of-the-art uncertainty and sensitivity analyses with SA codes.

In total, 22 institutions from 18 member states contributed to two major CRP exercises, named the QUENCH-06 test application uncertainty exercise and the plant application uncertainty exercise, which was divided into five subtasks addressing existing reactor lines: PWRs (including water-cooled SMR designs), boiling water reactors, pressurized heavy water reactors (CANDU), and water-water energetic reactors (VVER). The CRP exercises were carried out as per the flow diagram shown in Fig. 1, with each addressing a specific plant application exercise and outlining relevant research results with lessons learned for best practices on WCRs.

Among them, the plant application exercise was aimed at consolidating existing experience accumulated by analysts to develop a strong technical basis for establishing uncertainty and sensitivity methodologies in SA analyses with the aim to increase the sophistication and competency of practitioners in this field. The insights gained from the plant application exercise may lead to newly generated knowledge that can be reflected in uncertainty and sensitivity analyses and methods for SA codes, with the intent of capturing the best practices and lessons learned. For reference, the workflow for the probabilistic/statistical uncertainty analyses, which were employed for the plant application exercise, is summarized in Fig. 2.

The task scopes and methods employed by the respective institutions and the results of the analyses are summarized in Secs. II and III, respectively. Relevant insights and general conclusions in terms of particular points of interest are summarized in Secs. IV and V, respectively.

II. SCOPES AND METHODS

As given in Fig. 1, eight institutions from seven member states participated in the plant application exercise for PWR- and SMR-type reactors, but this paper mainly focuses on seven institutions that agreed to share relevant results and insights. Respective motivations for the uncertainty and sensitivity analyses and points of interest are summarized in Table I.

The task scope and calculation framework for the analyses covered five types of plants, five different SA codes, three representative accident scenarios, and three accident progression phases (in-vessel only, in-/ex-vessel, and all phases, including containment), as shown in Table II. For reference, the main features and basic properties of the accident analysis codes employed by participating organizations are briefly described in Table III.

The uncertainty propagation and quantification (UQ) methods employed by participants included

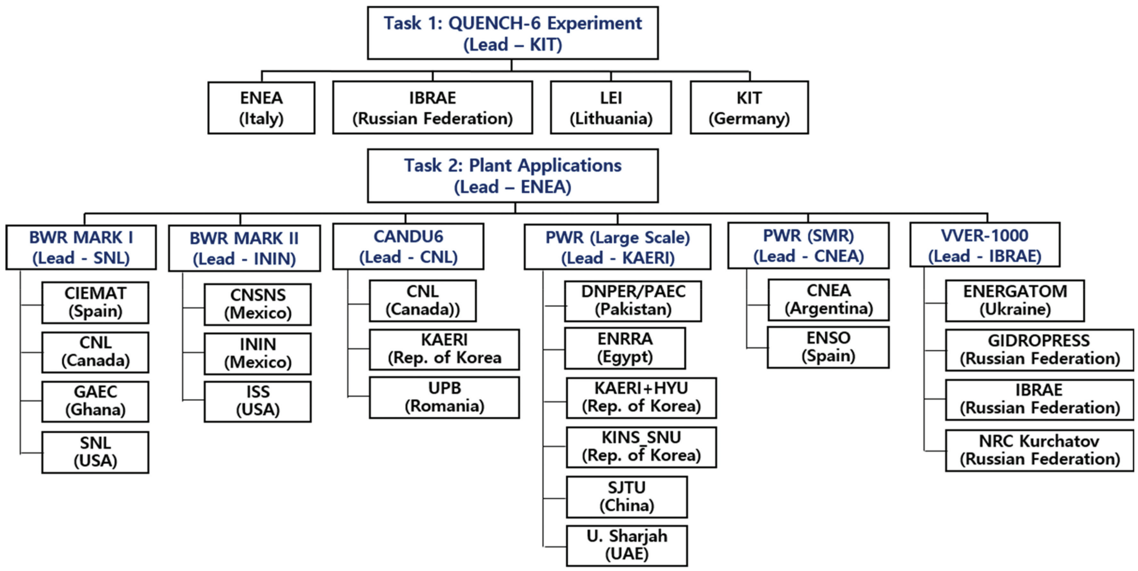


Fig. 1. CRP tasks and participants.

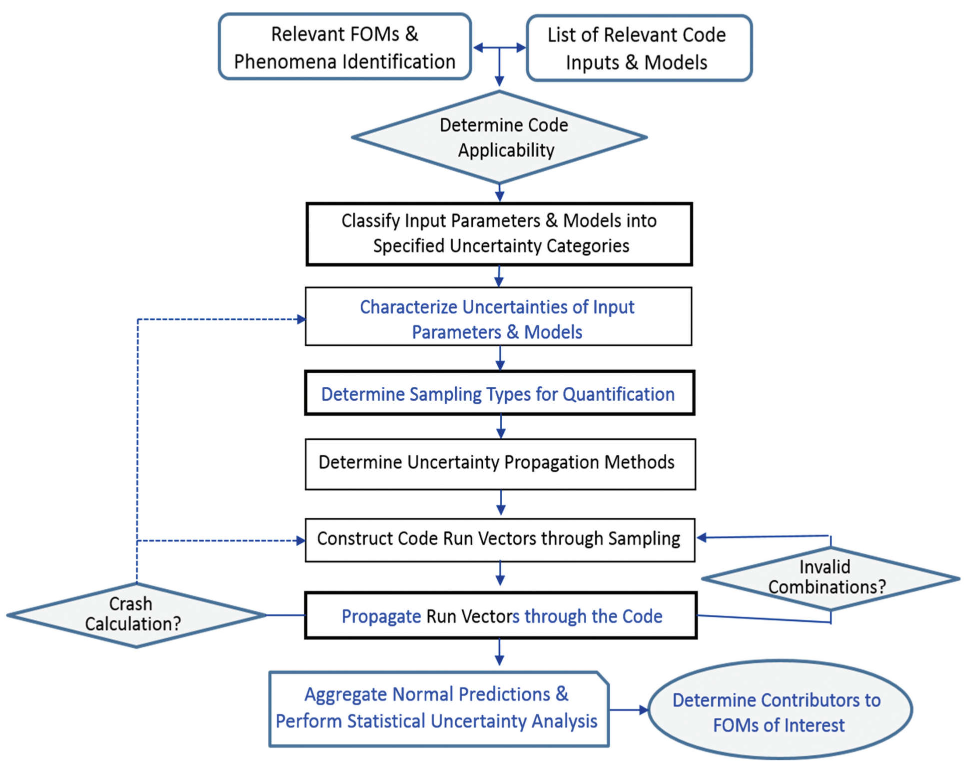


Fig. 2. Workflow for uncertainty and sensitivity analyses in the SA domain.

Monte Carlo methods, simple random sampling (SRS, a type of crude Monte Carlo sampling), and Latin hypercube sampling (LHS), as shown in Table IV. For reference, Fig. 3 illustrates key steps for a statistical propagation of input uncertainties to deduce relevant FOM uncertainty.[13]

The UQ tools applied were either based on in-house-developed ones or DAKOTA (Design Analysis Kit for Optimization and Terascale Applications) and integrated uncertainty analysis (IUA). The number of statistical samples N for the uncertainty and sensitivity analyses per institution was determined, considering

TABLE I

Motivations and Points of Interest

Reactor Type	Institution	Motivations	Points of Interest
Large PWR	DNPER	Regulatory safety review support	Exploring how to revise the base analysis using best-estimated parameters/ conditions with uncertainty analysis.
	KAERI	SAM and Level 2 probabilistic safety assessment support	Identifying difference of the SA-related uncertainty analysis results predicted from MELCOR and MAAP5 and the influence of relevant SAM strategies.
	KINS	Regulatory safety review support	Assessing uncertainty related to the long-term corium coolability in reactor cavity under various SAM actions.
	SJTU	SAM support	Assessing uncertainty addressed in the hydrogen source term UQ, and the influence of relevant SAM actions.
	UoS	Best-estimate plus uncertainty in reactor design	Demonstrating a method proposed to rate the importance of input parameters contributing to fuel temperature in the early phase of an accident.
SMR (iPWR)	CNEA	SAM support	Determining the time available for human actions and SAM guideline initiation in case of a SA.
	ENSO	Best-estimate plus uncertainty in SA	Demonstrating the RELAP/SCDAPSIM capability to carry out a best-estimate plus uncertainty calculation in a SA scenario.

the computational times, which could be on the order of several to tens of hours per sample calculation in the plant application, as well as unexpected code crashes that may take place relating to the settings of the sampled input parameters.

A suite of probabilistic sensitivity/importance analysis methods, which were based on statistical evidence or simulation results, were applied to this exercise: Pearson, Spearman, and Kendall correlation coefficients (CCs), partial correlation coefficient (PCC) or partial

TABLE II

Task Scope and Calculation Framework

Reactor Type	Institution	Reference Plant	Reference Scenario	Computational Codes
Large PWR	DNPER	ACP1000 (K-2 NPP)	SBO (in-/ex-vessel, containment)	MELCOR1.8.6[20]
	KAERI	OPR1000	STSBO (in-/ex-vessel, containment)	MELCOR2.2[21] and MAAP5.05[22]
	KINS	APR1400	SBO (in-/ex-vessel, containment)	MELCOR2.2 and COOLAP2[23]
	SJTU	CPR600	SBO (in-/ex-vessel)	MELCOR1.8.5[20]
	UoS	APR1400	SBO (in-vessel, early phase fuel temperature)	RELAP5/NESTLE-based 3KEYMASTER simulator[24] and SCALE6.1[25]
SMR	CNEA	CAREM-like iPWR	SBLOCA (in-vessel)	MELCOR1.8.6
	ENSO		SBO (in-vessel)	RELAP/SCDAPSIM/MOD3.5[26,27]

TABLE III

Accident Analysis Codes Employed by Participating Organizations[1,19]

Code	Main Features and Basic Properties
MELCOR	MELCOR, being developed by Sandia National Laboratories, is an integral system-level code for simulating various SA scenarios, including the release and transport of FPs in light water reactors and other nuclear facilities. For this purpose, the code employs several dedicated code packages that together model important plant systems/structures and the coupling interactions between them. Flexible nodalization of the RCS and containment employed by the code allows for the simulation of entire SA sequences for different kinds of reactors. The code was at first developed for fast-running SA analyses as required for PSA, with various functions for performing relevant sensitivity and uncertainty analyses. The recent versions of the code employ various improved functions and models, not only for best-estimate analyses, but also for assessing the effect of mitigation measures being carried out as part of the SAM strategy. As of 2024, the latest version released is MELCOR 2.2.
MAAP	MAAP, which is managed by the Electric Power Research Institute, is an industry standard integral systems code for analyzing plant-level Sas, including FPs. In the mid-1990s, MAAP4 was issued, and thereafter, it was greatly extended to evaluate more flexibly the response of advanced light water reactors, as well as current designs, including mitigation measures being taken as part of SAM. Due to the fast-running algorithms and parametric models employed by the code, the code is widely used by utilities for the PSA Level 2 analysis, but the fixed nodalization for the RCS of standard light water reactors limits its application to relevant experiments with different geometries. As of 2024, the latest version released is MAAP5.06.
RELAP, SCDAPSIM	RELAP, which is being developed at Idaho National Laboratory, is a best-estimate simulation code for analyzing nuclear reactor accidents, but containment and related components are not included in the code. To solve the thermal hydraulics of reactors in real time and to economically calculate system transients, the code solves nonhomogeneous and nonequilibrium models for two-phase systems using a fast and partially implicit numerical scheme. As of 2024, the latest version is RELAP 7. RELAP/SCDAPSIM, which is being developed by Innovative Systems Software as part of the international SCDAP Development and Training Program, employs various versions of RELAP, such as SCDAP/RELAP5/MOD3.2 developed for SA analysis and RELAP/MOD3.3 for best-estimate system analysis. Its latest version is MOD3.5.
3KEYMASTER,	3KEYMASTER, developed by the Western Service Corporation, is a simulator that simulates a power plant in real time, with a graphical visualization. The simulator employs various functions capable of performing reactor startup/shutdown and emergency operations for user training as well as calculating reactor power transients. For thermal-hydraulic and neutronics analyses, the code environment can adapt and embed relevant codes like RELAP5 and NESTLE (a two-energy neutronics code for calculating the neutron flux and the relevant reactor power in real time) within it.
SCALE	SCALE, which is being developed by Oak Ridge National Laboratory, is a neutronics code solving neutron transport equations to compute the forward and adjoint fluxes involved in the sensitivity calculations.
COOLAP	COOLAP, which is being developed by Seoul National University, Korea, is a lumped parametric code for evaluating the coolability of molten core debris discharged into the reactor cavity during the late phase of SAs in light water reactors. To solve preflooded reactor cavity–related issues, the code employs the simplified physical models of corium jet breakup during FCIs, corium particle sedimentation, particle debris bed formation, and debris bed heat transfer and dryout heat flux.

rank correlation coefficient (PRCC), standardized rank correlation coefficient (SRRC), and the principal component analysis (PCA)/parameter space analysis (PSA) methods, as given in the last column of Table IV. For reference,[28–31] the Pearson correlation and the PCC are indicators to identify linear relationships between two variables, while the Spearman and Kendall correlations, PRCC, and SRRC identify monotonic strengths or coherence between two variables based on nonparametric order statistics as provided in Table V.

