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RESEARCH REPORT

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Sensitivity and uncertainty analyses of the Fukushima Dai-ichi unit 1 MELCOR model

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Summary

Parameter sensitivities and uncertainties in the Fukushima Dai-ichi unit 1 MELCOR models were studied. Two sensitivity analysis methods were employed: the Morris method for global screening of parameter influences and correlation analysis based on Monte Carlo sampling. The study included two Fukushima unit 1 MELCOR models: the simplified and the original full-scale model. In addition to identifying and quantifying the uncertainties, the work aimed also to compare the behavior of the two MELCOR models and the sensitivity analysis methods.

Due to its faster calculation speed and better stability, the simplified model was used in more detailed analyses. Ten parameters assumed to be influencing cesium release to the environment were chosen. The Morris method highlighted the major influence of aerosol agglomeration shape factor (GAMMA), while showing also measurable effects on aerosol dynamic shape factor (CHI) and the decay heat multiplier (DECAYH). These findings aligned well with the correlation analysis. The uncertainty results showed a left-skewed distribution of cesium release, likely driven by the combined effect of GAMMA's influence and its probability distribution.

The original full-scale model was significantly slower, and it also suffered from instabilities. Both correlation analysis and uncertainty quantification were performed at two time instances: 30 and 200 hours. Due to high computational cost, the number of Monte Carlo samples was reduced, which limited the statistical reliability of the results. Despite this, the results highlighted GAMMA and CHI as the most influential parameters. The results from uncertainty analysis showed left-skewed distributions for Cs release, likely caused by the distribution of GAMMA and CHI.

Overall, the results highlighted the major influence of GAMMA and CHI on the predicted cesium release in both MELCOR models. The cesium releases between the models were of different orders of magnitude which could be explained by several things such as differences in the containment leak and venting assumptions, differences in random sampling and numerical noise. The results underline the importance of sufficient sample sizes and numerically stable long-term simulations when applying global sensitivity and uncertainty methods to severe-accident analyses. Future improvements should include increased sampling, improved numerical robustness of the full-scale model, and the use of additional or surrogate-based sensitivity methods.

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1. Introduction

Accident progression analyses and source term evaluations play a central role in the safety assessment of nuclear power plants, particularly in the context of severe accident management. Computational tools such as MELCOR enable detailed, mechanistic simulations of accident phenomena, but their predictive capability is inherently affected by uncertainties in model inputs. Understanding how these uncertainties influence the predicted outcomes is therefore essential for producing credible safety assessments.

The purpose of this work is to evaluate the uncertainties and parameter sensitivities of the Fukushima Dai-ichi Unit 1 MELCOR models using both screening-type global sensitivity methods and Monte Carlo -based correlation analysis. Two approaches to sensitivity analysis were tested and employed. First, the Morris method was used to identify the parameters with the largest overall influence and to characterize non-linearities and parameter interactions. Second, the SNAP/DAKOTA uncertainty module was used to conduct a Monte Carlo based uncertainty propagation, from which Pearson, Spearman, partial, and partial-rank correlation coefficients were calculated to quantify the strength and statistical significance of parameter influences.

The analyses were performed using both the simplified Fukushima Unit 1 model developed within the EU MUSA project and the original full-scale MELCOR model. The simplified model allowed faster and more robust execution of the large case sets required for sensitivity screening, and it was used for more detailed sensitivity and uncertainty analyses during the first 24 hours of the specified accident scenario. The full-scale model enabled evaluation of parameter effects under a more detailed and realistic representation of the accident scenario, and it was used for crude sensitivity and uncertainty analyses at two time instances: 30 h and 200 h.

Overall, this work aims to (1) identify which uncertain parameters most significantly affect radionuclide release predictions, (2) quantify the output uncertainty associated with these parameters, (3) compare the behavior and suitability of different sensitivity-analysis methods for severe accident applications, and (4) compare the behavior of different MELCOR models in the context of sensitivity and uncertainty analyses. Together, these results contribute to a more transparent and traceable understanding of MELCOR model behavior and support ongoing efforts to improve confidence in severe accident source term assessments.

2. Modelling approach

Two MELCOR models were employed to conduct sensitivity and uncertainty studies. The calculations were done with MELCOR version 2.2.15254, chosen for its stability in practical use. Editing, sampling and running the models were primarily carried out using Symbolic Nuclear Analysis Package (SNAP) and Python. The SNAP version in use was 4.3.1, and the versions of MELCOR and DAKOTA uncertainty plug-ins were 3.0.3 and 1.8.5 respectively.

2.1 MELCOR models

Two MELCOR models of the Fukushima Dai-Ichi unit 1 were used in this work. The first model is based on model version 3 [1] and it was developed during EU MUSA project [2]. In order to speed up the calculations, the accident scenario was simplified, and the simulations were stopped earlier, at 24 h. The second model is based on model version 4 [3] and simulates the full accident scenario, its simulation time reaching up to 200 h.

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The models have many minor differences. The simplified model lacks components like water measurement system and water injection by fire engines. There are also differences in settings regarding melt behavior, hydrogen explosions, fission product settling etc. The timings of transients are also different. The key events are listed in Table 1.

Table 1. Times of specific events during the accident scenario in both simplified and full-scale MELCOR models.

Event	Simplified model	Full scale model
Reactor scram	0 s	0 s
Loss of cooling	0 s	48 min
0.5 cm^2 leak assumed through both recirculation pump seals to the containment drywell	1 h	1 h
Water level below top of active fuel	1 h	2.5 h
Release of fission products from the fuel begins	1.7 h	3.6 h
Control rods begin to melt	2 h	4 h
Water level below bottom of active fuel	2.2 h	4 h
Fuel rods begin to collapse	2.6 h	4.5 h
All water in reactor evaporated	7.7 h	10 h
Debris ejection to the containment begins	10 h	12.5 h
Opening of wet well venting valves assumed	15 h	24 h
Drywell liner leak assumed	-	50 h
End of calculation	24 h	200 h

2.2 SNAP

SNAP is an analysis tool developed by Information Systems Laboratories (ISL) for creating, editing and running model inputs of multiple integrated analysis code applications such as MELCOR, CONTAIN, and TRACE. Via its plug-ins, it provides tools for post processing and uncertainty analysis. It also enables the visualization for the models. [4]

Dakota (Design Analysis Kit for Optimization and Terascale Applications) toolkit has been developed by Sandia National Laboratories (SNL) for optimization and uncertainty quantification [5]. The Dakota uncertainty plug-in SNAP enables the addition of the uncertainty step in the job stream. The main tasks of the uncertainty step are the input parameter sampling according to the user-specified probability distributions and sampling methods (Monte Carlo or Latin Hypercube), performing the sensitivity and uncertainty analyses, and post-processing of the result into a report form. The plug-in is also capable of calculating the minimum sample size according to the Wilks' formula. More about the formula can be found e.g. in [6].

