Sensitivity Analysis and Failure Damage Domain Identification of the Passive Containment Cooling System of an AP1000 Nuclear Reactor

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Abstract: The paper presents an application of a variance decomposition method for the sensitivity analysis of the thermal hydraulic (TH) model of the Passive Containment Cooling System (PCCS) of an Advanced Pressurized Reactor (AP1000). The Loss Of Coolant Accident (LOCA) is considered as the most representative accident for identifying the Failure Damage Domain (FDD) of the PCCS with respect to the individual and grouped inputs most affecting the final pressure at the end of the accidental transient.

Keywords: Passive Systems Reliability, AP1000, Variance Decomposition, Failure Damage Domain.

1. INTRODUCTION

The extension of nuclear safety considerations to severe accidents and the increased safety requirements have led to a growing interest in passive systems for the safety of the future nuclear reactors. As a result, all innovative reactor concepts make use of passive safety features, to a large extent in combination with active safety and operational systems [1],[2]. Passive systems are addressed as a resource for nuclear safety improvement because of their characteristics of simplicity, reduction of human interaction and reduction or avoidance of external electrical power and signals input [2].

On the other hand, passive safety systems are affected by uncertainties that have to be properly considered to guarantee their reliability by design [3]. In fact, passive systems rely only on natural forces, (such as gravity, natural circulation, compressed gas and other physical principles) for which the classical concepts of reliability analysis does not make sense as for the pumps, fans, diesels, chillers, or other devices used in active safety systems [4]. For example, to activate safety passive systems, usually only few fail-safe valves are required to open: in case of loss of power, they automatically open by stored energy (e.g. compressed gas or batteries). Anyway, although passive safety systems are significantly simpler than active ones because they comprise significantly fewer components (with straightforward benefits on the number of tests, inspections, and maintenance activities to be planned), uncertainty due to the lack of knowledge on the physical principles driving their performance, makes passive safety systems also exposed to potential failures for which they have been designed.

Quantification of failure probability is one main goal of the system safety assessment and is usually achieved with the support of numerical models simulating the behavior of the real system. Sensitivity analysis has been widely used in engineering design to help the designers understanding the behavior of a model and make informed decisions regarding where to spend the engineering effort. Sensitivity analysis is used both in deterministic design and design under uncertainty to quantify how much the output of a model depends on the inputs and ranking variables importance [5]. These characteristics make sensitivity analysis particularly suited for both the design and the safety assessment of passive systems. Various qualitative or quantitative approaches have been developed for performing sensitivity studies, e.g. Analytic Hierarchy Process (AHP), first-order differential analysis, response surface methodology, Fourier Amplitude Sensitivity Test (FAST) and Monte Carlo sampling [5],[6]. The AHP is a qualitative method based on the consultation of multiple experts, asked to express their judgments on the relative importance of parameters to determine the overall hierarchy with regards to the defined top goal. First-order differential analysis is a quantitative local approach that uses a finite difference approximation of small output variations around the nominal best estimate values to identify the critical parameters [7]. The Response surface methodology consists in approximating the model function $f(X)$ by a simple and faster mathematical model from a database of computations. FAST is a global, variance-based sensitivity analysis method based on the principle that a model (a function) can be expanded into a Fourier series and the Fourier coefficients and frequencies can be used to estimate the mean and variance of the model, and the partial variance of individual input parameters of the model [8]. Monte Carlo sampling consists of drawing samples of the basic variables according to their probability density functions and, then, feeding them into the performance function to retrieve the output probability density function.