The degree of estimated correlation indicators (r, $|r| \leq 1$)[31] is categorized as high (or very strong) if $|r| \geq 0.7$, moderate (or strong) if $0.3 \leq |r| < 0.7$, low (or weak) if 0.1 $|r| < 0.3$, and little or no relationship if $|r| < 0.1$. The aforementioned correlation-based sensitivity indicators, which have been used to capture the linear relationship between model inputs and outputs, have the advantage of being robust if they well represent a given model. Since the forgoing sensitivity indicators are easy to intuitively understand, they have been widely used in many science and engineering fields.

Relevant FOMs were defined, as shown in Table VI, and the underlying uncertainty input parameters and probability distribution functions (PDFs) that might affect the defined FOMs were proposed after a careful screening-out process by each participant, as shown in Table VII. These PDFs, characterized as the state of knowledge (epistemic) uncertainty, express that some values in the uncertainty range are more likely to be the appropriate parameter values than others; otherwise, aleatory uncertainty caused by random failures of the systems, structures, and components was not included in the present analyses.

III. RESULTS AND FINDINGS

According to the proposed framework for uncertainty and sensitivity analyses, each participant separately carried out the planned tasks, including plant modeling and nodalizations, simulation of the reference cases, and assessment of uncertainty and sensitivity through a coupling of the relevant SA codes with the corresponding uncertainty and sensitivity quantification tools. This section summarizes the analysis results for dedicated SA phenomena, except for the University of Sharjah (UoS) study whose scope was limited to the very early phase of the accident and is thus presented in the Appendix. More detailed descriptions of the relevant work and results are given in Ref. [19].

TABLE IV

Uncertainty and Sensitivity Methods

Reactor Type	Institution	UQ Method	UQ Tool	Sensitivity/Importance Analysis
Large PWR	DNPER	Monte Carlo method SRS: N = 2800	DST (MATLAB-based, in house)	Pearson, Spearman, and Kendall correlations
	KAERI	SRS: N = 200	DAKOTA,[33] (MELCOR)/ MOSAIQUE,[34] and (MAAP5, in house)	Pearson and Spearman correlations, and PRCC/ SRRC
	KINS	LHS: N = 100	DAKOTA + in house	Pearson and Spearman correlations
	SJTU	LHS: N = 120	MATLAB (in house) + Statistical Package for the Social Sciences	Pearson and Spearman correlations, and PCC/ PRCC
	UoS	SRS: N = 120 (perturbation of the parameter space)	DAKOTA + in house, Reduced Order Modeling-based Uncertainty/Sensitivity Estimator[35]	PSA/PCA methods[37]
SMR (iPWR)	CNEA	SRS: N = 59 (Wilks' one-sided tolerance limit, 95%/95%)[32]	DAKOTA + in house	Pearson and Spearman correlations, and PCC/ PRCC
	ENSO		IUA package[36]	Pearson, Spearman, and Kendall correlations

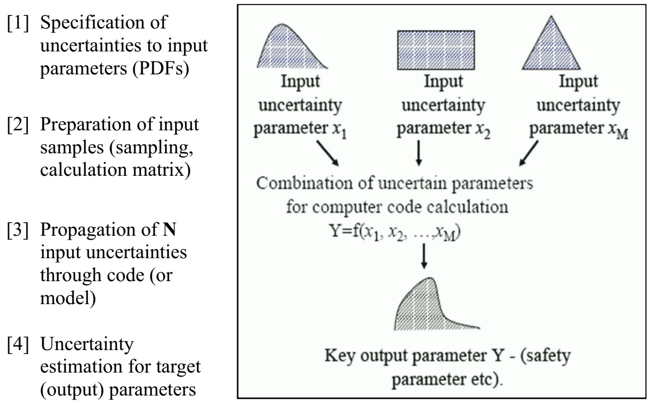


Fig. 3. Key steps for probabilistic statistical uncertainty propagation.

III.A. DNPER (Directorate of Nuclear Power Engineering-Reactor)

For a station blackout (SBO) accident of the K-2 NPP [ACP1000, three-loop 1100-MW(electric) PWR],[38] an in-house statistical tool, the DNPER statistical tool (DST), was used to generate sample values for code simulation and to handle uncertainty data, including statistical analysis. Based on the dedicated plant modeling and nodalization schemes, steady-state analysis was checked until 2000s for the main design parameters of the plant at the nominal values, where the initiated accident sequence was a SBO-induced transient scenario.

For 26 uncertainty input parameters, MELCOR (Methods of Estimation of Leakages and Consequences of Release) simulations for 2800 SRS samples were made to quantify uncertainties of the relevant FOMs; among them, 252 simulations led to failed code runs, representing a failure rate of almost 9%. Thus, the 2548 normal runs were finally used to assess the uncertainties addressed in the relevant FOMs, including a 95% probability level and a 95% confidence level. The uncertainty calculations were made until 72 h from the start of the SBO. Pearson, Spearman, and Kendall correlations were analyzed to determine the key contributors having stronger correlations with each relevant FOM.

As part of the uncertainty and sensitivity results, Fig. 4 illustrates the uncertainty spectra for FOM 8 (Cs release in-vessel), which exerted their influence at different timings, and also correlations for the uncertainty parameters. According to Fig. 4a, the total amount of Cs released in-vessel, which reached its maximum at the time of a reactor pressure vessel (RPV) breach (around 4.98 h), ranged from about 18 to 23 kg, with a mean value of 20 kg and a standard deviation of 0.019 kg. The subsequent small peaks were due to additional releases of Cs after the reactor/containment building (R/B) breach (around 23 h). The key contributors having a stronger correlation with each FOM, which were determined by equally weighting the relevant CCs, are summarized in Table VIII.

TABLE V

Sensitivity and Correlation Indicators Tested in the Present Exercise

Indicator	Definition
Pearson CC	A measure to identify a linear relationship between two variables that is obtained by dividing their covariance by the product of relevant standard deviations.
Spearman rank CC	A nonparametric measure to identify the monotonic strength between two variables. The coefficient uses ranks in ascending order instead of simulation results.
PCC/PRCC	The PCC is used to identify a linear relationship between any two variables among *p* variables in multivariate correlation analysis. The coefficient is often used to avoid masking the effects of correlations between any two variables while removing the effects of the rest. The PRCC is the corresponding nonparametric rank correlation measure, which is often used to improve the PCC.
Standardized regression coefficients (SRC)/SRRC	The SRC is the coefficient of a multiple regression model where relevant data for the response variable and input variables have been standardized so that their variances are equal to 1. The SRRC is the corresponding nonparametric rank correlation measure, which is often used to improve the SRC.
Kendall CC	A nonparametric measure of coherence between randomly chosen input parameter values and simulation results (or a measure of their disorder), based on ranks of two variables.

TABLE VI

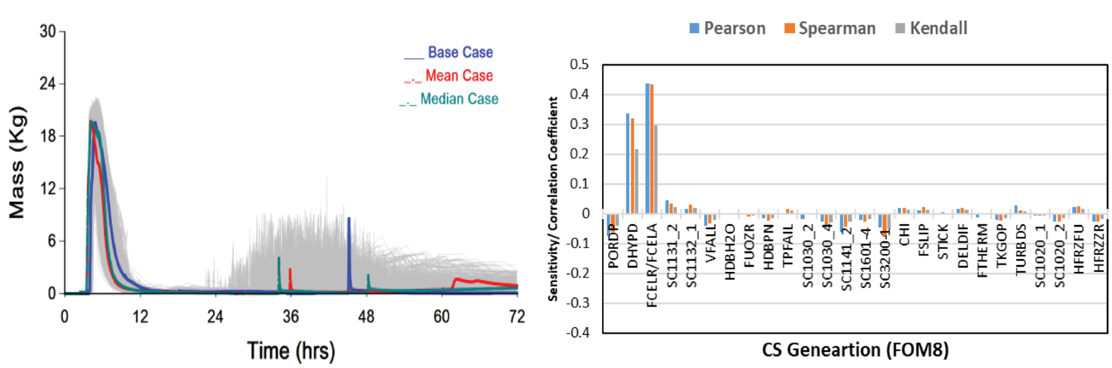
FOMs of Interest

Institution	FOMs: Code Response Parameters of Interest
DNPER	(1) Core uncovery time, (2) RPV LH time, (3) in-vessel H_2 generation, (4) ex-vessel $H_2/CO/CO_2$ generation, (5) in-vessel cesium iodide/Cs generation/release, (6) R/B failure time, and (7) release of total FPs to the environment: 10 FOMs
KAERI	(1) Core uncovery time, (2) RPV LH and R/B failure time, (3) in-vessel H_2 generation, (4) ex-vessel H_2/CO generation, and (5) Cs release to the environment: 7 FOMs
KINS	(1) R/B pressure, (2) cavity concrete ablation, and (3) ex-vessel H_2/CO generation: 3 FOMs
SJTU	In-/ex-vessel H_2 generation: 2 FOMs
UoS	Early phase fuel temperature before Zr oxidation (in-vessel): 1 FOM
CNEA	(1) Core uncovery time, (2) onset of core degradation, and (3) core relocation time to LP: 3 FOMs
ENSO	(1) Time to oxidation >0.1% of the nominal power, (2) time to $T_{\text{cladding}} > 1477$ K, (3) fuel rupture, debris formation, and core slumping/creep rupture times, (4) cumulative H_2 generation, (5) T_{cladding} when fuel rupture, and (6) cumulative FP (noncondensable and soluble): 10 FOMs

TABLE VII

Uncertainty Input Parameters and Relevant PDFs

Institution	Sources: Code Manual, Open Literature, Expert Judgment, and Deterministic/Parametric Sensitivity Analyses Whenever Necessary
DNPER	MELCOR1.8.6 (26 model parameters, in-/ex-vessel and FPs)
KAERI	MELCOR2.2 (26 model parameters, in-/ex-vessel and FPs) and MAAP5.05 (29 model parameters, in-/ex-vessel and FPs)
KINS	MELCOR2.2 (five model parameters)/COOLAP2 (eight model parameters): ex-vessel/reactor cavity
SJTU	MELCOR1.8.5 (18 model parameters, in-vessel)
UoS	3KEYMASTER simulator (44 parameters/44 groups the SCALE covariance library for the cross sections affecting the fuel early phase fuel temperature, in-vessel)
CNEA	MELCOR1.8.6 (11 model parameters and 1 for accident management, in-vessel)
ENSO	RELAP/SCDAPSIM/MOD3.5 (15 model parameters for in-vessel and 3 for safety systems)



(a) Time trend for uncertainty
(b) Sensitivity/importance results

Fig. 4. Uncertainty and sensitivity analyses results for FOM 8 in the DNPER study.