The main issue with SNAP/DAKOTA is the handling of the failed runs. It is a well-known problem that if even one of the MELCOR inputs fails during the MELGEN step, the uncertainty step will also

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fail, and no uncertainty report will be generated. Especially with long calculation runs this is a significant problem. Another type of failed run occurs when the calculation of single case is interrupted early by either code crash or some external problem. In such case, the uncertainty step considers the run successful and uses the potentially incorrect output value in the sensitivity and uncertainty analyses. This may lead to inaccurate results, especially if there are high number of crashes.

SNAP does offer an option to resample the failed code runs, but in the current version it does not seem to detect code crashes mid-execution. The resampling for model setup failures is done before starting any of the actual calculations. In practice, the user inputs the percentage of postulated case failures, and SNAP resamples a few extra samples in addition to the initial cases. The functionality didn't seem to work in older SNAP version despite the option being visible in the dialog box.

To better combat these issues, Python-directed job streams may be utilized. These make it possible to combine SNAP and Python functionalities, and to streamline the processes. For example, in the case of a severely instable model, Python can be used to monitor the completion of MELCOR runs and resample the cases in the case of code crashes. Python can also be used to extend SNAP/DAKOTA capabilities, by e.g. incorporating additional analysis methods such as Morris method and Student's T-test like in this work.

3. Methods

Two methods for sensitivity and one for uncertainty analyses were utilized in this work: Morris method for sensitivity analyses and Monte Carlo based uncertainty propagation from where sensitivity correlation coefficients were calculated.

3.1 Sensitivity analysis methods

3.1.1 The Morris method

The Morris method [7, 8], also known as the Elementary Effects (EE) method, is a global sensitivity analysis technique designed especially for computationally expensive models. It provides an efficient way to screen input parameters and their influence with a relatively small number of model evaluations.

In Morris method, the k-dimensional input space is explored by generating a set of trajectories, where each input parameter is varied one at time (OAT approach). The impact of changing the parameter values is then evaluated by calculating elementary effects:

$$EE_i = \frac{f(x_1, x_2, \dots, x_i + \Delta, \dots, x_k) - f(x_1, x_2 \dots, x_k)}{\Delta} \tag{1}$$

where Δ pre-defined step size on a grid with p levels, and k is the total number of parameters.

From the distribution of elementary effects for each parameter i, three commonly used measures are calculated. Mean of elementary effects μ describes the overall influence of a parameter. It is defined as

$$\mu_i = \frac{1}{n}\sum_{j=1}^{n} EE_{i,j} \tag{2}$$

where n is the total number of elementary effects.

Absolute mean μ^* similarly describes the overall influence of the input parameter but it avoids the cancellation of positive and negative effects and is often the preferred method. It's defined with

$$\mu_i^* = \frac{1}{n}\sum_{j=1}^{n} \left|EE_{i,j}\right| \tag{3}$$

Standard deviation σ indicates the nonlinear effects or interactions with the other parameters. It is calculated with:

$$\sigma_i = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(EE_{i,j} - \mu_i\right)^2} \tag{4}$$

Typically, higher values of μ or μ^* indicate stronger influence of the parameter. High standard deviation indicates the presence of nonlinearity and/or interactions between the input parameters. Having low values for both input parameters suggests very small overall influence.

The number of required model evaluations is calculated from the number of trajectories (r) and input parameters (k) as follows:

$$N = r \cdot (k + 1) \tag{5}$$

In this study, the Morris method was applied using Python's SALib package. Although the Dakota package provides a standalone implementation of this method, it is not incorporated within the SNAP/DAKOTA plugin.

3.1.2 Sensitivity correlation coefficients

Correlation coefficients quantify how strongly variations in input parameters are associated with the variations in the model output. In SNAP/DAKOTA, four correlations are calculated: Pearson correlation, Spearman correlation, partial correlation (called Pearson adjusted in the current SNAP version) and partial rank correlation (called Spearman adjusted in the current SNAP version).

Pearson correlation (called also simple correlation in older SNAP versions) measures the linear relationship between two datasets, in this case the input parameter and the figure of merit. Between parameters x and y, it can be calculated with

$$r_{xy} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \tag{6}$$

Partial correlation accounts for linear relationship while controlling for all other parameters. It isolates the direct effect of a single parameter while removing the confounding effects of the other parameters. In the case of single controlled parameter, it is calculated using the following equation:

$$r_{xy,z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}} \tag{7}$$

where r are the Pearson correlations between the input x, output y and the controlled parameter z.

Calculating partial correlation for a parameter while controlling for *all* the other input parameters is done by calculating Pearson correlation coefficients for each input-input and input-output parameter pair. This results in a correlation coefficient matrix $R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mm} \end{bmatrix}$, which is then inverted (R^{-1}). Partial correlation coefficient for each parameter is calculated with:

$$\rho_{ij} = -\frac{R_{ij}^{-1}}{\sqrt{R_{ii}^{-1}R_{jj}^{-1}}} \tag{8}$$

Both these correlations have also rank forms: Spearman correlation (rank form of Pearson correlation) and partial rank correlation. Rank correlations are obtained by replacing the dataset values with their corresponding ranks. The purpose of the rank-based correlations is to reduce the impact of outliers and capture monotonic but non-linear relationships.

3.2 Uncertainty quantification method

Uncertainty quantification (UQ) in this work was carried out using a probabilistic, sampling-based approach, as that's the only method supported by SNAP's uncertainty plug-in.

The input parameters were sampled using Monte Carlo method where each input parameter is treated as a random variable defined by a user-specified probability distribution. All the parameters were changed simultaneously. The number of samples was determined by SNAP, according to the Wilks' formula.

4. Uncertainty and Sensitivity Analyses Using the simplified Fukushima Dai-ichi Unit 1 MELCOR Model

The simplified Fukushima Dai-ichi unit 1 MELCOR model was employed for the sensitivity and uncertainty analyses described in this section. Due to its increased speed and greater stability compared to the full-scale model, the simplified model was also used to further test out the Python-based workflow previously developed for implementing the Morris sensitivity analysis method. Furthermore, the use of two distinct sensitivity analysis methods enabled a comparison of their respective approaches and results within the same modelling framework.

4.1 Sensitivity analyses

4.1.1 Morris method

A Python-based implementation of the Morris method, originally developed during the NKS STATUS-3 project [9], was refined and employed for this work. Originally the Morris procedure was executed inside of SNAP by Python-directed job stream, but due to technical issues with either SNAP or the hardware, only sampling was done in SNAP while MELCOR execution and Morris post-processing were run by standalone Python scripts.

In Morris method the number of model evaluations depends on the number of input parameters and the number of trajectories, as shown in Eq. 5. Some values are calculated and listed in Table 2 below.

Table 2. Examples of the number of the required model evaluations according to different amount of input parameters and parameter trajectories.

Parameters, r	Trajectories, k	Model evaluations, N = r*(k+1)
5	5	30
10	5	60
15	5	90
5	10	55
10	10	110
15	10	165
5	15	80
10	15	160
15	15	240
5	20	105
10	20	210
15	20	315

After considering the available computational resources, ten input parameters and ten trajectories were chosen for the analysis, resulting in a total of 110 model evaluations. The chosen input parameters are listed in Table 3 below. Their value ranges were mostly picked from the MUSA project reports [2]. As the input parameters were expected to affect mainly the release of fission products to the environment, cesium release fraction was chosen as the monitored output parameter i.e. figure of merit.