In this paper, we use the variance decomposition method [9] for performing the sensitivity analysis of a specific lumped thermal hydraulic (TH) model with the aim of quantifying the effects on the model output of the variability of not only single inputs but also groups of inputs, thus including also their interactions. The TH model simulates the behavior of a Passive Containment Cooling System (PCCS) when a Loss Of Coolant Accident (LOCA) occurs in an Advanced Pressurized reactor (AP1000). PCCS is an innovation used in AP1000 reactors design, aimed at improving safety [10]. PCCS operation is based on natural circulation, so that physical process failure (i.e., the actual conditions are such that natural circulation cannot be established or maintained at the time of the LOCA) becomes the important failure mode[11]. To analyze this we propose to use the outcomes of sensitivity analysis for identifying the Failure Damage Domain (FDD), a concept already used in the evaluation of risk-informed safety margins [12] and, more generally, to compactly represent the final state of a system as a function of the most important parameters which drive its response [13].

The paper organization is as follows. For self-consistency and completeness, in Section 2, the Monte Carlo method for uncertainty propagation and the Variance Decomposition method for sensitivity analysis are briefly recalled. In Section 3, the main characteristics of the AP1000 reactor design are given (Subsection 3.1) and the accident scenario considered is described (Subsection 3.2). In Section 4, the model for the long term PCCS pressure calculation is described. In Section 5, the results of the sensitivity analysis are provided and used for FDD identification. Finally, some conclusions are drawn in Section 6.

2. THE VARIANCE DECOMPOSITION METHOD FOR SENSITIVITY ANALYSIS

For simplicity of illustration, and without loss of generality, let us consider a model m whose output value y depends only on the values x_1 and x_2 of two uncertain input parameters X_1 and X_2, viz:

$$y = m(x_1, x_2) \tag{1}$$

No hypotheses are made on the structure of the model.

Monte Carlo is a global method for uncertainty analysis, which simply consists in drawing random samples of the uncertain input parameters values from their probability density functions and evaluating the model output for each set of sampled values.

Operatively, consider a set of s realizations of the two input parameters drawn from the assigned pdfs $f_{x_1}(x_1)$, $f_{x_2}(x_2)$, respectively:

$$\bar{x}^j = \left[x_1^j, x_2^j\right] \qquad j=1,2,\ldots s \tag{2}$$

The model is evaluated for each of the s independently generated vectors $\bar{x}^j$, j=1,2,…,s, to obtain a corresponding set of output values:

$$y^j = m\left(x_1^j, x_2^j\right) \qquad j=1,2,\ldots s \tag{3}$$

Such set represents an independent random sample of size s of the distribution of the output y and can be analyzed using classic statistical techniques for uncertainty analysis [5],[14].

The dependence of the value of the output variable (Y) on the value of one of the two input variables, e.g. X_1, can be approximated by the expected value of Y with respect to the other variable X_2, conditioned on X_1 being equal to a given value x_1:

$$y^*(x_1) = E_{X_2}(Y|x_1) = \int m(x_1, x_2) f_{X_2|X_1}(x_2|x_1) dx_2 \tag{4}$$

where $f_{X_2|X_1}(x_2|x_1)$ is the conditional probability density of X_2 given X_1. Note that, since X_1 is fixed at x_1, y^* depends only on the variable X_2.

To evaluate how the uncertainty in the input propagates to the output of the model, the variance of the distribution of the output variable Y is decomposed as follows (see [9],[15] for further details):

$$Var[Y] = Var_{X_1}\left[E_{X_2}(Y|X_1)\right] + E_{X_1}\left[Var_{X_2}(Y|X_1)\right] \tag{5}$$

where X_1 has been indicated explicitly as subscript of the variance and expectation operators to highlight that these are applied with respect to such variable.

The sensitivity relevance of X_1 can be associated to its contribution to the output variance, i.e. the term $Var_{X_1}\left[E_{X_2}(Y|X_1)\right]$ in (5). Quantitatively, it is then customary to take the following measure as an index of the importance of the variable X_1 with respect to its contribution to the uncertainty in the output Y:

$$\eta_1^2 = \frac{Var_{X_1}\left[E_{X_2}(Y|X_1)\right]}{Var[Y]} \tag{6}$$

An operative procedure based on Monte Carlo sampling for estimating the index of importance of X_1 according to the definition (6) may be summarized as follows [16]:

1. Sample a random population of s values of X_1 $\{x_1^1, x_1^2, ..., x_1^s\}$
2. For each value x_1^j, sample r values x_2^k, k=1,2,…,r from the conditioned distribution $f_{X_2|X_1}(x_2|x_1^j)$.
3. Evaluate r output values $y^{jk} = m(x_1^j, x_2^k)$; each of these values is an element of an output matrix of order *(s,r)*.
4. For each row j=1,2,…,s of the matrix, evaluate the estimate

$$\hat{y}^*(x_1^j) = \frac{1}{r}\sum_{k=1}^{r} y^{jk} \cong E_{X_2}\left[Y|x_1^j\right] \tag{7}$$

5. Estimate the expected value of Y

$$\bar{y} = \frac{1}{s}\sum_{j=1}^{s}\hat{y}^*(x_1^j) \cong E[Y] \tag{8}$$

6. Estimate the variances

$$\hat{V}_{X_1}\left[E_{X_2}(Y|x_1)\right] = \frac{1}{s-1}\sum_{j=1}^{s}\left[\hat{y}^*(x_1^j) - \bar{y}\right]^2 \tag{9}$$

$$\hat{V}[Y] = \frac{1}{sr-1}\sum_{j=1}^{s}\sum_{k=1}^{r}\left(y^{jk} - \bar{y}\right)^2 \tag{10}$$

7. Estimate the index of importance

$$\hat{\eta}_1^2 = \frac{\hat{V}_{X_1}\left[E_{X_2}(Y|x_1)\right]}{\hat{V}[Y]} \tag{11}$$

The extension of the procedure to more than two input variables and to the sensitivity analysis of groups of input variables considered simultaneously is straightforward [9],[15].

The main advantages of the variance decomposition method for performing sensitivity analysis is that it does not impose any limitative hypothesis on the structure of the model as it is, for example, with the regression methods. Moreover, it allows a straightforward evaluation of the sensitivity importance of groups of variables and not only individual ones. On the other hand, this flexibility is paid by a computational burden larger than that of other methods, e.g. regression-based methods, due to the need of computing the model output several times ($s \cdot r$) for the different input values sampled from the respective probability distributions.

3. BASIC ELEMENTS OF THE AP1000 REACTOR DESIGN

3.1. General Aspects

The Westinghouse AP1000 is a 1117 MWe (3415 MWth) pressurized water reactor (PWR), with layout simplification achieved through large operating margins and extensive implementation of passive safety systems for reduction of corrective maintenance actions in case of accident. The passive safety systems include passive Residual Heat Removal System (RHRS) and Passive Containment Cooling System (PCCS). The PCCS provides the safety-related ultimate heat sink for the plant. It cools the containment following an accident, so that the pressure is effectively controlled within the safety limits of 0.4 MPa. During an accident, heat is removed from the containment vessel by the continuous, natural circulation of air, supplemented by evaporation of the water that drains by gravity from a tank located on top of the containment shield building by means of three redundant and diverse water drain valves. The steel containment vessel provides the heat transfer surface through which heat is removed from inside the containment and transferred to the atmosphere. In addition, even in case of failure of water drain, air-only cooling is supposed to be capable of maintaining the containment below the failure pressure [10]. Figure 1 shows the PCCS of the AP1000 [Westinghouse Electric Company promotional image].