TABLE VIII

Key Contributors to Relevant FOMs in the DNPER Study*

FOM	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
FOM 1	SC3200_1 (–0.70)	FCEL (0.1)	HDBPN (–0.1)	SC1020_2 (0.1)	TPFAIL (0.1)
FOM 2	SC3200_1 (–0.70)	FCEL (–0.12)	SC1141_2 (0.12)	HDBPN (–0.1)	SC1020_2 (0.1)
FOM 3	HDBPN (–0.4)	DHYPD (–0.2)	SC1131_2 (0.17)	TPFAIL (0.16)	SC1141_2 (0.10)
FOM 4	SC3200_1 (0.55)	HDBPN (–0.2)	DHYPD (0.18)	SC1141_2 (–0.10)	FCEL (0.09)
FOM 5	SC3200_1 (0.58)	HDBPN (–0.2)	DHYPD (0.16)	FCEL (0.1)	SC1141_2 (–0.10)
FOM 6	SC3200_1 (0.70)	DHYPD (0.12)	FCEL (0.12)	SC1141_2 (–0.10)	SC1131_2 (0.09)
FOM 7	SC1141_2 (–0.30)	DHYPD (0.18))	SC3200_1 (–0.15)	SC1131_2 (0.12)	–
FOM 8	FCEL (0.45)	DHYPD (0.33)	–	–	–
FOM 9	SC3200_1 (–0.9)	DHYPD (0.12)	–	–	–
FOM 10	SC3200_1 (0.7)	HDBPN (0.11)	–	–	–

*FCEL: radioactive exchange factor for radiation heat transfer, DHYPD: particulate debris equivalent diameter, HDBPN: debris to penetration heat transfer coefficient, SC1020_2: time constant for the relocation of liquid material, SC3200_1: multiplier for ANS decay heat curve, SC1131_2: maximum ZrO_2 temperature to hold up molten Zr in cladding, SC1141_2: maximum melt flow rate after breakthrough, and TPFAIL: penetrations or LH failure temperature.

The main findings and lessons learned from the analysis are as follows:

1. In comparison with the base case scenarios, the best-estimate model and values with uncertainty treatment provided a much better understanding of the safety and regulatory limits for SAs.

2. Statistical indicators tested for the sensitivity/importance analyses suggested that uncertainty parameters exert their influence at different timings, and also that their effects vary in magnitude. Moreover, their impact of the selected uncertainty parameters was different for each FOM; among the 26 model parameters, only 7 parameters appeared to have more influence on the defined FOMs, indicating that more detailed analyses could be focused on the higher-impacting parameters only. According to the sensitivity analysis, the decay heat multiplier (SC3200_1) acted as the main contributors to most FOMs; larger decay heat led to faster boiling, uncovering of the coolant, and ultimately, containment failure causing the release of fission products (FPs) into the environment.

3. To obtain more realistic uncertainty results, it is necessary to identify the proper sources of uncertainties in different phenomena, models, and their associated probability distributions. Besides, larger input population sets seem to be necessary to compensate for the possibly incomplete executions and divergent cases. For incomplete code executions, further investigation is needed to identify the sources of relevant errors.

4. For in-vessel and ex-vessel phenomena, being two different phenomena, separate uncertainty parameters should be explored to avoid unnecessary computational burden.

III.B. KAERI (Korea Atomic Energy Research Institute)

In the KAERI study, three reference scenarios were considered related to a short-term station blackout (STSBO) of the reference plant, the OPR1000 [Optimized Power Reactor, two-loop 1000-MW(electric) PWR],[39] as shown in Table IX. A STSBO is a core damage sequence induced by a complete loss of all onsite and offsite alternating current (ac) powers, leading to the unavailability in this scenario of all safety-related systems driven by ac power.

Two mitigation scenarios were considered to explore the influence of relevant severe accident mitigation (SAM) measures that use mobile equipment provisioned for emergency situations after the Fukushima Daiichi NPP accident. The latest versions of two SA codes, MELCOR2.2 and MAAP5.05 (Modular Accident Analysis Program Version 5.05), were utilized to compare with the results of interest.

For the dedicated plant modeling and nodalization schemes, the steady-state analysis showed that the present input models could simulate within an error bound of 1.8% for MELCOR2.2 and 1% for MAAP5, compared to the OPR1000 final safety analysis report.[40] For the quantification of the relevant uncertainties, two software tools were utilized for this study: SNAP/DAKOTA for MELCOR and an in-house code MOSAIQUE (Module for SAmpling Input and QUantifying Estimator) for MAAP5. Simple random samples of N = 200 were tested for the purpose of this study.

The uncertainty calculations were made until 72 h from the start of the SBO, taking an average run time of

TABLE IX

Three Reference Scenarios for the OPR1000 Analysis

Cases	RCS Prebled[a]	Feed and Bleed Operation
Base case	No mitigation	No mitigation
Mitigation case 1	Opening of two safety depressurization system valves at the SAM guideline entry condition[a]	Mobile pump starts at 4 h to inject external water into RCS.
Mitigation case 2		Mobile pump starts at 4 h to inject external water into SG.

[a]RCS prebled via the safety depressurization system, which was intended to allow for the utilization of the cooling water inventory of the safety injection tanks.

almost 51 h in the dedicated PC system for MELCOR (operating system: MS Windows 2008 R2 Enterprise, 64 bit, RAM: 128 GB, processor: Intel(R) Xeon(R) CPU E5-2697 v2 @ 2.70 GHz, 2701 Mhz, 12 core/24 logic processor) and almost 1.3 h in the dedicated PC system for MAAP5 (operating system: MS Windows 10 Enterprise, 64 bit, RAM: 64 GB, processor: AMD Ryzen Threadripper 3960X 24-core 3.79 GHz).

Among the total 200 SRS samples tested for the uncertainty analysis, almost 50 code crashes were observed during the MELCOR simulation, leading to a failure rate of 25% without sharing any specific tendency. These errors might have been due to either physically unreasonable random combinations beyond the code capability or a numerical problem, by which relevant thermal-hydraulic behavior is often not converged, or both.

Among the normal realizations, N = 100 samples (slightly exceeding the minimum sample size of 93 required for the second-order Wilks formula at the one-sided 95%/95% tolerance limit[32]) were randomly taken for an analysis of the results. For MAAP5, among the 200 SRS samples, only 2 samples led to code failure. Accordingly, 198 normal realizations (corresponding to the fourth-order Wilks formula at the one-sided 95%/99% tolerance limit) were used for the final processing. A suite of sensitivity indicators, namely, Pearson and Spearman correlations, PRCC, and SRRC, were evaluated to identify the influence of the selected uncertainty inputs on each relevant FOMs.

As part of the uncertainty and sensitivity analysis results, Fig. 5 illustrates the time trends of the uncertainties for the environmental release of Cs (FOM 7) in the base case scenario, cumulative distribution functions (CDFs) at 72 h after the accident, and key contributors having stronger correlations with each FOM than the others. For the multiple linear regression–based sensitivity measures (i.e., PRCC and SRRC), a coefficient of determination R^2 greater than 0.5 was used to determine the final ranks of the selected uncertainty input parameters.

Figure 6 shows the key contributors, i.e., those having stronger correlations with each FOM than the others, determined based on a weighted average of relevant sensitivity measures. For the multiple linear regression–based sensitivity measures (i.e., PRCC and SRRC), a coefficient of determination R^2 greater than 0.5 was used to determine the final ranks of the uncertainty inputs.

The main findings and lessons learned from the analysis are as follows.

1. For the explored SBO scenario, both codes similarly predicted the general trend of the SA evolution and plant responses, implying no significant difference when implementing a specific accident management strategy. On the other hand, predictions of the generation of flammable gases by the two codes significantly differed.

2. The sensitivity/importance analysis showed that the model parameters sensitive to a particular FOM may not have the same degree of impact on other FOMs, and also that inputs influencing the uncertainties of relevant FOMs in one scenario may not necessarily have the same degree of impact in other scenarios. Moreover, the model parameters having a very strong correlation with the FOMs of interest were limited to a few cases for both codes, the decay power (DP) multiplicative factor was the primarily important contributor over the various FOMs of interest, compared to the rest.

3. Regarding the code crashes observed during the simulations, it is necessary to investigate their patterns from the parameters' coverage map related to simulations with relevant errors, and also to identify the types of error sources in order to better understand model behavior and to improve model robustness.

4. The correlation/regression methods employed for the present study were fundamentally based on a linear relationship between inputs and the relevant FOMs; consequently, their usability was often limited for highly complex nonlinear and/or nonmonotonic relationships between inputs and FOMs, like as in SA codes.