Table 3. Input parameters and their ranges for Morris sensitivity analysis.

Parameter name	**Parameter description**	**Value range**
DECAYH	Multiplier of decay heat power	0.94, 1.0, 1.06
GAMMA	Aerosol agglomeration shape factor	1, 5
CHI	Aerosol dynamic shape factor	1, 5
FSLIP	Particle slip coefficient	1.2, 1.3
STICK	Particle sticking coefficient	0.5, 1.0
TURBDS	Turbulence dissipation rate	0.00075, 0.00125
TKGOP	Gas-to-particle thermal conductivity ratio	0.006, 0.06
FTHERM	Thermal accommodation coefficient	2.0, 2.5
DELDIF	Diffusion boundary-layer thickness	5E-6, 2E-4
RHONOM	Nominal aerosol density	1000, 4900

Each case was run for 24 hours, which took around 6 hours of CPU time. The total calculation time was around a week, and there were no code crashes.

The results from Morris analysis are presented in Figure 1. As mentioned before, typically relatively high values of μ^* indicate significant overall influence and high σ indicates the presence of nonlinear effects or interactions with the other parameters. In this case GAMMA (Aerosol agglomeration shape factor) seems to have the greatest influence on the model output. The results also suggest that it has some nonlinear behavior or that it interacts with the other parameters. CHI (Aerosol dynamic shape factor) and RHONOM (Nominal aerosol density) also show some elevated influence but not as strong as GAMMA.

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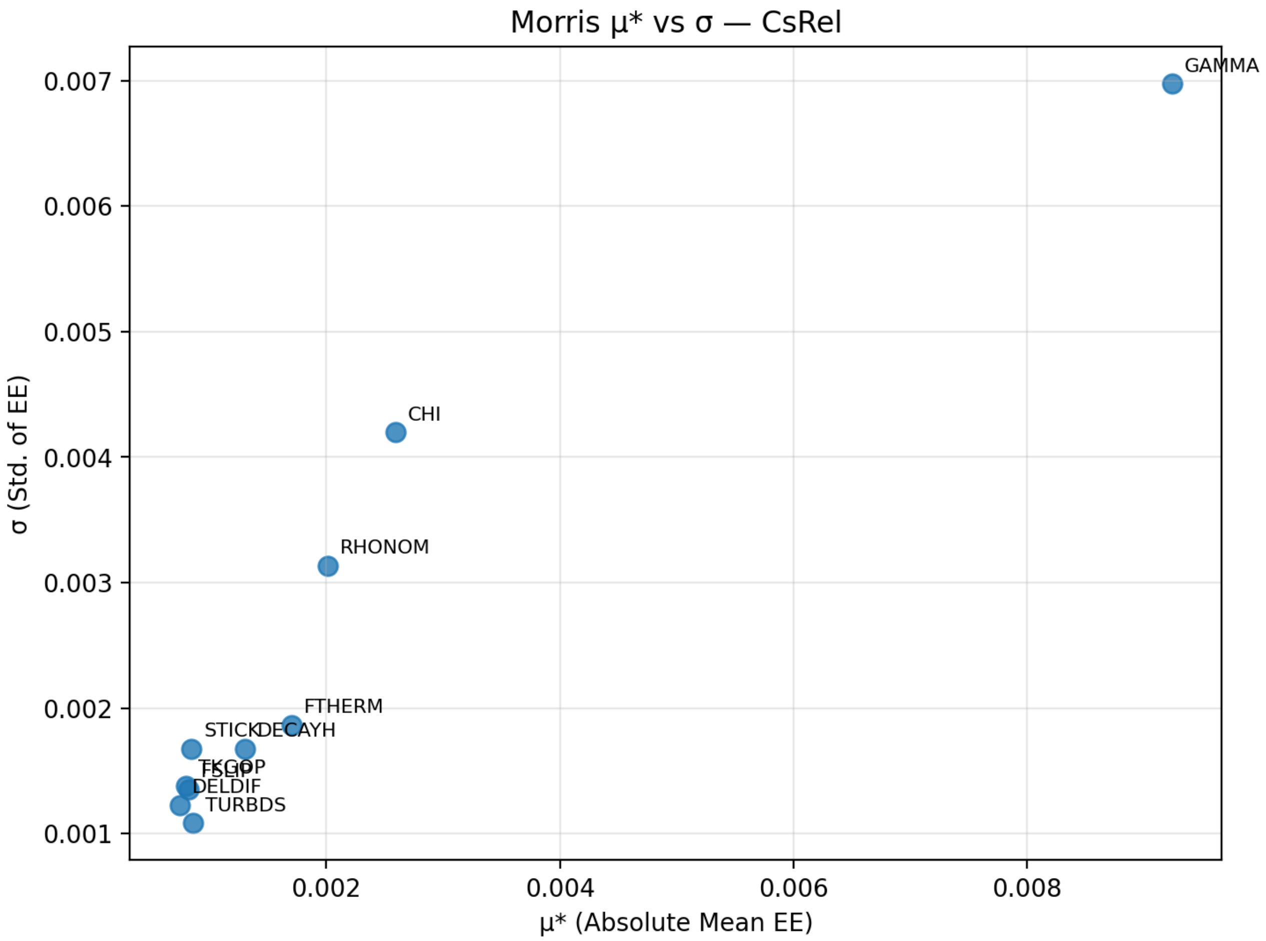

Figure 1. Absolute mean vs. standard deviation for Cs release.

4.1.2 Sensitivity coefficients correlations

Another sensitivity analysis, based on the sensitivity coefficient correlations, was carried out with SNAP/DAKOTA. In SNAP both the sensitivity and uncertainty analyses are run simultaneously, so the settings are shared by both analyses. SNAP determined that the sufficient number of Monte Carlo samples for an *uncertainty* analysis with 95% probability and confidence would be 59. This was deemed acceptable for the sensitivity analysis with a relatively low number of input parameters. However, it should be noted that this might still be too low to capture accurately the smaller parameter influences, and it might affect the calculation of the partial correlation coefficient.

The input parameters and their ranges were the same as in the Morris analysis, with the exception of RHONOM that was omitted from the analyses by a mistake. The values and probability distributions were picked up from the MUSA documentation [2]. Cesium release fraction to the environment remained as the figure of merit.

Table 4. Input parameters, their probability distributions, and their value ranges, used in SNAP sensitivity studies.

Parameter name	**Parameter description**	**Probability distribution**	**Value range**
DECAYH	Multiplier of decay heat power	Triangular	0.94, 1.0, 1.06
GAMMA	Aerosol agglomeration shape factor	Beta (P=1, Q=5)	1, 5
CHI	Aerosol dynamic shape factor	Beta (P=1, Q=5)	1, 5
FSLIP	Particle slip coefficient	Beta (P=4, Q=4)	1.2, 1.3
STICK	Particle sticking coefficient	Beta (P=2.5, Q=1)	0.5, 1.0
TURBDS	Turbulence dissipation rate	Uniform	0.00075, 0.00125
TKGOP	Gas-to-particle thermal conductivity ratio	Log-uniform	0.006, 0.06
FTHERM	Thermal accommodation coefficient	Uniform	2.0, 2.5
DELDIF	Diffusion boundary-layer thickness	Uniform	5E-6, 2E-4

The cases were run for 24 hours. Due to the increased stability compared to the full-scale model, no calculation runs needed resampling.