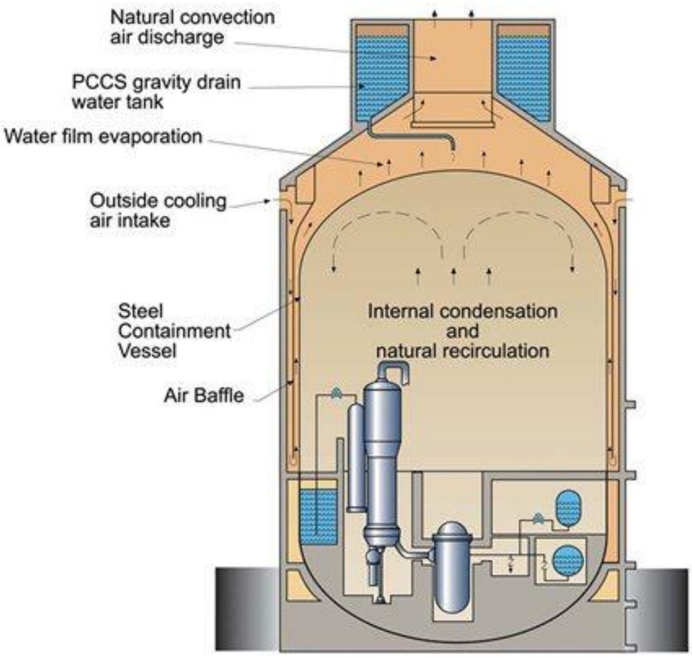

Figure 1 AP1000 Passive Containment Cooling System [Westinghouse Electric Company]

For the analysis of the functional performance of PCCS of the AP1000, TH analysis is carried out for safety assessment [17][18]. WGOTHIC [18] has been developed by Westinghouse as a conservative lumped parameter model for heat transfer with non-condensed gas, circulation and stratification for TH response analysis following i) loss of coolant accident (LOCA) ii) steam line break (SLB) accident, and containment integrity analysis.
In this paper, we aim at the identification of the FDD after a LOCA; the simplified TH model used has been developed by [19].

3.2. LOCA

The LOCA is a most dangerous accident in Pressurized and Boiling Water Reactors (PWR and BWR, respectively), whereby the stored energy of the high pressure, high temperature coolant is released to

the containment by rupture of an exposed pipe. Thus, it is to be considered among the design basis accidents for AP1000 reactor design.
In general a LOCA scenario develops as follows [20]:

1) A double-ended “guillotine” pipe break in a primary coolant line allows the coolant flowing out from both ends;
2) Coolant flashes into steam due to the large amount of stored energy and is discharged rapidly into the containment building;
3) Reactor trip is automatically triggered by the protective system to assure continued sub-criticality of the reactor core;
4) The Emergency Core Cooling Systems (ECCS) cools down the core and prevents excessive decay heat-driven damage to its structures;
5) Radioactivity in the coolant is retained by the containment structure with natural deposition processes and active removal systems, eventually reducing the overall levels of radioactivity;
6) RHRS maintains ECCS effectiveness and reduces containment pressure.

A TH code for simulating a LOCA is typically divided into four phases: 1) blowdown, that includes the accident initiation (when the reactor is in a steady-state full power operation condition) to the time at which pressure equalizes to the containment pressure; 2) refill, which includes the time from the end of the blowdown to the time when the ECCS refills the vessel lower plenum; 3) reflood, which begins when water starts flooding the core until when it is completely quenched; 4) post-reflood, which starts after the core quenching and energy is released to the Reactor Coolant System (RCS) by the RCS metal, core decay heat, and the steam generators that maximize the containment pressure.

4. THERMAL HYDRAULIC MODEL

In the post-reflood phase, the steam produced in the RCS is cooled at the internal face of the steel containment vessel, and then the heat is conducted by the vessel and transferred to the air in the air channels, (see Figure 1). Cold air enters the channel through the three rows of air inlets and flows down to the bottom of the channels, where it is heated by the steel vessel up to the air diffuser to the environment.
In this paper, a steady state, lumped parameters TH model is used to analyze the effect of the air temperature and reactor power on the PCCS function. The parameters of the TH model used for calculating the PCCS capability of condensing the steam produced, and their distributions, are listed in Table 1. If the steam cannot be condensed, the vapor cumulates in the containment and results in an overpressure accidental scenario: then, the success criteria for the PCCS is set at Pcontainment < 0.4 MPa.
The selection of the distributions of the parameters in Table 1 is based on expert judgment and literature review [3],[21]. Three distributions have been used: seasonal, normal and uniform. Seasonal relates to the external air temperature T_{inlet} and pressure P_{air} variability, as inferred by historical data collected by a representative Chinese Automatic Weather Station (CAWS) in different months. Normal distributions, e.g. for the LOCA steam temperature, T_{steam}, are listed as truncated distributions with mean μ and support equal to 4σ where σ is the standard deviation. For uniform distributions, e.g. for the steam mass flow rate G, the supports from “Lower value” to “Upper value” are reported.