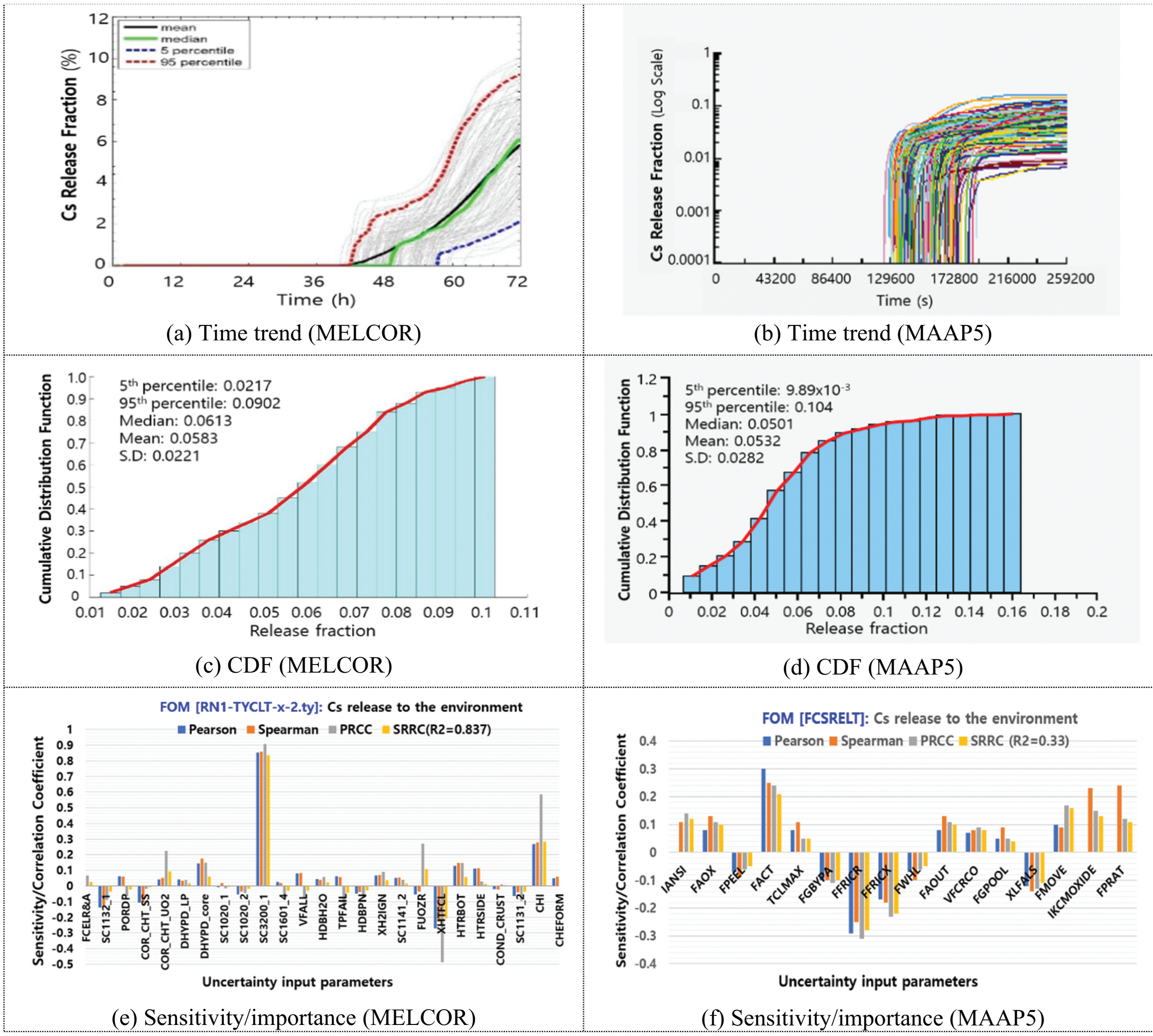


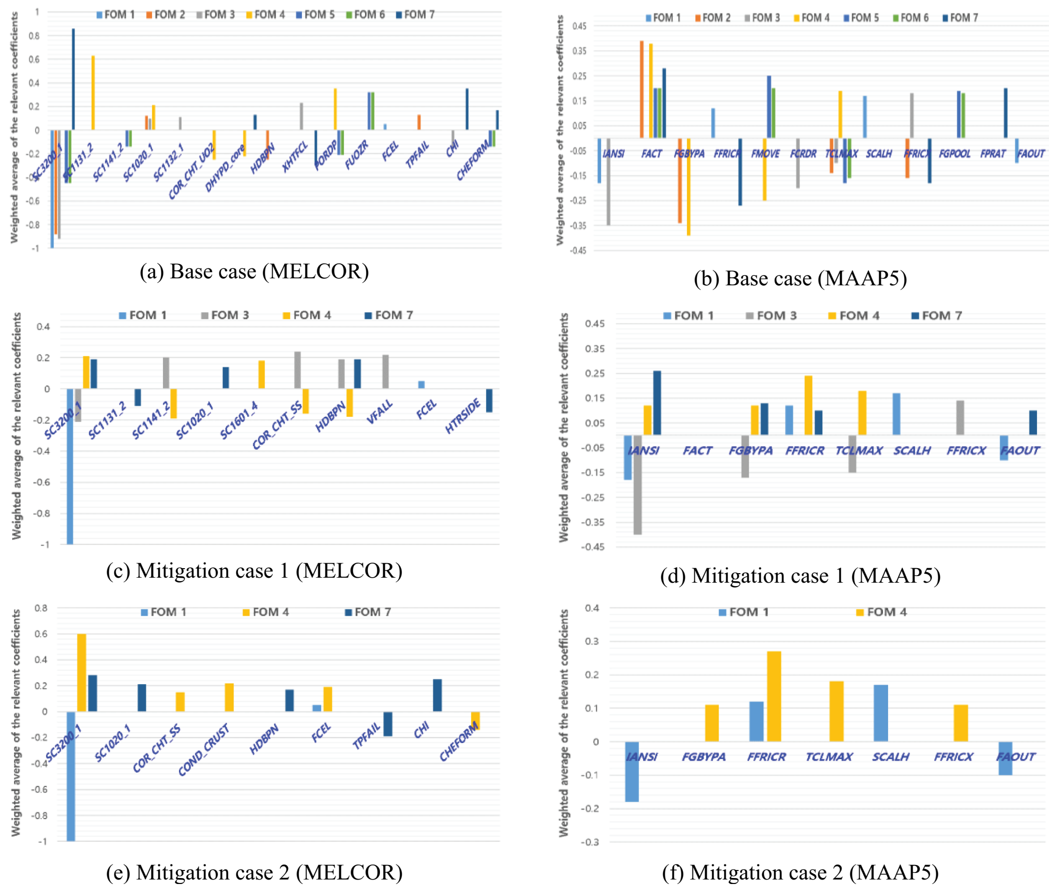
Fig. 5. Uncertainty and sensitivity analyses results for the base case (FOM 7) in the KAERI study.

For such code cases, it is advisable to additionally explore sensitivity indicators that provide a more exhaustive picture of the relative importance of each input to the FOM of interest.

III.C. KINS (Korea Institute of Nuclear Safety)

In the KINS study, a coupled analysis of MELCOR2.2 and COOLAP was performed for a SBO accident of the APR1400 [Advanced Power Reactor two-loop 1400-MW (electric) PWR].[41] For this, the COOLAP code was used to define the initial conditions for the MELCOR analysis. For the MELCOR analysis, the two-cavity model was used to overcome the limited capability of the present MELCOR code to handle the relocation of corium with two different characteristics, i.e., melted and debris corium. Its basic concept is to divide the cavity volume into two regions where the coolable (debris) and noncoolable (melted) corium are separately placed, depending on the COOLAP analysis results.

If the ratio of 1 to 9 (1:9) is considered, the cavity area of the noncoolable corium (cavity 1) becomes 10% and coolable corium (cavity 2) is 90%. To establish the steady state, several initial thermal-hydraulic conditions (including pressurizer pressure, steam pressure, feedwater flow rate, and temperature) were appropriately adjusted at full power. Using SNAP/DAKOTA coupled to MELCOR, relevant uncertainty analyses were made for 13 model input parameters. The uncertainty calculations were made until 250 000 s (~70 h) from the start of the SBO. Pearson and Spearman correlations were used for a sensitivity/importance analysis of the selected uncertainty input parameters.



(a) Base case (MELCOR) (b) Base case (MAAP5)

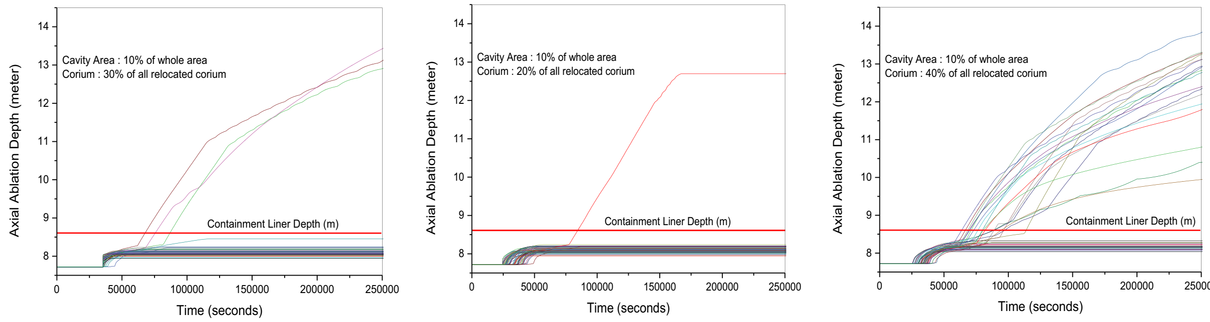
(c) Mitigation case 1 (MELCOR) (d) Mitigation case 1 (MAAP5)

(e) Mitigation case 2 (MELCOR) (f) Mitigation case 2 (MAAP5)

Fig. 6. Key contributors to the relevant FOMs (MELCOR, MAAP5) in the KAERI study. MELCOR parameters include COND. CRUST: thermal conductivity multiplier for the crust, COR.CHT: candling heat transfer coefficient for UO_2 or SS, XHTFCL: atmosphere heat transfer scaling factor, FUOZR: transport parameters for UO_2 in molten zircaloy, CHI: aerosol dynamic shape factor, CHEMFORM: Cs fraction transformed to Cs_2MoO_4, SC1601_4: total strain causing failure, VFALL: velocity of falling debris, and HTRSIDE: debris-to-surface heat transfer multiplier. MAAP5 parameters include FACT: reduced hydraulic diameter multiplier, FAOUT: fraction of SG tubes carrying out flow in the hot-leg natural circulation model, FCRDR: fraction of core mass below which the remaining core is dumped into the LP, FFRICR: friction for axial gas flow between core and RPV upper plenum, FFRICX: cross-flow friction for in-vessel natural circulation of the gas flow, FGBYPA: gas flows in the core to the bypass channel, FGPOOL: geometric factor to define the height of the in-core molten pool, FMOVE: amount of solid U-Zr-O embedded in liquid U-Zr-O, FPRAT: FP release correlations, IANSI: American National Standards Institute decay heat type, SCALH: scale factor for heat transfer to passive heat sinks, and TCLMAX: temperature to calculate the Larson-Miller parameter.

For a preflooded cavity condition, taken to retain the molten core material inside the reactor vessel during a SA in the APR1400 (i.e., cavity flooding), three case studies were made to explore the influence of noncoolable and coolable corium configurations in the reactor cavity: one base case having a noncoolable/coolable corium mass ratio of 3:7 (CR-1) over a cavity area of 10% and two sensitivity cases with the respective corium mass ratios of 2:8 and 4:6 (CR-2 and CR-3). For each case study, 100 LHS samples were tested until 250 000 s (~70 h) from the start of the SBO, taking the average run time of almost 85 000 s (~24 h) per sample in the dedicated PC system [Del Precision 7920 Tower, operating system: MS Windows 10, RAM: 192 GB, processor: Intel(R) Xeon(R) Gold 5220 CPU @ 2.20 GHz and 2.19 GHz (two CPUs)]. Among them, eight samples led to code failure; thus, 92 normal realizations were used for the final processing.

As part of the uncertainty analysis results, Fig. 7 illustrates the time trends for the uncertainties of the basemat axial ablation depth (FOM 2) evaluated for the three cavity conditions. According to the figure, for CR-1 and CR-2, just a few sample cases exceeded a limit of containment liner melt-through (flat red line). The foregoing result reflects the impact of the random combinations of the input parameter values selected for the uncertainty analysis [mainly related to the physical model parameters and material properties (MPs) of



(a) CR-1 (Base case) (b) CR-2 (Sensitivity case 1) (c) CR-3 (Sensitivity case 2)

Fig. 7. Uncertainty results for the cavity basemat axial ablation depth (FOM 2) in the KINS study.

corium]: scenarios that resulted in containment liner melt led to a harsher environment on the containment liner melt in the reactor cavity.

Of course, it was highly expected that the containment liner melt would be more for dry cavity conditions with no mitigation. As part of the subsequent sensitivity/importance analysis, Table X shows the final rankings of the key contributors to FOM 2 of CR-1 (base case) based on the Pearson and Spearman correlations.

The main findings and lessons learned from the analysis are as follows:

1. The main sources of uncertainty resulted from the limited understanding of the physical phenomena associated with the problem addressed in the analysis. Another source of uncertainty resulted from the wide combination of parameters associated with the scenario and the plant design–specific accident progression.

2. MELCOR can provide meaningful predictions on cavity basemat ablation if it is adequately coupled with a model that is able to analyze the corium relocation process and corium coolability in the reactor cavity. Nonetheless, closely related phenomena, including molten corium–concrete interaction (MCCI), highly depend on the intermittent physical phenomena related to the RPV failure modes and the fuel coolant interaction (FCI). The foregoing factors are also closely related to the remaining two FOMs, i.e., R/B pressurization (FOM 1) and generation of combustible gases (H_2/CO) (FOM 2).

3. For the sample size of 100, the LHS method quantified relatively well the uncertainties of the FOMs of interest. A sensitivity analysis showed that even when increasing the LHS sample size from 100 to 300, there was no essential difference in the uncertainties of the relevant FOMs.

4. More comprehensive analyses with carefully selected uncertainty input parameters and underlying PDFs are needed to obtain more robust results. For incomplete code executions, further investigation is needed to identify the sources of relevant errors.