The results of the sensitivity analysis are presented in Table 5 and Figure 2 below. In addition to the correlation coefficients, the statistical significance of the result was assessed by calculating the t-test P-value for the partial correlations. This was done with Python's SciPy module, but Excel's regression tool seems to give out similar results. P-value tells the probability of the correlation being caused by chance, and smaller (< 0.05) P-value usually means that the correlation is statistically significant.

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Table 5. Sensitivity correlation coefficients and the t-test P-value. Statistically significant are bolded.

Parameter name	**Pearson**	**Spearman**	**Partial**	**Partial rank**	**P-value**
TURBDS	-0.082	-0.060	-0.152	-0.179	0.2560
FTHERM	-0.084	-0.095	-0.063	-0.118	0.6390
DELDIF	-0.001	-0.024	0.010	-0.176	0.9400
TKGOP	-0.053	-0.027	-0.017	0.066	0.8984
DECAYH	**-0.156**	**-0.137**	**-0.276**	**-0.357**	**0.0357**
CHI	**0.314**	**0.207**	**0.421**	**0.456**	**0.0010**
GAMMA	**-0.762**	**-0.860**	**-0.795**	**-0.900**	**9.04E-14**
STICK	-0.136	-0.162	0.006	-0.062	0.9660
FSLIP	0.099	0.104	-0.040	-0.104	0.7661

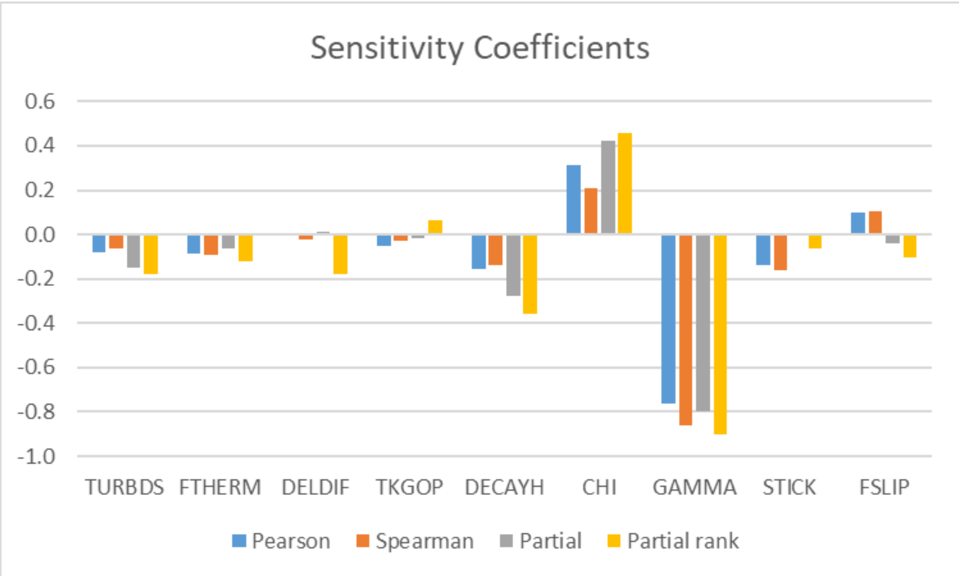

Figure 2. Sensitivity correlation coefficients.

The results show that GAMMA, i.e. aerosol agglomeration factor, has very high correlation coefficients and very small P-value. This indicates that GAMMA is the most influential input parameter in these calculations. The P-values suggest that CHI (aerosol dynamic shape factor) and DECAYH (decay heat power multiplier) would also be statistically significant, even though their correlations are significantly lower than those of GAMMA.

The strong ‘negative’ effect of GAMMA on the Cs release is demonstrated in the scatter plot shown in Figure 3.

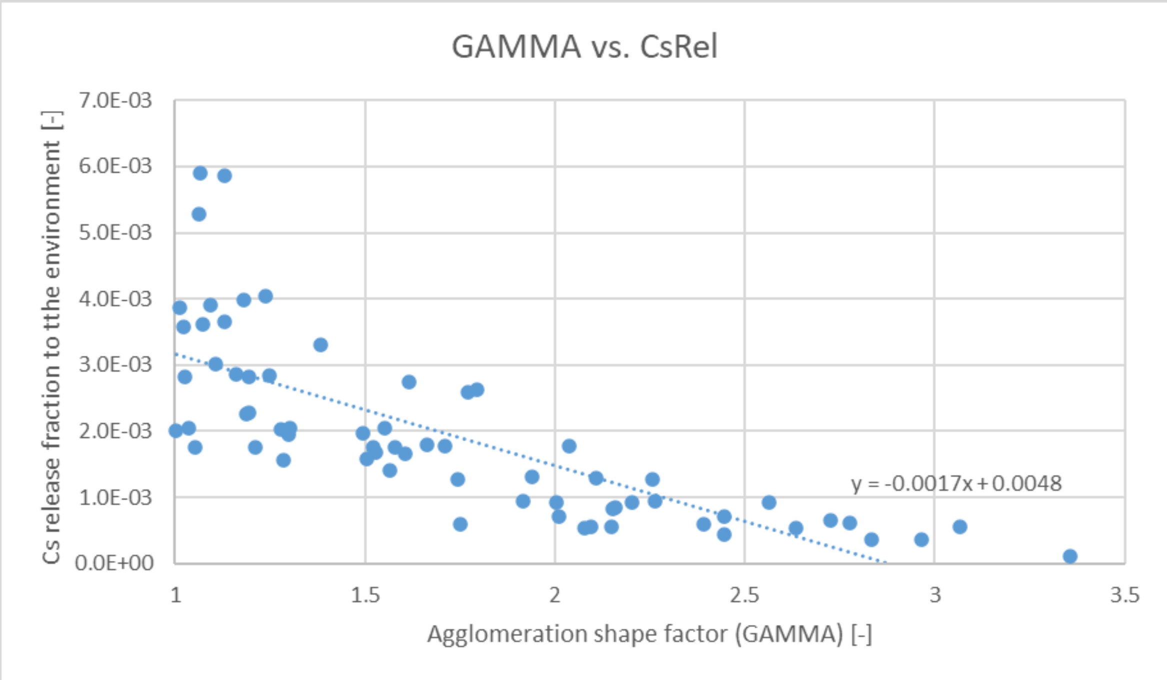

Figure 3. Agglomeration shape factor (GAMMA) vs. Cs release fraction.

In comparison to the Morris analysis, it seems both methods agree on the significance of GAMMA and CHI.