Figure 2 shows the distribution of the steady state containment pressure values obtained from 10000 runs of the TH code, with parameters values randomly sampled from the distributions of Table 1; the total computational time is 1894 s on a laptop machine powered by an Intel core2duo P7550 dual core processor running at 2.26 GHz. A value of 0.55 MPa is automatically assigned to the pressure, when it exceeds the safety limit of 0.4 MPa.

Table 1: List of parameters distributions

	Parameter	Description	Unit	Type of distribution	Lower value	Upper value		
1	G	Steady state LOCA mass flow rate	kg/s	uniform	6	11		
2	T_{inlet}	External air temperature	°C	seasonal	2	39		
3	P_{air}	Pressure of inlet air	MPa	seasonal	0.09837	0.1010965		
	Parameter	**Description**	**Unit**	**Type of distribution**	**Mean value, μ**	**Standard Deviation, σ (% of μ)**	**μ-4σ**	**μ+4σ**
4	T_{steam}	LOCA steam temperature	°C	normal	250	5	200	300
5	P_{steam}	LOCA steam pressure	MPa	normal	0.1	5	0.08	0.12
6	$\rho_{primary}$	Water density in primary circuit	kg/m^3	normal	666.7	2	613.36	720.04
7	$P_{primary}$	Pressure of primary circuit	MPa	normal	15.5	2	14.26	16.74
8	V	Containment volume	m^3	normal	58333	1	55999.68	60666.32
9	t	Containment wall thickness	m	normal	0.04455	0.5	4.37E-02	4.54E-02
10	D	Containment diamenter	m	normal	39.62	0.5	38.83	40.41
11	H	Containment height	m	normal	34.12	0.5	33.44	34.8
12	W	Width of air buffle outside containment	m	normal	0.92	0.5	0.9	0.94
13	H_1	Height of the download in air buffle	m	normal	38.11	0.5	37.35	38.87
14	H_2	Height of the upload in air buffle	m	normal	59.89	0.5	58.69	61.09
15	D_3	Diameter of the air outlet	m	normal	9.75	0.5	9.56	9.95
16	H_3	Height of the air outlet	m	normal	6	0.5	5.88	6.12
17	D_4	Diameter of uphead	m	normal	39.62	0.5	38.83	40.41
18	H_4	Height of uphead	m	normal	11.47	0.5	11.24	11.7
19	d	Diffusive coefficient (water)	m^2/s	normal	2.55E-05	20	5.10E-06	4.59E-05
20	λ	Heat conduction of the wall	W/(m K)	normal	54	5	43.2	64.8
	Parameter	**Description**	**Unit**	**Type of distribution**	**Lower value**	**Upper value**		
21	K	Air channel rugosity	-	uniform	0.00285	0.00315		
22	f_1	Friction factor of corner	-	uniform	0.475	0.525		
23	f_2	Friction factor of inlet	-	uniform	0.9025	0.9975		
24	f_3	Friction factor of pipeup	-	uniform	0.1425	0.1575		
25	f_4	Friction factor of pipeout	-	uniform	0.1425	0.1575		
26	f_5	Friction factor of pipecold	-	uniform	0.1425	0.1575		