III.D. SJTU (Shanghai Jiao Tong University)

In the SJTU study, for a SBO accident of the reference plant CPR600 [two-loop 600-MW(electric) PWR],[42] the hydrogen source term, whose burning or rapid deflagration may cause damage to equipment and systems and might even threaten the integrity of containment, was evaluated using MELCOR 1.8.5, and the relevant influence on mitigation

TABLE X

Key Contributors to FOM 2 (CR-1) in the KINS Study*

Correlation	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Pearson	COND_MET (0.317)	ZO (0.085)	SC2315_2 (0.079)	COND_CRUST (0.063)	SC2315_3 (0.044)
Spearman	COND_MET (0.317)	SC2315_2 (0.151)	ZO (0.121)	COND_CRUST (0.042)	SC2315_3 (0.027)

*COND_CRUST/MET: melt pool conductivity multiplier (CRUST = crust and MET = metallic layer), SC2315_2/3: melt eruption and water ingress parameters (2 = debris diameter and 3 = debris layer void fraction), and ZO: axial ray origin.

measures [opening of the pressurizer safety/relief valves (PSVs)] was explored to provide technical support for SAM. The reference scenario SBO assumed a loss of all off-site ac power and failure to operate of the emergency diesel generators and turbine-driven auxiliary feed pump. The only means available to cool down the reactor core were the initial inventory of the reactor coolant system (RCS) and steam generators (SGs), the pressurizer level control, the reactor coolant pump (RCP) seal injection, the active safety injection systems, and the motor–driven auxiliary feedwater system.

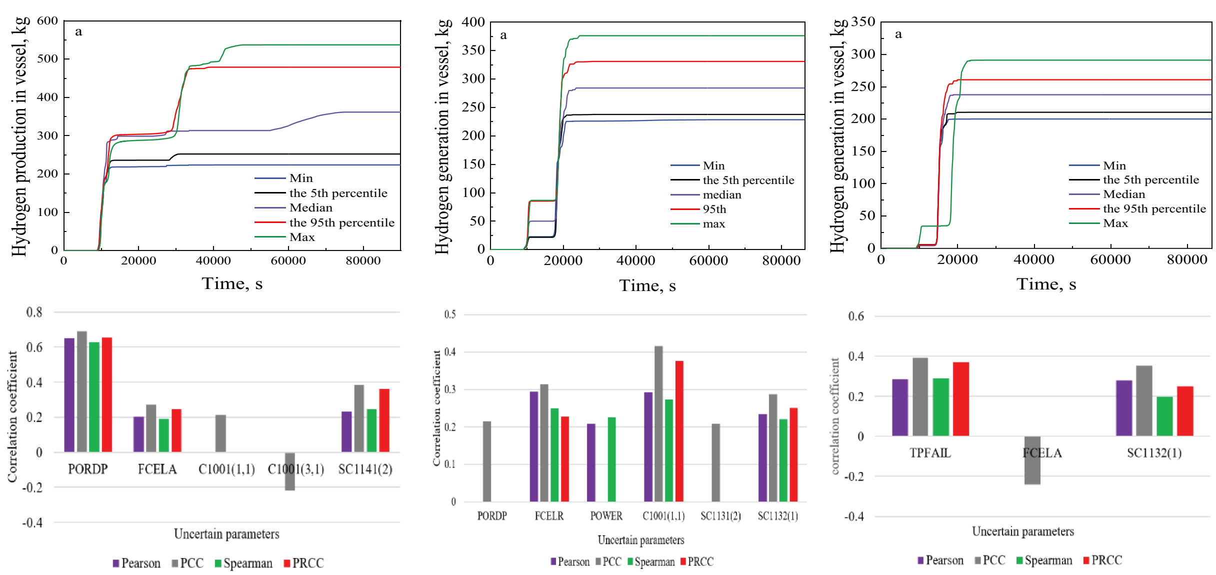
The plant model included primary and secondary loops, the pressurizer, the pressure relief tank, and the containment. With a calculation time of 5000 s, the steady-state analysis carried out for some important plant variables (e.g., reactor power, average coolant temperature, pressurizer pressure, pressurizer water level, etc.) showed that the input models were within an error bound of 1.0% compared to the reference values.

Based on 18 model parameters selected for uncertainty analysis, MELCOR simulations for 120 LHS samples were made until 24 h from the start of the SBO; code failures were not reported for the simulation. Pearson and Spearman CCs, PCC, and PRCC were analyzed to determine the key contributors influencing the relevant FOMs. As part of the analysis results, time trends and relevant PDFs for in-vessel H_2 generation (FOM 1) are summarized in Fig. 8 and sensitivity results of three mitigation measures of H_2 generation from in-vessel and ex-vessel MCCI (FOMs 1 and 2) are given in Tables XI and XII.

For different pressure relief measures, only a few uncertainty parameters showed correlation with the hydrogen source term in the vessel. Among them, the maximum temperature of the oxidized fuel rod, which can maintain its geometric shape when there is incompletely oxidized zirconium in the cladding [SC1132(1)], exhibited a nonnegligible positive correlation with respect to the hydrogen source term under both nonrelief and pressure-relief conditions. For the hydrogen generation ex-vessel, the heat transfer coefficients in the radial and the bottom direction of the cavity (HTRSIDE/HTRSIDE) always presented the most important positive correlation effect on the hydrogen generation ex-vessel.

The main findings and lessons learned from the analysis are as follows:

1. For a SBO accident, the opened number of PSVs taken as one of the mitigation strategies obviously influenced H_2 generation and relevant uncertainty (see Fig. 8). The opening of three PSVs (leading to a mean value of



(a) Opening of one PSV (b) Opening of two PSVs (c) Opening of three PSVs

Fig. 8. Uncertainty and sensitivity analysis results for FOM 1 (in-vessel H_2 generation) in the SJTU study. Terms include C1001 (1,1): constant coefficients of Zircaloy oxidation rate (low temperature range), C1001(3,1): constant coefficients of Zircaloy oxidation rate (high temperature range), FCELA/FCELR: radiative exchange factors for radiation heat transfer upward axially and outward radially (treated as the same parameter), POWER: plant thermal power, SC1131(2): maximum temperature of ZrO_2 allowed to hold up molten zirconium, SC1132(1): temperature that an oxidized fuel rod can endure without unoxidized zirconium in the fuel cladding, SC1141(2): maximum flow rate of molten core material after breakthrough per unit width, and TPFAIL: penetration failure temperature or LH failure temperature.

TABLE XI

Key Contributors to FOM 1 to In-Vessel H_2 Generation in the SJTU Study*

FOM (H_2 Generation)	Parameter Importance Ranking		
	Rank 1	Rank 2	Rank 3
Base case (no mitigation)	SC1132(1)	PORDP	—
Mitigation case 1 (opening of one PSV)	PORDP	SC1132(1)	FCELA
Mitigation case 2 (opening of two PSVs)	C1001(3,1)	FCELA	SC1132(1)
Mitigation case 3 (opening of three PSVs)	TPFAIL	SC1132(1)	—

*TPFAIL: penetration failure temperature or LH failure temperature, FCELA: radiative exchange factors for radiation heat transfer upward axially and outward radially (treated as the same parameter), SC1132(1): temperature that an oxidized fuel rod can endure without unoxidized zirconium in the fuel cladding, C1001(3,1): constant coefficients of Zircaloy oxidation rate (high temperature range).

TABLE XII

Key Contributors to FOM 2 for Ex-Vessel H_2 Generation in the SJTU Study*

FOM (H_2 Generation)	Parameter Importance Ranking		
	Rank 1	Rank 2	Rank 3
Mitigation case 1 (opening of one PSV)	HTRSIDE	HTRBOT	PORDP
Mitigation case 2 (opening of two PSVs)	HTRSIDE	HTRBOT	TPFAIL
Mitigation case 3 (opening of three PSVs)	HTRSIDE	HTRBOT	TPFAIL

* TPFAIL: penetration failure temperature or LH failure temperature, HTRBOT: Debris-to-surface heat transfer treatment on debris bottom surface, and HTRSIDE: debris-to-surface heat transfer treatment on debris radial surface.

237 kg and an uncertainty range of 5th/95th percentiles over 210 to 261 kg) had a lower influence than the opening of two PSVs (leading to a mean value of 282 kg and an uncertainty range over 237 to 331 kg) or one PSV (leading to a mean value of 368 kg and an uncertainty range over 252 to 488 kg), as well as no mitigation measure (leading to a mean value 276 kg and an uncertainty range over 241 to 336 kg). For reference, the 5th/95th percentiles estimated for the three mitigation cases 1, 2, and 3 were equivalent to the H_2 production from a zirconium-water reaction of 36%/70.4%, 38%/48%, and 30%/37.6%, respectively, and 34.7%/48.5% for no mitigation (base case).

2. The PDF types of the uncertainty parameters may affect the uncertainty range of the hydrogen source term and relevant sensitivity results. For instance, when the probability distribution of the porosity of debris (PORDP) was changed from the original normal PDF to uniform, the median value of FOM 1 decreased from 377 to 361 kg and the relevant 5th/95th percentiles changed from 252 to 488 kg to 241 to 525 kg, while the median value of FOM 2 decreased from 535 to 533 kg with changes in the 5th/95th percentiles from 425 to 644 kg to 397 to 675 kg. In addition, compared with the normal distribution, PORDP in uniform distribution showed a stronger correlation with the hydrogen source term, reflecting that the PDF type of the model parameters influences to some extent the relevant FOMs.

3. For the sample size of 120, the LHS method quantified relatively well the uncertainties of the FOMs of interest. A sensitivity analysis showed that even when increasing the LHS sample from 120 to 300, there was no essential difference in the mean/median values and uncertainty range of the relevant FOMs. However, it was clear that a reasonable LHS sample size would be dependent on the number of selected uncertainty input parameters.

III.E. CNEA (National Atomic Energy Commission, Argentina)

In the CNEA study, the reference plant was a CAREM-like integral PWR (iPWR)[43] generating a core thermal power of 100 MW(thermal) and employing 12 identical mini helical SGs of the once-through type. All the major components of a typical primary system were located inside the RPV, the power was removed by natural circulation, and passive safety systems were implemented by design. The reference scenario, a small-break loss-of-coolant accident (SBLOCA), intrinsically included a SBO event with the failure of all defense-in-depth Level 2 and Level 3 heat removal and injection systems to strengthen the design to cope with extreme external events, except for the RPV external cooling system after core degradation (in-vessel melt retention).

The relevant MELCOR model included the primary system, containment system, and most of the safety-important systems. A simplified secondary-system model was included as a boundary condition (BC) for steady-state operation, and a steady-state analysis was made for some of the main plant characteristic variables, including the primary system and containment. DAKOTA 6.10 coupled to MELCOR was employed as the tool for the uncertainty analysis. Relevant uncertainty and sensitivity analyses were made for three FOMs: core uncover time (FOM 1), onset of core degradation (FOM 2), and core relocation time to the lower plenum (LP) (FOM 3). The uncertainty calculations were made until 24 h from the start of the accident.

The first order of the Wilks' formula[32] was applied to estimate a confidence level of 95% and probability contents of 5% and 95% of the defined FOMs; for this, a minimum sample size of N = 59 was required. A total of 73 SRS samples were tested to obtain the corresponding 59 realizations, during which 13 simulations failed, leading to a failure rate of almost 18%. The crashed code runs were mostly a result of modeling issues in the bypass region of the core.

For the uncertainty calculation, the average run time of almost 14 h was taken using the dedicated PC system (operating system: MS Windows 7, 64 bit, RAM: 16 GB, processor: Intel(R) Core(TM) i7-4770 CPU @ 3.40 GHz, four Cores/eight Threads). Table XIII and Fig. 9 present the uncertainty analysis results for the 59 normal samples based on the assumptions made in the analysis.

A suite of sensitivity/importance indicators, including the Pearson correlation, Spearman rank correlation, PCC, and PRCC, were evaluated to identify the influence of the selected inputs on each relevant FOM. As part of the sensitivity/importance analysis, the estimated CCs for the uncertainty input parameters and relevant FOMs are summarized in Table XIV.

The main findings and lessons learned from the analysis are as follows:

1. The tested uncertainty inputs led to an uncertainty of the FOMs ranging from 30% up to 50% of the best-estimate (base case) value. For all uncertainty inputs, additional parametric analyses made with uniform PDFs showed a quite small sensitivity to extreme values of the relevant FOMs.