4.1.3 Uncertainty quantification

As mentioned before, the uncertainty quantification shares the settings with the sensitivity analysis carried out on SNAP. According to the Wilks' formula used by SNAP/DAKOTA to determine the number of samples, 95% probability and confidence levels should be achieved with 59 Monte Carlo samples. The input parameters, their ranges and their probability distributions were shown in Table 4.

The results from the uncertainty analysis are presented in Table 6 and Figure 4.

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Table 6. Key measures from the uncertainty analysis.

	Cs release
Minimum value	1.03E-04
Maximum value	5.89E-03
Mean	1.93E-03
Median	1.76E-03
Standard deviation	1.33E-03

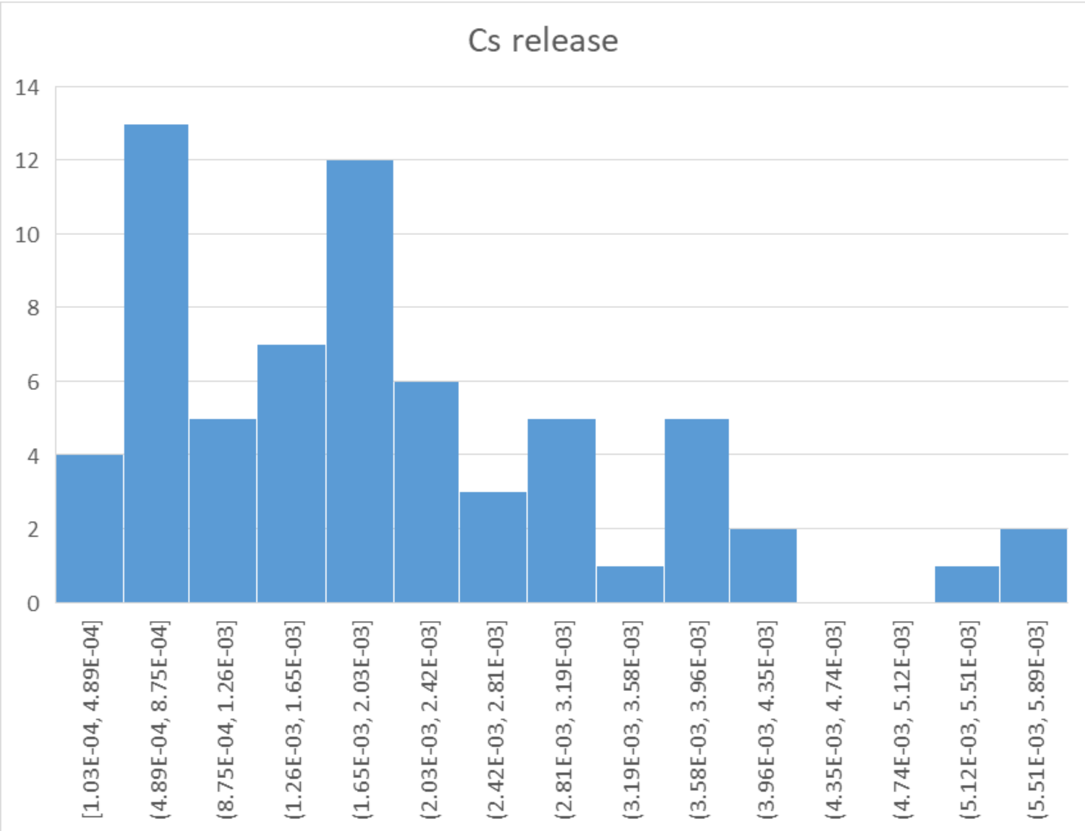

Figure 4. The distribution of Cs release.

The histogram shows that the distribution of Cs release is left-skewed, implying that lower values of Cs release are more likely under the specified conditions. Sensitivity analyses revealed that the parameter GAMMA may exert considerable influence on the model output. Given that the initial probability distribution function for GAMMA shows most sample points clustered toward the lower end, near 1, it is plausible that this skewness arises from GAMMA's effect.

The Cs release data from each simulation run are presented in Figure 5, illustrating the variation across the different cases. During the first 24 hours, almost all of the Cs release occurs right after the start of filtered containment venting at 15 hours. A couple of outliers of higher release can also be observed.

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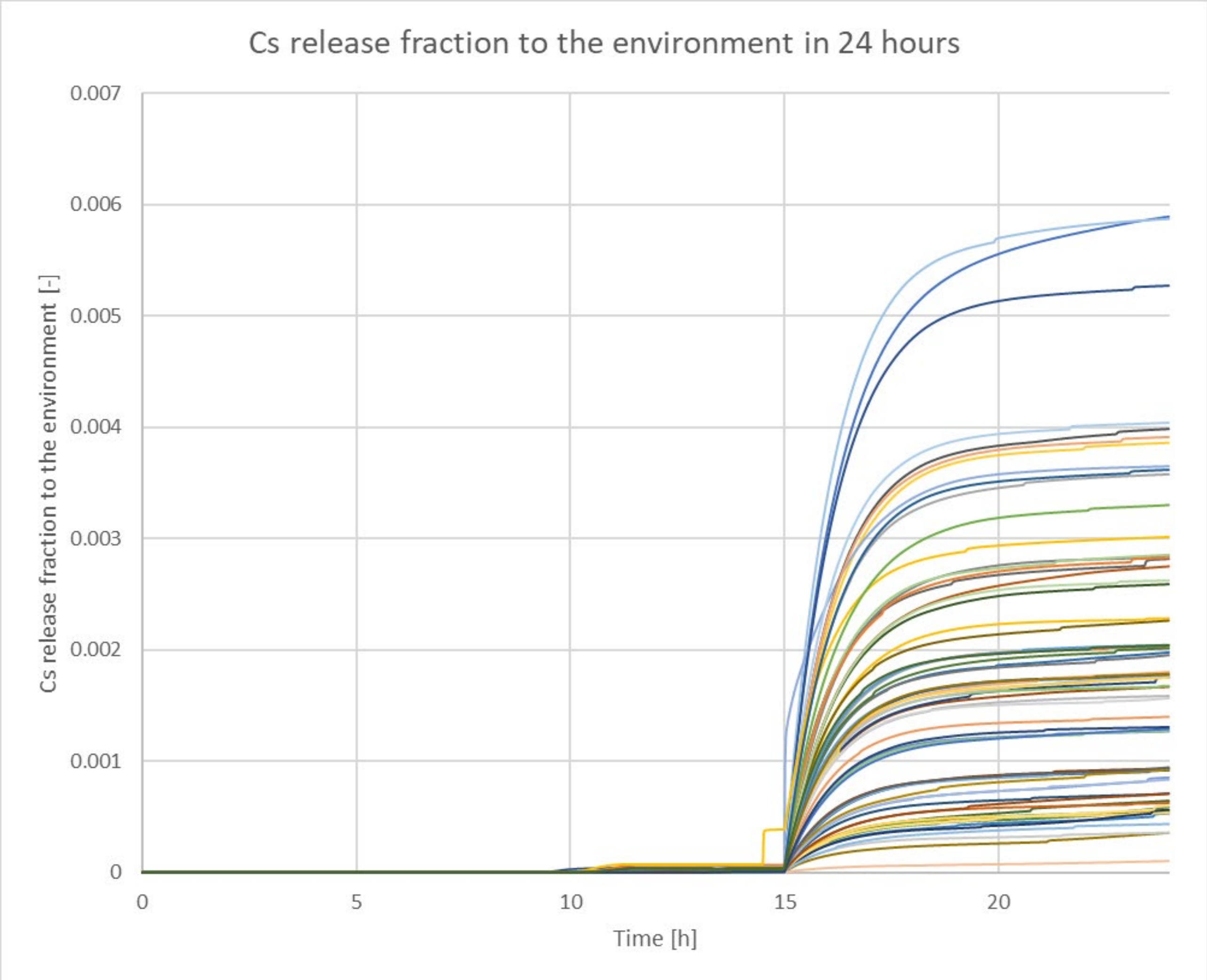

Figure 5. Horsetail plot of the Cs releases during the first 24 hours in all cases.