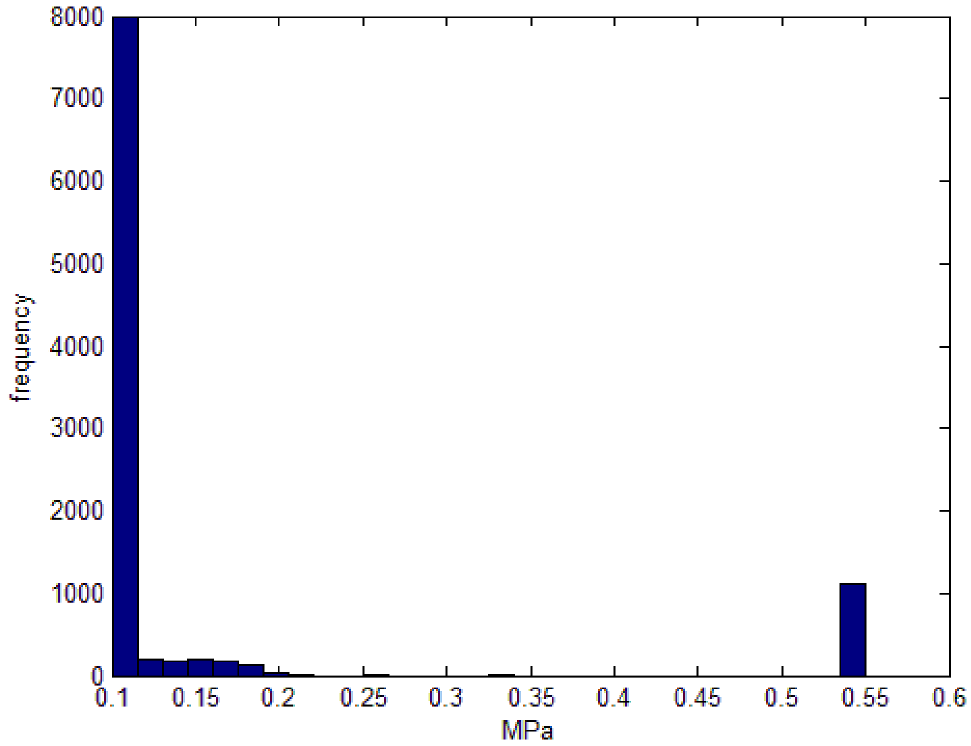

Figure 2 Histogram of the steady state containment pressure from 10000 runs of the TH code.

5. FDD BY VARIANCE DECOMPOSITION SENSITIVITY ANALYSIS

The majority of input sampled vectors lead the system to succeeding in maintaining the pressure within the limit of 0.4 MPa, but there is a not negligible probability of exceedance of approximately 10%.

5.1. Variance Decomposition Sensitivity Analysis

For variance decomposition sensitivity analysis, in our case, we select s=90 and r=140 so that 12600 runs of the TH code are performed for each one of the 26 parameters listed in Table 1, for a total of 327000 simulations (total computation time is 58251 s). The η^2 importance indexes of all the parameters are reported in Figure 3. The importances of G and T_{inlet} are clearly predominant and the importances of the other parameters are negligible.