2. Statistical indicators tested for sensitivity/importance analysis showed similar results. The most influential parameters on the defined FOMs corresponded to the MELCOR physical model parameters (PM-1 to PM-4), among which the decay heat multiplier (PM-1) was the most important.

3. A relatively high rate of code failures was observed during the MELCOR simulations, ranging from 6% to 20% depending on the PDF range of the uncertainty inputs, but no correlation or clustering was found between the issue and the values of the sampled parameters. A deeper investigation is needed to identify the sources of relevant errors. Besides, the 59 samples employed for the study were primarily good for 95 percentile using the Wilks' formula, but more samples seem be needed to get more robust mean and median values.

4. Almost 60% of the time required for the present task was spent on characterizing the uncertainty inputs (identification, quantification, and screening), as well as on analyzing the relevant FOMs and implementing the feedbacks.

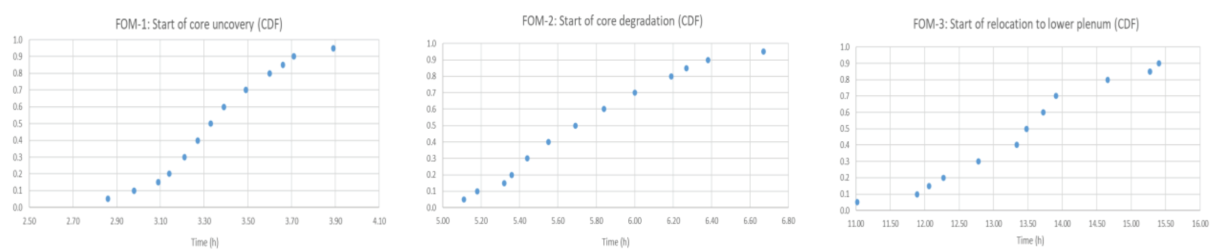
III.F. ENSO (Energy Software, Spain)

As like CNEA, the reference plant in the ENSO study was a CAREM-like iPWR[43] with natural circulation

TABLE XIII

Uncertainty Results for Relevant FOMs of Statistical Values H in the CNEA Study

FOM	Mean/Standard Deviation	Base Case	Tolerance Limit	
			Lower Bound (5/95%)	Upper Bound (95/95%)
FOM 1	3.36/0.29	3.3	2.44	3.97
FOM 2	5.77/0.47	5.5	4.83	6.78
FOM 3	13.6/1.46	14.0	10.9	16.9



(a) FOM 1: Start of core uncovery (b) FOM 2: Start of core degradation (c) FOM 3: Core relocation to LH

Fig. 9. Uncertainty results for relevant FOMs (PDFs and CDFs) in the CNEA study.

TABLE XIV

Estimated CCs in the CNEA Study*

Input/FOM	IC-1	IC-2	RM-2	AM-1	PM-1	RM-1	PM-2	PM-3	PM-4	RM-3	RM-4
FOM 1	0.099[a]	0.003	–0.024	0.068	**–0.852**	0.000	0.001	0.047	0.149	–0.098	0.116
	0.11[b]	–0.030	–0.050	0.126	**–0.915**	–0.026	0.015	0.113	0.110	–0.009	0.083
	0.039[c]	–0.029	–0.057	0.094	**–0.867**	0.148	–0.119	0.058	0.278	0.029	0.184
	0.163[d]	–0.022	0.009	0.155	**–0.924**	0.138	–0.089	0.114	0.249	0.126	0.169
FOM 2	0.074[a]	0.012	–0.003	0.011	**–0.989**	–0.095	0.102	0.098	–0.054	–0.099	0.009
	0.052[b]	–0.035	–0.051	0.077	**–0.992**	–0.097	0.082	0.140	–0.061	–0.034	0.034
	0.095[c]	–0.012	0.094	–0.230	**–0.995**	–0.174	**0.418**	**0.610**	–0.528	0.013	–0.313
	0.167[d]	–0.187	0.188	0.042	**–0.997**	–0.069	**0.349**	**0.547**	–0.708	–0.046	0.081
FOM 3	0.096[a]	–0.015	0.088	0.043	**–0.801**	–0.085	**0.421**	**–0.330**	0.082	–0.059	–0.042
	0.151[b]	–0.024	0.068	0.059	**–0.746**	–0.114	**0.432**	**–0.328**	0.127	–0.060	–0.033
	0.276[c]	–0.107	0.347	0.013	**–0.945**	0.035	**0.829**	**–0.785**	0.118	–0.046	–0.209
	0.394[d]	–0.042	0.353	0.099	–0.923	–0.014	0.798	–0.769	0.148	–0.169	–0.157

*AM-1: delay in RPV external water injection time, IC-1: temperature at which oxidized fuel rods can stand, IC-2: maximum ZrO_2 temperature to hold up molten Zr, PM-1: DP multiplicative scale factor, PM-2/PM-3: radiative exchange factor for radiation (radial/axial), PM-4: Zircaloy oxidation rate constant (low temperature range), RM-1: particulate debris equivalent diameter, RM-2: porosity of particulate debris, RM-3: fraction of channel volume denied to particulate debris, and RM-4: time constant for the radial relocation of solid material.

[a]Pearson CC.

[b]Spearman CC.

[c]PCC.

[d]PRCC.

operation. The reference scenario SBO was analyzed using the RELAP (Reactor Excursion and Leak Analysis Program)/SCDAPSIM (Severe Core Damage Analysis Package SIMulator)/MOD3.5 (RS/3.5) code, and the plant nodalization included the major components of a typical PWR primary system within the RPV, the passive safety systems [secondary shutdown system, emergency injection system, passive residual heat removal system (PRHRS), pressure relief valves and external core cooling system], and the environmental heat losses at the top and bottom of the RPV, as well as in the pipes of the passive safety systems. The selected uncertainty input parameters were related to heat transfer, critical heat flux (CHF), interphase heat transfer, MPs, cladding behavior, radiation, core power, safety systems, and natural circulation. The code simulations were terminated by either a trip of the RPV creep rupture signal or a maximum end time set to 5 days.

The uncertainty analysis was carried out with the IUA2.0 module[36] integrated into the RS/3.5 code using an input-propagation methodology with a statistical description of the uncertainty and the Wilks' first-order formula. Based on the Wilks' first-order formula, a SRS sample of N = 59, i.e., the minimum sample size required for a confidence level of 95% and probability contents of 5% and 95%,[32] was explored to quantify the uncertainty of the FOMs.

An analysis of the accident was divided into two parts: one to identify the effect of the input uncertainties on the plant availability, which was related to FOMs O-1 and O-2 in Table XV, and one to identify the effect of the

TABLE XV

Uncertainty Results for Relevant FOM Statistical Values in the ENSO Study

	FOM	Mean	Standard Deviation	Base Case	Tolerance limit Lower Bound (5%/95%)	Tolerance limit Upper Bound (95%/95%)
O-1	Oxidation > 0.1 MW (h)	75.4	10.8	77.8	38.0	102.4
O-2	$T_{cladding}$ > 1477 K (h)	75.4	10.8	77.8	37.9	102.4
O-3	Fuel rupture (relative to O-2) (s)	178	32	173	142	314
O-4	Debris formation (relative to O-2) (h)	6.9	1.0	6.9	5.5	9.3
O-5	Core slumping (relative to O-2) (h)	13.4	2.7	13.7	7.2	19.1
O-6	Creep rupture (relative to O-2) (h)	14.2	2.8	15.1	7.6[a]	20.4[a]
O-7	Cumulative H_2 generation (kg)	27.4	2.5	26.2	22.7	32.3
O-8	$T_{cladding}$ at fuel rupture (K)	2196.0	5.0	2194.8	2180.2	2205.4
O-9	Cumulative FP (NC) release (kg)	0.12	0.02	0.12	0.09	0.25
O-10	Cumulative FP (soluble) release (kg)	0.07	0.01	0.06	0.05	0.14

[a]Qualitative, only cases with creep rupture.

input uncertainties on the SA phenomena once core damage occurred, which was related to FOMs O-3 to O-10.

Among the 59 code simulations tested, 1 failure took placed during the steady-state analysis, 15 failures occurred right after core slumping, two calculations reached the end time of the calculation without creep rupture, and one calculation reached the end time of the calculation without core slumping or creep rupture. For a proper use of the Wilk's formula, all code runs need to terminate successfully and failed simulations cannot be discarded, otherwise the nature of the random sampling required for the application of the Wilk's formula will be lost.

Nevertheless, code failures can be treated conservatively by assuming that their unknown result is the most adverse (extreme rank) and can therefore be discarded when applying the Wilk's formula to higher orders. However, it was not practical to increase the Wilks' formula to higher orders, for instance, because the Wilks' 4th and 17th orders would require 153 and 482 samples, respectively, taking an average run time of almost 36 h in the dedicated PC system (operating system: MS Windows 10, 64 bit, RAM: 16 GB, processor: Intel i7-8700 3.2 GHz).

Accordingly, for the present analysis, all code failures were re-executed by either reducing the time step (core slumping failures) or by broadening the bounds of only the active control of the RCS (secondary main feedwater). With the modifications indicated, the repetition of the calculations using the same set of random input values led to a fixed steady-state failure, and four calculations fixed after core slumping reached creep rupture.

Due to some sample calculations that failed to reach the creep rupture conditions (or the end time of the calculations), a quantitative uncertainty analysis was performed up to the core slumping, and uncertainties related to the creep rupture were qualitatively examined, as summarized in Table XV.

To support the uncertainty analysis, Pearson, Spearman, and Kendall correlations were analyzed for the uncertainty input parameters and relevant FOMs. The statistical significance (SS) of the CCs[44] was tested against the null hypothesis of no correlation, and the *p*-value measuring the probability of observing a correlation by chance was calculated from the Student's *t*-distribution for Pearson and Spearman, and from the standard normal distribution for Kendall.

A potential correlation between the input and output values was identified at the generally accepted significance value of 0.05. As part of the sensitivity/importance analyses, Table XVI presents the CCs along with their