5. Uncertainty and Sensitivity Analyses Using the Full-Scale Fukushima Dai-ichi Unit 1 MELCOR Model

The full-scale Fukushima Dai-ichi unit 1 MELCOR model was employed to carry out rough uncertainty and sensitivity studies in SNAP/DAKOTA. The input parameters were kept the same as in the previous analyses (Table 4), but the number of samples was reduced to 22 due to limited computational resources. Also, the probability and confidence levels for uncertainty analysis were lowered to 90% respectively. As a result of these constraints, the findings should be interpreted with caution, as smaller or nonlinear effects may not be captured, and the uncertainty estimates are less robust than in previous analyses.

Analyses were performed by extracting data at two different time instances: 30 hours and 200 hours. The 30-hour mark was selected because it closely aligns with the 24-hour mark used in prior simplified model analyses, enabling direct comparison of results. The 200-hour mark represents the maximum duration achievable before simulation instability, providing insight into long-term behavior. The goal was to run the calculations until Cs release finally settles but that wasn’t quite reached due to model instabilities.

A single 200 h calculation took around 30 – 40 hours of CPU time. Five cases crashed and were resampled.

5.1 Sensitivity analysis

5.1.1 30 hours

Results at the 30-hour mark are presented in Table 7 and Figure 6. Based on a P-value threshold of 0.05, only CHI is statistically significant (P = 0.014361), while GAMMA (P = 0.070005) and DECAYH (P = 0.052175) approach significance. These three parameters emerged as the most influential in the previous sensitivity analysis as well. However, in this analysis, GAMMA's effect appears reduced, suggesting a possible shift in parameter importance under the current conditions.

Table 7. Sensitivity correlation coefficients from the full-scale model runs at t = 30 h. The most statistically influential parameters are bolded.

	Pearson	Spearman	Partial	Partial rank	P-value
TURBDS	-0.01363	-0.01525	-0.05941	0.116875	0.840119
FTHERM	-0.11225	-0.01976	-0.25794	-0.09301	0.373276
DELDIF	-0.19236	-0.01186	-0.25663	0.08975	0.375808
TKGOP	-0.03974	0.022022	0.368421	0.415151	0.194922
DECAYH	-0.49254	-0.42518	-0.52823	-0.48251	0.052175
GAMMA	-0.58681	-0.74026	-0.49791	-0.56818	0.070005
CHI	**0.534974**	**0.569735**	**0.636625**	**0.67089**	**0.014361**
STICK	-0.05044	-0.08639	-0.27099	-0.1321	0.348692
FSLIP	0.074797	0.255788	0.157268	0.241789	0.591308

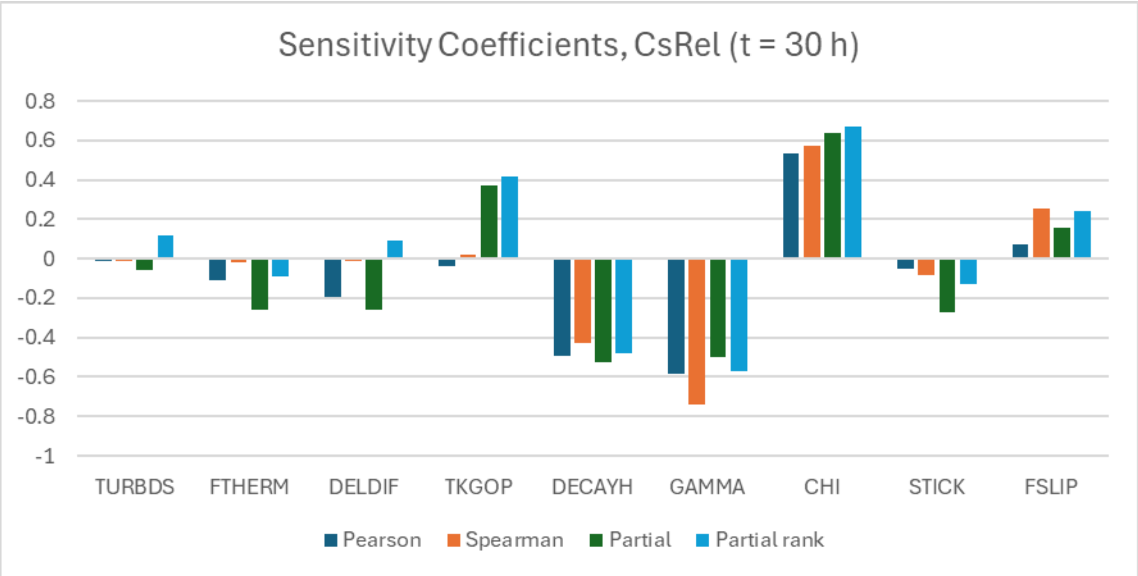

Figure 6. Sensitivity correlation coefficient calculated from Cs release at t = 30 h.

5.1.2 200 hours

Results at the 200-hour mark are presented in Table 8 and Figure 7. Based on a P-value threshold of 0.05, GAMMA (P = 0.005148) and CHI (P = 0.000954) seem to be the most influential parameters. Compared to the 30 h mark, the significance of DECAYH has reduced significantly. These results align with the other results obtained during this work as well.

Table 8. Sensitivity correlation coefficients from the full-scale model runs at t = 200 h. The most statistically influential parameters are bolded.

