Proc. of the European Safety and Reliability Conference (ESREL 2026)
Edited by José C. Matos, Paulo B. Lourenço, Michael Beer, Daniel Oliveira,
Edoardo Patelli, Hélder S. Sousa, Rui A. Silva and Monica Santamaria

doi: 10.3850/ESREL2026061419_esrel26-p26291-cd

BEPU Analysis of an Extended SBO Accident in a Typical Three-Loop PWR

José Ordóñez Ródenas

Dept. of Chemical and Nuclear Engineering, MEDASEGI research group, Universitat Politècnica de València, Valencia, Spain. E-mail:joorro1@iqn.upv.es

Jose Felipe Villanueva

Dept. of Chemical and Nuclear Engineering, MEDASEGI research group, Universitat Politècnica de València, Valencia, Spain. E-mail: jovillo0@iqn.upv.es

Sofía Carlos

Dept. of Chemical and Nuclear Engineering, MEDASEGI research group, Universitat Politècnica de València, Valencia, Spain. E-mail: scarlos@iqn.upv.es

Ana Sánchez

Dept. of Applied Statistics and Operational Research, and Quality, MEDASEGI research group, Universitat Politècnica de València, Valencia, Spain. E-mail: aisanche@eio.upv.es

Sebastián Martorell

Dept. of Chemical and Nuclear Engineering, MEDASEGI research group, Universitat Politècnica de València, Valencia, Spain. E-mail: smartore@iqn.upv.es

Rafael Mendizábal

Consejo de Seguridad Nuclear (CSN), Madrid, Spain. E-mail: rmsanz@csn.es

Ignacio Molina

Consejo de Seguridad Nuclear (CSN), Madrid, Spain. E-mail: ignacio.molina@csn.es

In line with the guidelines of the IAEA SSG-2 Safety Guide and the Instruction IS-37 of the Spanish Nuclear Safety Council (CSN), this work focuses on the analysis, using the BEPU methodology, of the uncertainties associated with a design extension condition scenario. The study is applied to a typical three-loop PWR reactor under a Station Blackout accident in which the emergency diesel generators are unavailable and the recovery of off-site power is not assumed. Under these conditions, a key component for maintaining core integrity is the turbine-driven pump of the auxiliary feedwater system. Once the battery supplying this system is depleted, a mobile pump may be deployed, thereby extending the time available to recover off-site power and maintain system integrity. The analysis focuses on three figures of merit (FoMs) considered to be of particular interest: the peak cladding temperature, the pressure difference between the primary and secondary systems, and the loss of primary inventory through the relief valves. The results show that no critical values that would significantly destabilize the system are exceeded, and they identify the uncertainty parameters that have the greatest impact on each of the three FoMs.

Keywords: BEPU, LEPL, SBO, DEC, PWR, Mobile Pump.

1. Introduction

The MEDASEGI research group at the Universitat Politècnica de València (UPV) collaborates with the Spanish Nuclear Safety Council (CSN) on R&D projects aimed at assessing the safety of nuclear power plants, with particular emphasis on the thermal–hydraulic analysis of accident scenarios. Within this framework, CSN–UPV cooperation agreements support safety studies on experimental facilities and their applicability to Pressurized Water Reactors (PWR), as illustrated by the CAMP (SN-027-2020) and MASA-2 (SN-025-2020) projects. The nuclear industry relies on the defense-in-depth principle and the preservation of safety margins to manage the uncertainties inherent in plant design and operation. The availability of reliable computational tools for more detailed safety analyses has promoted the use of advanced best-estimate codes. In accordance with the International Atomic Energy Agency (IAEA) SSG-2 Safety Guide (IAEA 2009) and CSN Instruction IS-37 (CSN 2015), this work analyzes the uncertainties associated with an extended Station Blackout (SBO) in Design Extension Condition (DEC) in a three-loop PWR reactor using the Best Estimate Plus Uncertainty (BEPU) methodology. This methodology enables the realistic best-estimate prediction of plant response while also identifying cliff-edge scenarios in which plant conditions deteriorate rapidly (IAEA 2008b, Unal 2011, Wilsom 2013). The study does not assume the recovery of off-site power.

Under these conditions, the auxiliary feedwater system plays a key role in preserving core integrity, as its operation initially depends on a turbine-driven pump (TDP) that must remain functional for a defined period. Once the battery supplying this system is depleted, the deployment of a mobile pump may extend the time available to restore off-site power and ensure plant integrity. The BEPU study was conducted using results derived from accident scenario simulations carried out with a plant thermal–hydraulic model implemented in TRACE V5 code including both, primary and secondary systems.

BEPU methodologies assume that uncertainties in safety results arise from both the code input data and the computational model itself. Most regulatory-accepted BEPU approaches apply Wilks' methods to determine the number of simulations required, based on selected figures of merit (FoMs), to demonstrate compliance with acceptance criteria at a 95/95 confidence level (Wilks 1941). As a complement to the BEPU methodology, the Linear Error Propagation Law (LEPL) has also been applied to propagate the uncertainties of the parameters considered in the study through the computational model and to obtain the associated uncertainty intervals. Accordingly, analysts compare FoM values against tolerance limits to ensure that safety margins are maintained.