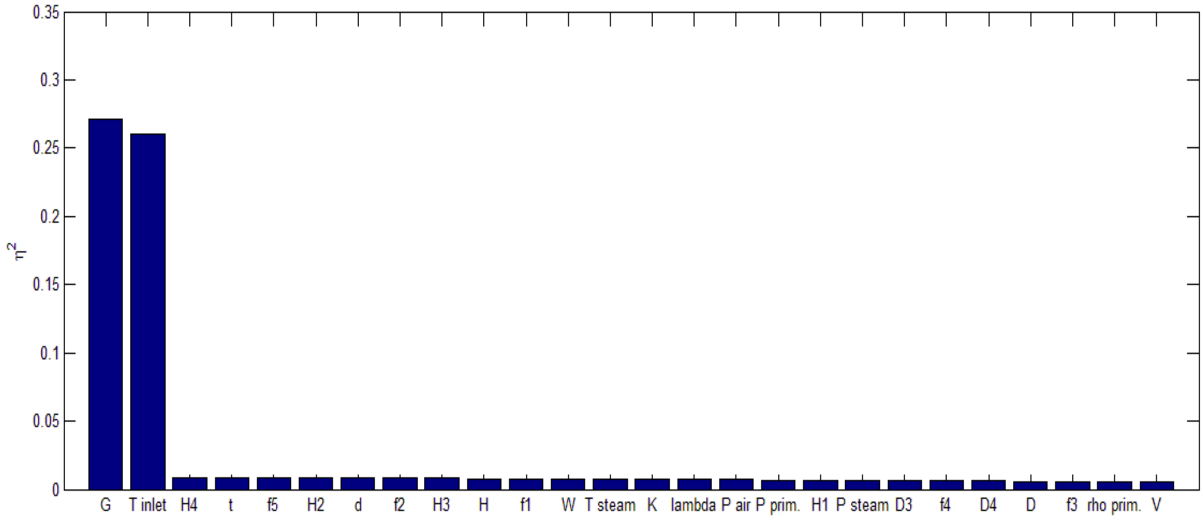

Figure 3 η^2 of the 26 parameters.

A group analysis is also performed, in which the importance index η^2 of groups of parameters is computed. Four groups have been considered: external conditions, primary coolant conditions, system geometry, materials properties and friction factors. For each group, $(s \cdot r)$ simulations with s=90, r=140, (50400 in total) have been performed.
The specific groups are:

- *a.* External conditions: T_{inlet}, P_{air}
- *b.* Primary coolant conditions: G, P_{steam}, T_{steam}, $\rho_{primary}$, $P_{primary}$,
- *c.* System geometry: V, t, D, H, W, H_1, H_2, D_3, H_3, D_4, H_4
- *d.* Material properties and friction factors d, λ, K, f_1, f_2, f_3, f_4, f_5

The results of the group variance decomposition (Table 2), again show a clear predominance of T_{inlet} and G in determining the variance of the steady state containment pressure: in fact, the groups *a* and *b* have values of η^2 greatly larger than groups *c* and *d*.

Table 2 η^2 for groups of inputs

Group	η^2
External conditions	0.2935
Primary coolant conditions	0.2648
System geometry	0.0078
Material properties and friction factors	0.0095

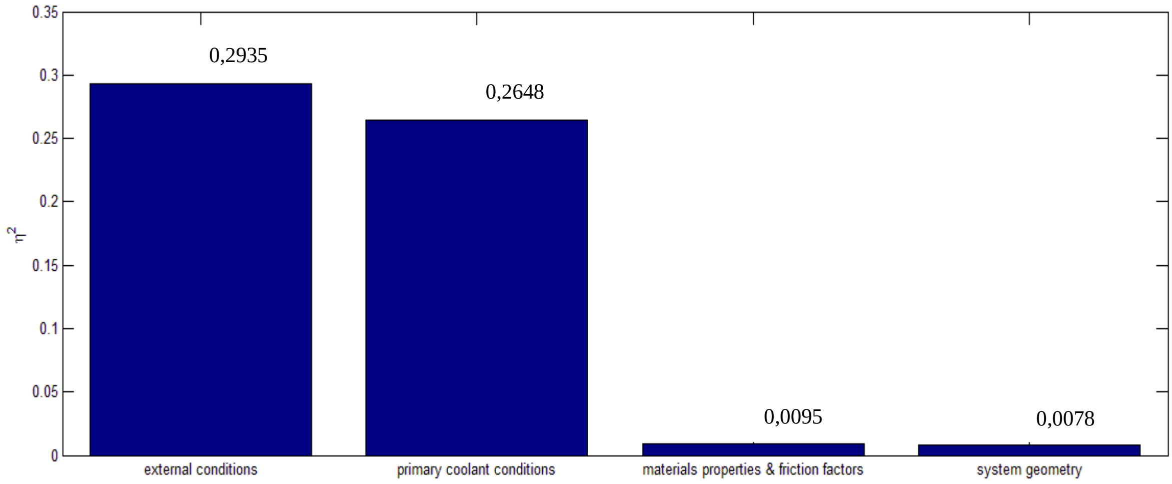

Figure 4 η^2 of the four groups of parameters.