TABLE XVI

Estimated CCs and Their SSs in the ENSO Study*

Input/ FOM	Coefficient	HT-1	HT-3	HT-5	IPH-1	IPH-2	OXI	SA-1	SA-3	BC-3	DSG	DP
O-1	CC	−0.14[a]	0.03	−0.11	0.03	−0.10	0.10	0.19	−0.11	−0.21	0.23	−0.88
		−0.10[b]	0.11	−0.15	−0.06	−0.11	−0.01	0.21	−0.09	−0.19	0.27	−0.91
		−0.06[c]	0.07	−0.11	−0.03	−0.07	−0.00	0.15	−0.06	−0.12	0.18	−0.77
	SS	0.29[a]	0.79	0.42	0.82	0.44	0.46	0.15	0.38	0.12	0.07	**0.00**
		0.44[b]	0.40	0.27	0.65	0.39	0.91	0.10	0.48	0.15	**0.04**	**0.00**
		0.51[c]	0.44	0.24	0.77	0.40	0.98	0.10	0.51	0.17	**0.05**	**0.00**
O-2	CC	−0.14[a]	0.035	−0.11	0.031	−0.10	0.1	0.19	−0.12	−0.21	0.23	−0.88
		−0.10[b]	0.11	−0.15	−0.06	−0.11	−0.01	0.21	−0.09	−0.19	0.27	−0.91
		−0.06[c]	0.07	−0.11	−0.03	−0.07	−0.00	0.15	−0.06	−0.12	0.18	−0.77
	SS	0.29[a]	0.79	0.42	0.81	0.44	0.46	0.15	0.38	0.12	0.07	**0.00**
		0.44[b]	0.40	0.27	0.65	0.39	0.91	0.10	0.48	0.15	**0.04**	**0.00**
		0.51[c]	0.44	0.24	0.77	0.40	0.98	0.10	0.51	0.17	**0.05**	**0.00**
O-3	CC	0.13[a]	−0.05	−0.03	−0.02	−0.10	−0.06	−0.09	−0.22	−0.27	0.16	−0.22
		−0.02[b]	−0.02	−0.17	0.03	−0.18	−0.13	−0.01	−0.46	−0.28	0.18	−0.53
		−0.01[c]	−0.024	−0.132	0.03	−0.13	−0.091	−0.00	−0.348	−0.197	0.12	−0.41
	SS	0.33[a]	0.71	0.83	0.90	0.43	0.65	0.50	0.09	0.04	0.22	0.10
		0.86[b]	0.90	0.20	0.82	0.18	0.34	0.94	**0.00**	0.03	0.17	**0.00**
		0.92[c]	0.84	0.16	0.75	0.15	0.33	0.96	**0.00**	0.04	0.19	**0.00**
O-4	CC	−0.07[a]	0.11	−0.06	0.05	−0.22	0.19	−0.03	−0.034	−0.13	0.27	−0.871
		−0.09[b]	0.20	−0.16	0.00	−0.26	0.12	0.00	−0.06	−0.15	0.27	−0.87
		−0.07[c]	0.14	−0.08	0.01	−0.18	0.10	0.00	−0.04	−0.10	0.19	−0.72
	SS	0.58[a]	0.40	0.63	0.71	0.09	0.14	0.81	0.80	0.32	0.40	**0.00**
		0.48[b]	0.12	0.43	0.98	**0.05**	0.35	0.98	0.66	0.25	**0.04**	**0.00**
		0.44[c]	0.11	0.37	0.92	**0.04**	0.27	0.98	0.67	0.27	**0.03**	**0.00**
O-5	CC	−0.18[a]	0.26	−0.19	−0.26	−0.30	0.06	0.09	0.17	−0.16	0.13	−0.76
		−0.19[b]	0.30	−0.18	−0.26	−0.30	0.03	0.09	0.14	−0.19	0.16	−0.77
		−0.12[c]	0.12	−0.13	−0.18	−0.22	0.04	0.05	0.09	−0.13	0.11	−0.62
	SS	0.16[a]	**0.04**	0.14	**0.05**	**0.02**	0.65	0.50	0.20	0.24	0.31	**0.00**
		0.16[b]	**0.02**	0.17	**0.05**	**0.02**	0.82	0.49	0.30	0.16	0.21	**0.00**
		0.18[c]	**0.03**	0.15	**0.04**	**0.01**	0.65	0.61	0.29	0.15	0.24	**0.00**
O-6	CC	−0.16[a]	0.23	−0.09	0.09	−0.05	0.07	0.067	−0.04	0.14	−0.13	0.30
		−0.32[b]	0.33	−0.17	−0.06	−0.20	0.09	0.11	0.07	−0.00	−0.04	−0.23
		−0.20[c]	0.24	−0.11	−0.05	−0.16	0.04	0.07	0.05	−0.00	−0.03	−0.22
	SS	0.16[a]	0.08	0.48	0.49	0.97	0.61	0.62	0.76	0.30	0.34	**0.02**
		0.01[b]	**0.01**	0.19	0.63	0.12	0.50	0.39	0.58	0.98	0.78	0.08
		0.02[c]	**0.01**	0.20	0.60	0.05	0.51	0.47	0.61	0.97	0.76	**0.01**
O-7	CC	−0.19[a]	0.33	−0.21	−0.21	−0.18	0.22	0.13	−0.06	−0.26	0.12	−0.64
		−0.18[b]	0.33	−0.20	−0.19	−0.19	0.24	0.14	−0.08	−0.23	0.13	−0.66
		−0.12[c]	0.24	−0.14	−0.12	−0.12	0.18	0.10	−0.05	−0.16	0.07	−0.45
	SS	0.16[a]	**0.01**	0.10	0.12	0.17	0.09	0.33	0.52	0.05	0.37	**0.00**
		0.16[b]	**0.01**	0.12	0.15	0.14	0.06	0.29	0.55	0.07	0.33	**0.00**
		0.16[c]	**0.01**	0.10	0.17	0.16	**0.04**	0.28	0.58	0.08	0.40	**0.00**

(Continued)

TABLE XVI (Continued)

Input/ FOM	Coefficient	HT-1	HT-3	HT-5	IPH-1	IPH-2	OXI	SA-1	SA-3	BC-3	DSG	DP
O-8	CC	0.22[a]	−0.05	−0.17	−0.05	0.27	0.44	−0.26	−0.36	0.09	0.15	−0.07
		0.26[b]	−0.18	−0.12	−0.03	0.24	0.38	−0.34	−0.33	0.13	0.15	−0.02
		0.17[c]	−0.13	−0.09	−0.02	0.18	0.25	−0.24	−0.24	0.09	0.10	0.05
	SS	0.09[a]	0.70	0.19	0.73	**0.04**	**0.00**	**0.05**	**0.00**	0.50	0.26	0.62
		0.05[b]	0.18	0.38	0.84	0.06	**0.00**	**0.01**	**0.01**	0.31	0.27	0.85
		0.06[c]	0.15	0.30	0.82	**0.05**	**0.01**	**0.01**	**0.01**	0.29	0.25	0.53
O-9	CC	0.09[a]	0.05	−0.15	0.20	0.18	0.18	0.02	−0.49	−0.17	0.17	0.035
		0.13[b]	0.23	−0.27	0.07	0.05	0.25	0.08	−0.54	−0.16	0.08	−0.29
		0.08[c]	0.16	−0.19	0.05	0.05	0.17	0.04	−0.37	−0.11	0.06	−0.18
	SS	0.48[a]	0.69	0.25	0.13	0.17	0.17	0.87	**0.00**	0.19	0.18	0.79
		0.34[b]	0.08	**0.04**	0.58	0.69	**0.05**	0.53	**0.00**	0.23	0.52	**0.03**
		0.37[c]	0.08	**0.03**	0.56	0.54	**0.05**	0.67	**0.00**	0.21	0.52	**0.05**
O-10	CC	0.09[a]	0.05	−0.15	0.20	0.18	0.18	0.02	−0.49	−0.17	0.17	0.03
		0.13[b]	0.23	−0.27	0.07	0.05	0.25	0.08	−0.53	−0.16	0.08	−0.29
		0.08[c]	0.16	−0.19	0.05	0.05	0.17	0.04	−0.37	−0.11	0,058	−0,18
	SS	0.48[a]	0.69	0.24	0.13	0.17	0.17	0.87	**0.00**	0.19	0.18	0.80
		0.34[b]	0.08	**0.04**	0.58	0.69	**0.05**	0.53	**0.00**	0.23	0.52	**0.03**
		0.37[c]	0.08	**0.03**	0.56	0.54	**0.05**	0.67	**0.00**	0.21	0.52	**0.05**

*BC-3: BC for steady-state reactor power, DP: decay power multiplicative factor (ANS79-3), HT-1/HT-2: film boiling heat transfer coefficient for liquid/vapor across solid surfaces, HT-3: nucleate boiling heat transfer coefficient (subcooled), HT-5: single-phase heat transfer coefficient (vapor), IPH-1/IPH-2: heat transfer and friction in vapor/liquid interphase, SA-1: rupture strain (cladding), SA-3: shroud thickness, and OXI: Zr oxidation rate and thickness.

[a]Pearson CC.

[b]Spearman CC.

[c]Kendall CC.

SS, with highlights in bold for values with a SS equal to or less than the significance level of 0.05.

The main findings and lessons learned from the analysis are as follows:

1. The analysis results showed that the correlation between DP and plant availability (O-1, O-2) was strong. The correlation of shroud thickness (SA-3) was particularly strong with fuel cladding rupture (O-3, O-8) and with the release of FPs (O-9, O-10). The correlation of oxidation correlations (OXI) and rupture strain (SA-1) also seemed to have an impact on the progression of the SA. Moreover, the heat transfer (HT) parameters seemed to play an important role in SA progression during the cooling of the molten pool. The correlation of the area of the PRHRS [correlation for the area of the PRHRS (DSG)] with plant availability was significant, but this may have been due to the rather large associated uncertainty. The correlation of the interphase phenomena (IPH) with accident progression was also identified as significant, whereas the effect of the BCs, MPs, and CHF was not significant.

2. With regard to the FOMs, it is advisable to carefully select between relative and absolute times to avoid dragging the effect of uncertainties into posterior events. It is also important to consider that the cumulative release of FPs and the cumulative generation of H_2 are also affected by the uncertainty propagated from design-basis accident conditions. As mentioned in the CNEA study, the 59 random samples were primarily good for 95 percentile using the Wilks' formula, but more samples seem be necessary to get more robust statistical values, such as mean and median.

3. Relating to the sensitivity measures, the Kendall formulation is advisable because it seemed to be less dependent on singular data points than the Spearman correlation. To try to avoid the masking effects of strong correlations, it is advisable to consider other types of sensitivity coefficients, such as PCC or PRCC.

IV. KEY MESSAGES FOR BEST PRACTICE

From the best-practice uncertainty and sensitivity analyses for SAs, the key messages of the foregoing studies are summarized in the following section.

IV.A. Analysis Process

The uncertainty and sensitivity analyses are a replicative process:

1. First, do deterministic sensitivity analysis to find out which input parameters would be important to focus on for the uncertainty analysis, and then perform uncertainty analysis for those parameters.

2. Next do a probabilistic sensitivity/importance analysis to identify the probabilistic influence of the selected input parameters on the relevant FOMs based on the forgoing uncertainty analysis results.

3. Whenever necessary, conduct additional uncertainty analyses based on higher-influencing input parameters identified from the foregoing sensitivity/importance analysis to get a bit of a different angle on insights into the relevant uncertainty.

The former type of sensitivity analysis (i.e., deterministic), which is mainly implemented in the preliminary stage of an uncertainty analysis, simulates the code a few times with different parameter combinations varying one at a time for a crude analysis of their impact on the code output. This method gives only the local information around a given parameter or set of parameters, while the input parameters may often have a wide range of variation. Whereas the latter type of sensitivity analysis (i.e., probabilistic), as implemented in the present studies, identifies the global influence of selected uncertainty inputs on the relevant FOMs.

IV.B. Uncertainty Analysis

The selection of the uncertainty input parameters and relevant PDFs could have a paramount impact on the uncertainty results. Thus, more relevant inputs in terms of influencing FOMs should be chosen to get more robust conclusions on their uncertainty, whereas the influence of the PDF type on the FOMs of interest would be case sensitive as implemented in the SJTU and CNEA studies. Accordingly, a relevant distributional sensitivity analysis[45] is recommended for the highly influential uncertainty inputs.

While Monte Carlo sampling is a straightforward way to perform calculations to study the propagation of uncertainties associated with the input parameters through the model and to the output, one of the challenges encountered in applying such a method is to determine a sufficient sample size to ensure that the analysis results well represent their full space of the population, including their mean and variance. As the sample size increases, each sample becomes more representative of the population, and the sample mean approaches the actual population mean. However, there is no generally accepted criterion on how many samples should be performed to ensure sufficient confidence in the analysis results.

The following approaches can be utilized to determine a reasonable number of simulations to adequately estimate the uncertainty of the code output:

1. The Wilks' formula,[32,46] based on order statistics theorems, allows for precisely determining the smallest sample size required for the distribution-free tolerance limits α at the desired cumulative probability (or confidence) level β for the analysis results. However, the formula should only be applied to independent random samples and is most useful for ensuring compliance with a particular acceptance limit (i.e., α/β) of the simulation results, rather than an estimation of the simulation result itself.

2. As a measure of the precision of the sample mean, the standard error of the mean (SEM, $\sigma/\sqrt{N}$)-[47,48] measures how precisely a sampling distribution represents a population, i.e., the degree of dispersion of sample means around the population mean or a confidence interval of the mean value. Here, σ is the standard deviation of the sampling distribution and N is the number of samples. The forgoing idea underlies the sample size calculation for a controlled number of samples. The process may be stopped when increasing the number of samples does not significantly change the SEM or the SEM reaches a predefined small error value.