	Pearson	Spearman	Partial	Partial rank	P-value
TURBDS	0.178105	0.23679	0.147338	0.380891	0.615211
FTHERM	-0.19081	-0.20514	-0.28442	-0.40187	0.324359
DELDIF	-0.27169	-0.19667	-0.46066	-0.17558	0.097381
TKGOP	-0.40993	-0.46341	-0.11202	-0.39814	0.703019
DECAYH	-0.25322	-0.13111	-0.11945	-0.18122	0.684215
GAMMA	**-0.65116**	**-0.62899**	**-0.7018**	**-0.57046**	**0.005148**
CHI	**0.733866**	**0.719978**	**0.781897**	**0.72554**	**0.000954**
STICK	0.284808	0.284826	0.155935	0.437926	0.594495
FSLIP	0.097597	0.241311	0.159269	0.284781	0.586538

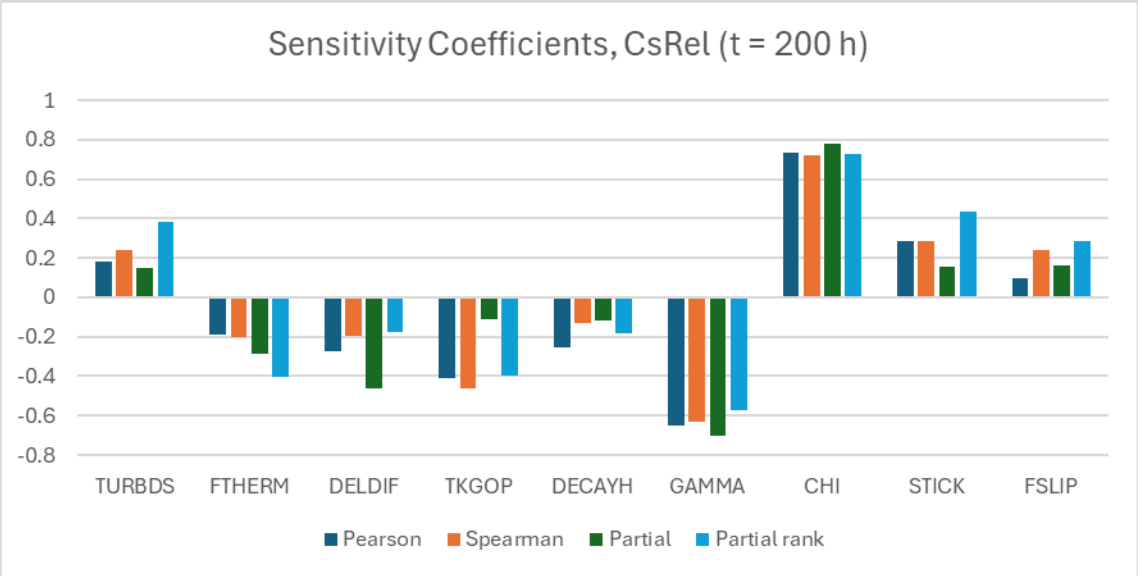

Figure 7. Sensitivity correlation coefficient calculated from Cs release at t = 200 h.

5.2 Uncertainty quantification

Results of the uncertainty quantification are presented in Table 9, Figure 8 and Figure 9. The horsetail plot of Cs release in all cases is presented in Figure 10.

Table 9. Key measures from the uncertainty analyses of the full-scale model along with the measures from the simplified case.

	Simplified model, 24 h	**30 h**	**200 h**
Min value	1.03E-04	9.830E-05	7.260E-03
Max value	5.89E-03	2.230E-03	1.850E-02
Mean	1.93E-03	7.887E-04	1.210E-02
Median	1.76E-03	5.660E-04	1.120E-02
Standard deviation	1.33E-03	6.697E-04	3.024E-03

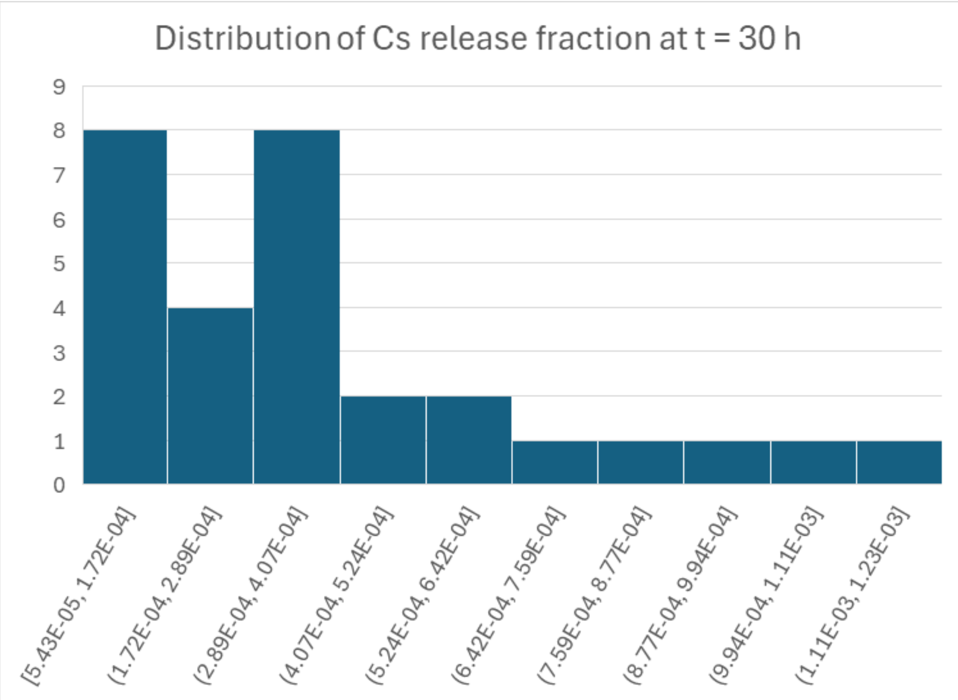

Figure 8. Distribution of Cs release fraction at t = 30 h.

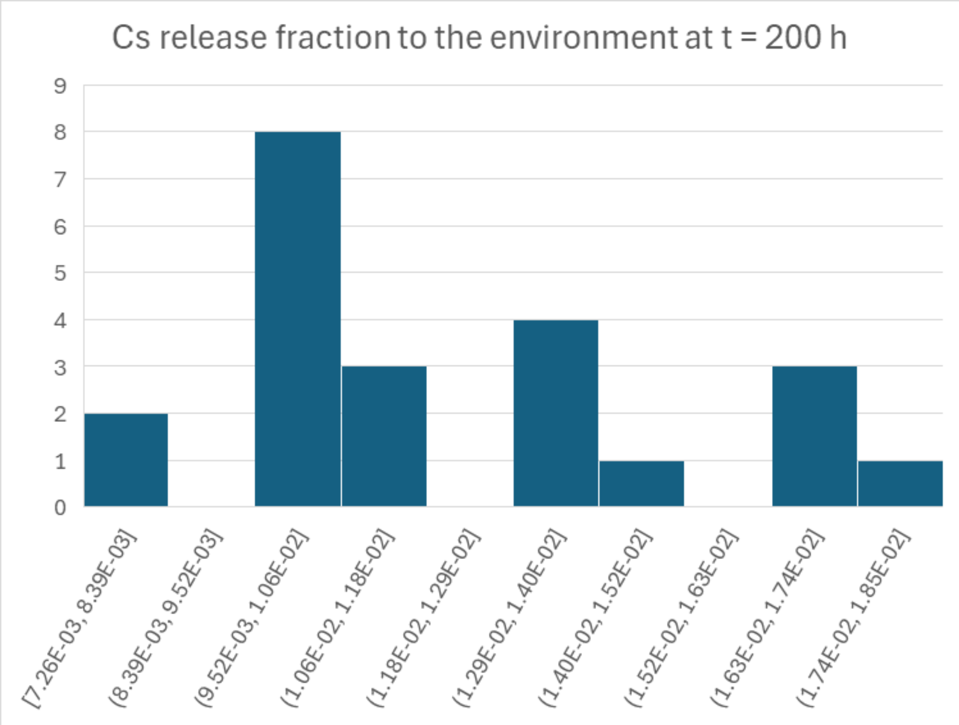

Figure 9. Distribution of Cs release fraction at t = 200 h.