2. Scenario Description

The transient considered in the BEPU analysis consists of an extended loss of AC power (ELAP) combined with the additional unavailability of the emergency diesel generators. The plant application of the transient presented in this work is based on a study performed on the OECD/PKL i4.2 experiment (Framatome 2020). In this transient, the TDP of the auxiliary feedwater system (AFWS) initially injects into all three steam generators (SGs) and subsequently supplies only one of them (SG #2), while the remaining two are kept isolated. In parallel, a partial depressurization of the active SG #2 is carried out to support heat removal and to prepare it for the connection of a mobile pump once the TDP battery is depleted (Fig. 1).

Another important aspect to consider is the integrity of the primary system, which may be compromised even if the TDP operates as intended. This loss of integrity may occur due to the opening of the pressurizer power-operated relief valves (PORVs) to relieve primary system pressure. In addition, there is a non-negligible probability that at least one PORV may remain stuck open following actuation, since the operator would be unable to manually close the valves in the absence of electrical power.

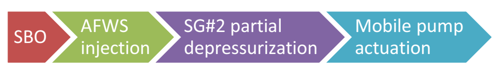

Fig. 1. Main Actions Simulated in the SBO Transient

3. Uncertainties Analysis

3.1.*Methodology*

BEPU study was conducted using the DAKOTA statistical analysis and uncertainty propagation tool, integrated within the SNAP interface and coupled to thermohydraulic simulations using the TRACE code, with the objective of evaluating reactor behavior. The BEPU approach provides a framework in which conservative assumptions are replaced by realistic safety margins while preserving regulatory compliance, thereby enabling a more accurate characterization of plant behavior through uncertainty quantification and supporting improved safety evaluations and operational efficiency (IAEA 2008a, Unal et al. 2011, d'Auria et al. 2012).

For this study, a total of 124 independent simulations were performed using a Monte Carlo sampling scheme to capture the inherent variability of uncertain input parameters. Although this approach can be computationally demanding, it remains one of the most straightforward and cost-effective methods to implement from a methodological standpoint (Devictor 2005). In addition, Monte Carlo sampling naturally captures discontinuities and transitions between physical regimes, allows for the explicit treatment of correlations among input parameters, and is well suited for input variables characterized by wide uncertainty ranges (Gorham 1993). The number of simulations was determined based on the use of a third-order statistic, which ensures adequate coverage of the uncertainty space under consideration at the 95/95 confidence level (Wilks 1941).

The simulations were carried out using representative thermal–hydraulic models of the reactor design, incorporating the dynamic response of the relevant passive and active systems. The adopted sampling strategy enables a robust analysis of uncertainty propagation to the output variables of interest. The analysis focuses on three figures of merit (FoMs) considered to be of particular relevance: the peak cladding temperature (PCT), the pressure difference between the primary and secondary systems, and the loss of primary inventory through the pressurizer power-operated relief valves (PORVs). The adopted approach aims to provide a realistic and statistically robust assessment of reactor safety under severe accident conditions, thereby contributing to compliance with regulatory requirements associated with probabilistic safety assessments (PSA) and uncertainty analyses.

Table 1 lists 17 key uncertainty parameters along with their corresponding ranges and probability distributions such us Uniform (U) and Normal (N) (Tran 2025). The statistical characterization of these parameters follows the principles described below: normal distributions are assigned to well-characterized physical parameters with reliable estimates (e.g., reactor power, setpoint values fuel properties), whereas uniform distributions are applied to operational parameters and model coefficients for which only bounding ranges are known with confidence (e.g., heat transfer correlations, auxiliary feedwater system timing parameters or initial values).

Table 1. Uncertainty parameters included in the study

Parameter	Range
X1 Nominal power	0.98 - 1.02 (N)
X2 Decay heat power	0.92 - 1.08 (U)
X3 PORV setpoint press.	0.982 - 1.017 (N)
X4 Initial PSZ pressure	0.974 - 1.026 (U)
X5 Initial sec. pressure	0.974 - 1.026 (U)
X6 AFWS operating time	3.0 - 6.6 h (U)
X7 AFWS temperature	0.99 - 1.016 (U)
X8 Initial AFWS pressure	0.93 - 1.23 (U)
X9 RCP1 mass flow rate	0.95 - 1.05 (U)
X10 RCP2 mass flow rate	0.95 - 1.05 (U)
X11 RCP3 mass flow rate	0.95 - 1.05 (U)
X12 RCPs inertia	0.80 - 1.20 (N)
X13 Fuel conductivity	0.90 - 1.10 (N)
X14 Fuel capacitance	0.98 - 1.02 (N)
X15 Dittus–Boelter liquid heat transfer multiplier	0.85 - 1.15 (U)
X16 Dittus–Boelter vapor heat transfer multiplier	0.80 - 1.20 (U)
X17 Nucleate boiling model multiplier	0.80 - 1.20 (U)

In addition, the Linear Error Propagation Law (LEPL) was applied to propagate parameter uncertainties through the computational model, and the resulting uncertainty intervals were evaluated (Mendizábal 2023). Parameters are numerical quantities that are neither dependent nor independent variables, but upon which the model output depends. Two types of parameters are considered: input parameters, which represent initial and boundary conditions, and model parameters. The latter may have a physical meaning (e.g., geometrical and topological parameters) or may be "free" parameters used to adjust (calibrate) the models. In all cases, parameters can be broadly regarded as inputs to the model.