3. The LHS method (also called stratified random sampling)[49,50] is a widely used statistical approach to control the number of samples in large simulations and to improve SRS accuracy. This sampling scheme does not require more samples for more dimensions (input variables), and thus, even with a significantly smaller number of samples, the LHS approach ensures a robust sampling of distributions in a large range of conditions as compared to the SRS approach. One previous study[51] showed that although it may not adequately estimate the code output uncertainty, the following sample size N might give a reasonable convergence of the statistical estimators for the model response, such as the mean and standard deviation, and can adequately identify the sensitive input parameters $N = (4/3)k$ for time-consuming computer models with k uncertain input variables; otherwise $N = 2k \sim 5k$. However, there might be situations in which the statistical estimators obtained using LHS do not converge more rapidly than those obtained with SRS, depending on the model and input parameters. But in general, if low probability–high consequence tails in the input distributions are present, LHS is superior to SRS.

In the case of highly complex computational systems like SA codes, it seems necessary to understand that the uncertainty input parameters are always affected by uncertainties coming from different sources and that they also affect each other, thus leading to some code crashes during simulations. For such kinds of failed runs observed in the code simulations, it is necessary to investigate their patterns from the parameters' coverage map related to simulations with relevant errors, and to identify the type of error sources in order to better understand model behavior and to improve model robustness as well.

The failed runs could be partly resolved through fine tuning of the relevant code models and/or properly setting the numerical time step below the minimum time-step limit wherever effective. When failed code runs are expected to take place, SRS is more recommended in general over a stratified random sampling approach such as LHS, which may distort the statistical meaning of the relevant FOM results.

IV.C. Sensitivity Analysis

Sensitivity/importance analysis provides potential insights to find errors in the modeling if the code calculation results contradict the common understanding of the phenomenon. As mentioned previously, two types of sensitivity analyses can be implemented: deterministic (or local) and probabilistic (or global). If a sufficient number of code simulations have been done for all identified uncertainty parameters, the correlation- or regression-based probabilistic approaches are more preferred to conduct global sensitivity/importance analyses on input parameters, as implemented in the present study.

Both linear relationships between code inputs and response parameters and nonlinear effects beyond them are important in determining the key contributors to the relevant response parameters. Whereas the usability of correlation/regression analyses based on a linear relationship between inputs and relevant FOMs is often limited for highly complex nonlinear relationships between inputs and FOMs, like as in SA codes.

In such a case, employing sensitivity methods that can capture a more exhaustive picture of nonlinear relationships, e.g., recursive partitioning coefficient, multivariate adaptive regression splines,[15,16] and alternating conditional expectation algorithm-based surrogate models,[52] may offer more flexibility. Reference [53] may help understand both the linear and nonlinear relationships in the reactor accident.

When a suite of correlation/regression methods is used for better coverage of the potential relations between the uncertainty inputs and FOMs of interest,[54] it is necessary to understand the nature of the relevant sensitivity indicators[55] whose impact can somewhat depend on the type of uncertainty inputs and the phenomenological time window, as follows:

1. While some uncertainty inputs have a sensible correlation with a particular FOM, they may not have a meaningful correlation with other FOMs and/or the uncertainty inputs that influence the uncertainties of relevant FOMs in one accident scenario may not necessarily have the same impact in other scenarios.

2. When strong correlations are observed between some uncertainty inputs and relevant FOMs, it is advisable to additionally consider PCC and/or PRCC that indicate the strength of an association between two variables while removing the effect of the rest, thereby avoiding the masking effects of the remaining uncertainty inputs.

3. When the uncertainty inputs are given in the form of singular or discrete data points, the Kendall correlation is advisable because it is less dependent on data points of such a type.

4. If there is no preference for particular sensitivity indicators, a weighted average of several sensitivity indicators can give a general insight into the overall sensitivity.

V. CONCLUSION AND FUTURE IMPLICATIONS

Based on the respective frameworks for the uncertainty and sensitivity analyses employed in the context of SAs, each CRP participant presented in this paper successfully implemented their own planned tasks. As a result, the ranges of the relevant FOMs were well estimated per each participant and the key contributors to the FOMs of interest were clearly identified through sensitivity/importance analyses.

Despite the insights and lessons learned through the tasks, a deeper understanding of several aspects is still required to ensure the applicability of the utilized approaches in the context of SAs and/or to explore more advanced methodologies for best practices. More specifically,

1. Understanding the underlying basis of the sampling-based methods used for a statistical uncertainty analysis (such as SRS, LHS, and the Wilks' formula) in terms of their merits and disadvantages.

2. Specifying more relevant inputs influencing the FOMs of interest to get more robust results on their uncertainties and more relevant PDFs that could well characterize the uncertainties of given input parameters.

3. Checking the influence of uncertainty sources related to plant nodalization schemes and/or code-specific modeling approaches (e.g., the different submodels and correlations employed by each code).

4. Checking the influence of the sample sizes applied to the uncertainty analysis in terms of how many statistical samples are enough to ensure confidence in the analysis results, if possible, such that the mean and standard deviation of the relevant FOMs converge with the number of samples.

5. Checking the influence of possible code crashes (failed code runs) and/or biases, including outliers in the simulation results, that are often observed in sampling-based uncertainty analyses.

6. Exploring sensitivity/importance indicators that are less dependent on singular data points (e.g., Kendall formulation) and able to avoid masking the effects of strong correlations, which indicate the strength of an association between two variables while removing the effect of the rest (e.g., PCC and/or PRCC).

7. Understanding the limitations of the linear regression-/correlation-based sensitivity measures employed by the CRP participants, as well as exploring other types of sensitivity/importance indicators that can well capture nonlinear relationships between the input and response variables as a possible alternative.

8. Further investigating possible alternative uncertainty analysis methods, such as machine learning or high-fidelity surrogate models.

Although the methods, tools, uncertainty inputs, and FOMs of interest employed for the plant application exercise were quite heterogeneous across the participants, as were the different analysis purposes and scopes, the insights obtained can lead to newly generated knowledge that can be referred to in uncertainty and sensitivity analyses and methods for SA codes, with the intent of capturing the best practices.

APPENDIX

UNIVERSITY OF SHARJAH (UoS) STUDY

In the UoS study of a SBO accident at the APR1400 plant,[41] an efficient PCA-based Monte Carlo UQ scheme[37] was used to assess the contribution of nuclear data cross sections in the uncertainty of the fuel temperature. The proposed approach paved the way for the inclusion of a large number of sources in UQ practices in SA analyses. The major steps were as follows:

1. Calculate the reduced uncertainty sources' space basis.
2. Determine the suitable space dimension *r* given the error tolerance criteria.
3. Collect Monte Carlo–based samples for the purpose of UQ.
4. Calculate the reduced parameters' perturbation matrix.
5. Estimate the sensitivity matrix for each relevant FOM with respect to the reduced parameters' space.
6. Map the sensitivity matrix from the reduced space to the original space.
7. Based on the sensitives calculated in step 6, identify the uncertainty contribution of each parameter (uncertainty source).

The 3KEYMASTER simulator[24] was used to simulate the APR1400 plant's response following the SBO accident, considering the uncertainties of the cross sections. Since 3KEYMASTER uses a two-group neutronics code, the perturbations were generated and collapsed to the right structure via SCALE6.1 (Comprehensive Modeling and Simulation Suite for Nuclear Safety Analysis and Design Version 6.1).[25] Figure A.1 shows the reference case results made until 85 min from the start of the SBO. According the figure, the fuel temperature continued to increase until the fuel started to melt down, which was around 1 h into the SBO, the maximum fuel temperature reached ~800^{o}C, and the simulator stopped at this temperature where the cladding oxidation occurred, which was set as a simulation limit.

Relevant uncertainty calculations were completed with 120 model runs instead of the 2800 runs that would have been required without the proposed algorithm, taking an average run time of almost 0.5 h in the dedicated PC system [operating system: MS Windows 10 Enterprise, 64 bit, RAM: 32 GB, processor: 11th Gen Intel(R) Core(TM) i5-1145G7 @ 2.60 GHz and 1.50 GHz].

The analyses indicated a minor contribution of the cross sections on the FOM of interest, as presented in Fig. A.2 and Tables A.I and A.II. According to Fig. A.2, the standard deviation decayed over time right after the reactor shutdown. This might be because the overall reactor heat became more and more dominated by decay heat while the fission-related heat source became weaker overtime due to the shutdown. The Monte Carlo uncertainty in the FOM estimated for certain time steps (Table A.I) was then used to segment the overall uncertainty into the various cross-section uncertainty matrices available in the 44-group cov library (Table A.II).

The main findings and lessons learned from the analysis are as follows:

1. In general, cross sections have a minor effect on the uncertainty of the fuel temperature post shutdown (<1%). However, as the fuel temperature increases, U^{238} uncertainty starts to become the major contributor of the cross section–related fuel temperature uncertainty.
2. Nuclear data cross sections resulted in a minor uncertainty of the fuel temperature after reactor shutdown as a response to a SBO accident.

When using PCA and Monte Carlo sampling coupled approaches, relevant uncertainty analysts can efficiently determine the uncertainty in the FOMs due to the large number of input parameters.

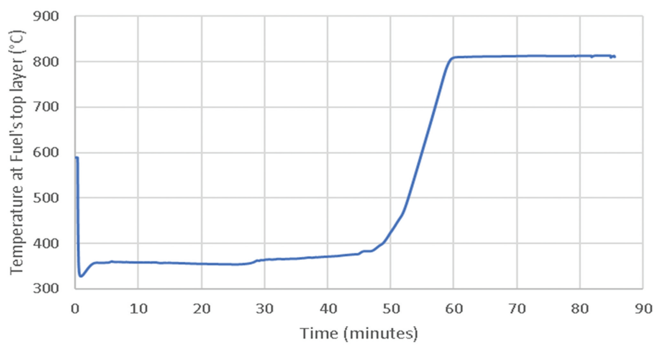


Fig. A.1. Reference case results for FOM 1 (fuel temperature) in the UoS study.

TABLE A.I

FOM Uncertainty due to Cross Sections Only in the UoS Study

Time (min)	Reference Fuel Temperature (°C)	Standard Deviation
0	590	0.90%
10	352	0.39%
30	363	0.37%
45	385	0.30%
50	414	0.30%
60	813	0.10%

TABLE A.II

Top Cross Sections Contributing to the Overall FOM Uncertainty in the UoS Study

Time	Top Three Contributors	% Contribution, Δ T/T_{ref}
Just before the SBO	U^{238} (n, γ)	0.41%
	U^{235} (υ)	0.35%
	U^{235} (n, fission)	0.15%
60 min after the SBO (once T_{max} was reached)	U^{238} (n, γ)	0.64%
	U^{238} (υ)	0.52%
	U^{238} (n, fission)	0.23%

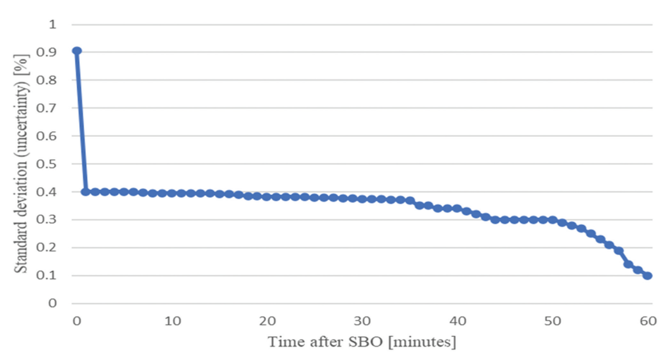


Fig. A.2. Uncertainty analyses results for cross sections related to the standard deviation in the fuel temperature in the UoS study.

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ORCID

Kwang-Il Ahn http://orcid.org/0000-0002-1491-0078

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