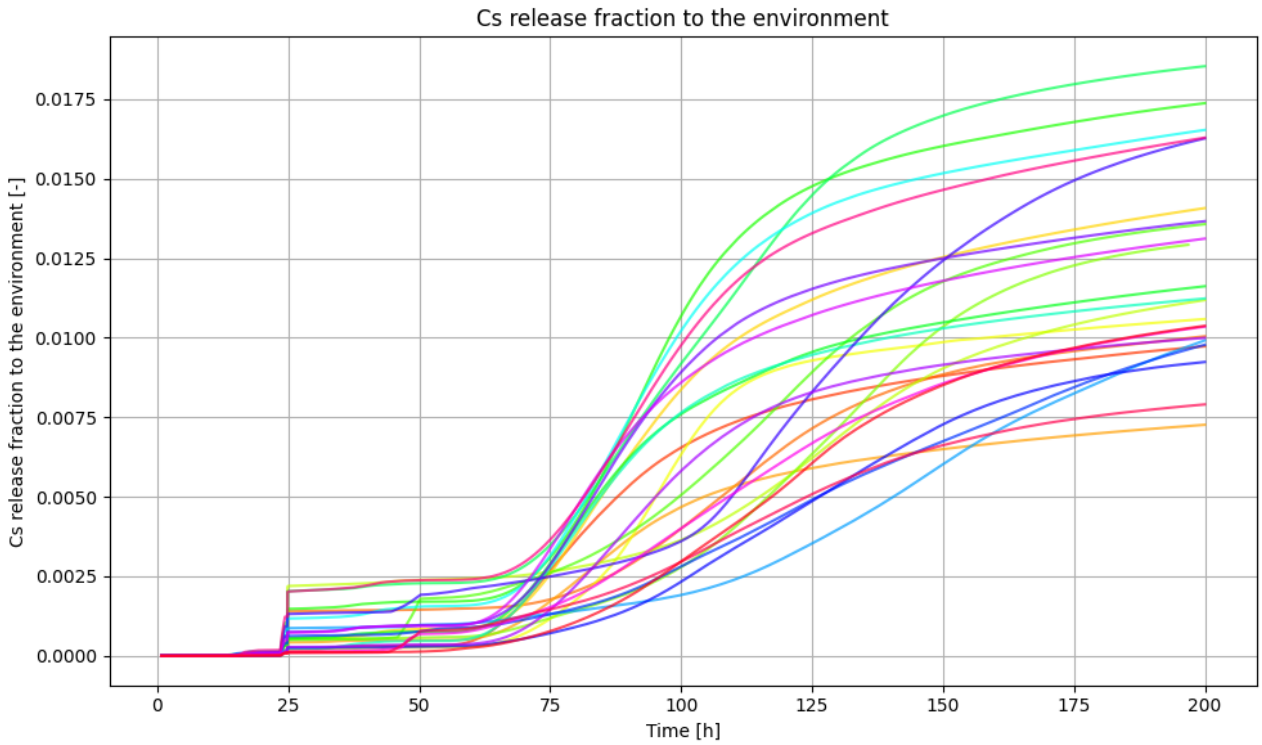

Figure 10. Cs release fraction in all cases.

The key measures from the simplified case and both full-scale cases are compared, and it can be seen that the results have quite some variation. Means and medians are of different orders of magnitude in each case. Between 30 h and 200 h calculations this is expected, since, as the Figure

10 shows, the Cs release seems to start increasing significantly after ~70 hours. The reason is the assumed drywell liner leak at 50 h, indicated by the decrease of the measured drywell pressure during the accident. The time delay between the increased leakage and the release to the environment is caused by the time that it takes for the cesium to migrate from the basement of the reactor building up to the reactor hall and from there to the environment. Besides the different leakage assumptions, the difference between the models could be caused by a number of things such as differences in the model input, random sampling, numerical noise etc. To increase the accuracy of the results the sample size should be increased, the sampling method should be reconsidered and additional methods like bootstrapping could be employed.

The histograms present distributions skewed to the left. Similarly to the simplified case, these are very likely caused by the distribution of the influential GAMMA and CHI parameters.

6. Conclusions

This work investigated the influence of key uncertain parameters on the Fukushima Daiichi Unit 1 MELCOR model by combining global sensitivity analysis and Monte-Carlo-based uncertainty quantification. Two complementary modelling approaches were evaluated: the simplified model and the original full-scale MELCOR model. The simplified model was used to test out the sensitivity and uncertainty analysis methods more thoroughly for a relatively shorter transient time, whereas the full-scale model was used to perform rough sensitivity and uncertainty analyses for a shorter time of 30 hours and longer time of 200 hours.

Morris method and the sensitivity correlation coefficients were used to study the sensitivity and parameter influence of the simplified Fukushima model. The methods were in good agreement with each other and highlighted the same the most influential parameters (aerosol dynamic shape factor, CHI, and aerosol agglomeration shape factor, GAMMA). The uncertainty studies showed a left-skewed distribution for the Cs release, which was most likely caused by the great influence of GAMMA.

The sensitivity and uncertainty analyses carried out with the full-scale model at time instances 30 h and 200 h had quite similar results. Despite the too low sample size for a proper sensitivity analysis, the results highlighted CHI and GAMMA as the most influential input parameters. The correlations were, however, significantly lower, which probably was caused by the small sample size. The distributions obtained from the uncertainty analysis showed once again skewedness to the left, which was most likely caused by the distribution of CHI and GAMMA parameters. The key measures from the uncertainty analysis were naturally quite different, since the cesium release was observed increasing significantly after ~70 hours. Comparing the simplified 24 h case and the full-scale 30 h cases showed that the results were of different order of magnitude. This could be caused by multiple things, such as differences in the containment leak and venting assumptions, differences in random sampling, numerical noise etc. To gain confidence in the results, more samples would be needed.

Overall, the results highlighted the significant influences of the aerosol agglomeration shape factor (GAMMA), aerosol dynamic shape factor (CHI), and in some cases the multiplier of decay heat power (DECAYH). This is in line with analyses carried out in the previous projects as well, where the influence of GAMMA typically was highlighted as well. However, this means that GAMMA could potentially dominate the results too much and thus drown the influence of the other parameters. That’s why it would be good practice to re-run the simulations without GAMMA or reconsider its initial probability density.

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The study underscores the importance of selecting sensitivity and uncertainty methods that are appropriate to computational constraints, model stability, and the level of detail required. Future work should include expanding the Monte Carlo sample size, improving numerical robustness of long-term MELCOR simulations, and exploring variance-based or surrogate-assisted sensitivity methods to better capture interactions and non-linear phenomena.

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