We can conclude that under the assumptions of Table 1, G and T_{inlet} are by far the most important parameters for obtaining the PCCS response in terms of steady state containment pressure. This result aligns with our prior expectations for what regard the predominance of G and T_{inlet} with respect to the other parameters. In fact, not only G and T_{inlet} are directly linked to the energy entering (G) and leaving (T_{inlet}) the PCCS but they have also, by far, the largest uncertainties, as reported in Table 1. The other input parameters have low uncertainties due to better knowledge, and their effects on the output are modest even when sampled at maximum or minimum values of their range.
On the other hand, the finding that G and T_{inlet} are almost equally important (i.e. equally responsible for the output variability) is an information difficult to suppose a priori of the sensitivity analysis. because of the different distributions and the different relations (also nonlinear) with the model output.

5.2. Failure Damage Domain

An intuitive way to gather together all the information resulting from the previous analysis is the FDD map. This map resumes the information provided by both the MC uncertainty propagation (Figure 2) and the variance decomposition analysis (Figures 5 and 6). It can be useful for i) further sensitivity analysis without TH calculations, ii) safety margins visualization, iii) identification of mitigation strategies, iv) discussion with the regulator [13].
Figure 5 shows the FDD in the plane of the two most important parameters T_{inlet} and G, representing the failure probability of the PCCS after a LOCA.

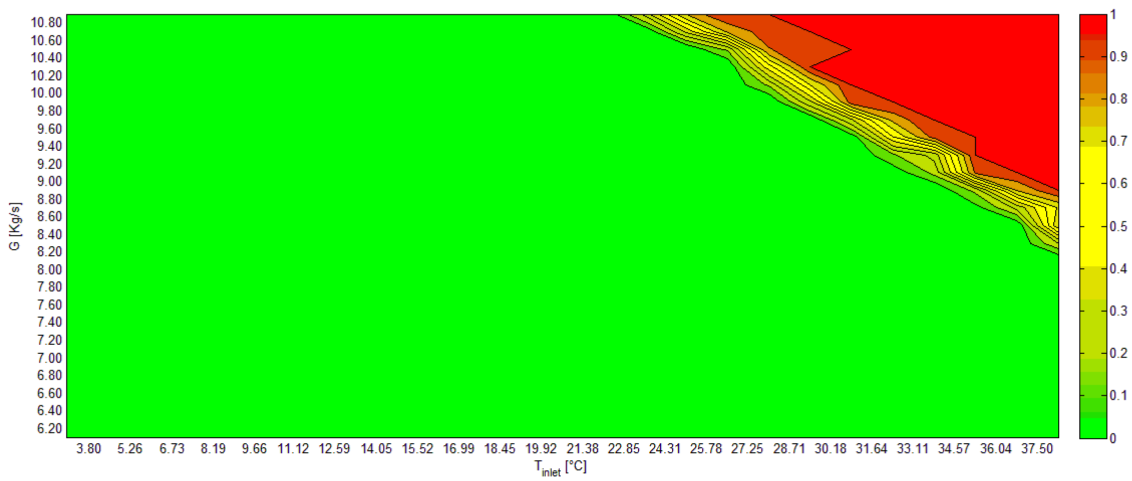

Figure 5 Failure damage domain map

6. CONCLUSIONS

In this work, we have performed a Monte Carlo sampling uncertainty propagation, variance decomposition sensitivity analysis and FDD identification with respect to a TH code that calculates the post reflood steady state pressure after a LOCA in the AP1000 passive pressure containment. The sensitivity analysis has highlighted that among all the input parameters of the code, G and T_{inlet} are by far the most important. The results of the analysis have been used to generate the FDD, which gives useful safety insights. Computational time is an aspect of primary importance in sensitivity analysis and might be a limiting factor when resorting to variance decomposition. Thus, future work will tackle this problem by developing an innovative sensitivity method that limits the need of repeating several model solutions in correspondence of different sampled input values for properly mapping the input-output relationship.

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