A deterministic computational model is considered, that is, a model that always produces the same output for a given set of inputs. The model behavior can be represented by a numerical input–output function R, e.g. Eq(1):

$$Y = R(X_1, \dots, X_q) \tag{1}$$

where $X_1, \dots, X_q$ denote scalar input parameters, Y represents the model output (FoM) and R denotes the input–output transformation performed by the model or code.

In its most common or standard implementation, the LEPL relies on one-at-a-time (OAT) perturbations of each parameter by one standard deviation. More general formulations of the LEPL can also be considered, in which each parameter is perturbed OAT by a multiple or a fraction of its standard deviation, allowing for greater flexibility in the characterization of parameter uncertainties as shown in Eq. (2). In this equation, K is a positive real number, commonly referred to in some contexts as a coverage factor. Positive integer values of K correspond to different multiples of the standard deviation.

The application of the LEPL provides an estimate of the variance of Y (Eq.3), which serves as a descriptor of the uncertainty associated with Y. Another possible descriptor is the uncertainty interval derived from the LEPL, e.g. Eq (4):

$$\Delta_{j,K}R \equiv \frac{R\left(X_1^0, \dots, X_j^0 + K\sigma_j, \dots, X_q^0\right) - R_0}{K} \quad (2)$$

$$Var(Y) \cong \sum_{j=1}^{q} \left[\Delta_{j,K}R\right]^2 ; \ \sigma_Y \equiv \sqrt{Var(Y)} \quad (3)$$

$$IC = (R_0 - K_Y \cdot \sigma_Y, R_0 + K_Y \cdot \sigma_Y) \quad (4)$$

While the LEPL provides an efficient and computationally inexpensive framework for propagating parameter uncertainties, it is inherently based on linear approximations of the model response. In contrast, BEPU approaches based on Wilks' formula and Monte Carlo sampling account for the combined effects of multiple uncertainties and capture nonlinear interactions among parameters. Consequently, the LEPL is well suited for preliminary analyses and sensitivity assessments, whereas BEPU methodologies offer a more comprehensive and robust evaluation of uncertainty propagation in safety-relevant transients.

3.2. *Results*

Table 2 summarizes the maximum values obtained up to the third-order statistic. In no case are critical thresholds exceeded for the peak cladding temperature (PCT), the loss of primary inventory due to PORV opening, or the pressure difference between the primary and secondary systems. The results for each of these figures of merit are presented in Fig. 2 through 4.

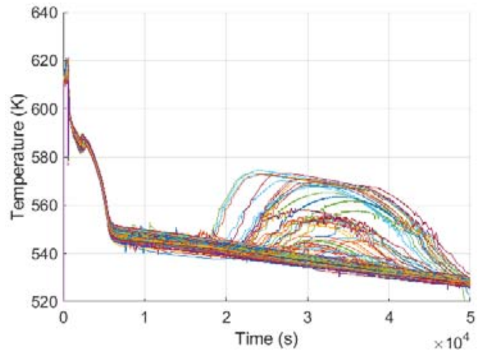

Fig. 2. PCT

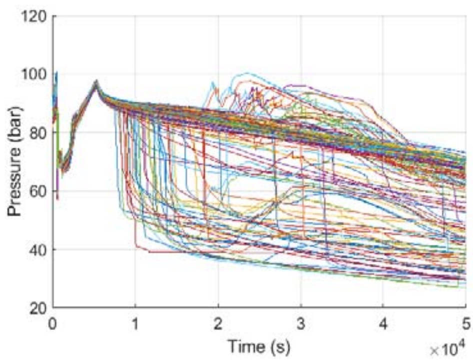

Fig. 3. Primary-secondary pressure difference

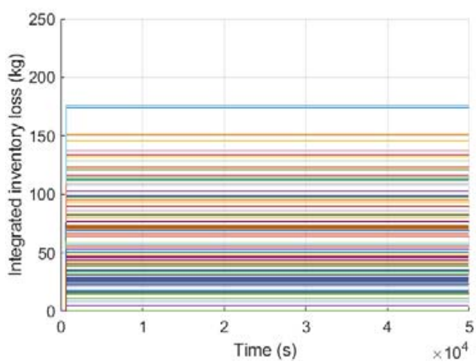

Fig. 4. Loss of primary inventory through the PSZ-PORV

Table 2. Maximum values obtained for each FoM

Statistic	PCT (K)	Inventory loss (kg)	ΔP Prim.-Sec. (bar)
1st order	621.4	176.2	101.1
2nd order	621.3	173.7	100.8
3rd order	621.1	151.0	100.6
Base case	613.8	13.2	95.8

The PCT exhibits a very stable behavior in the upper tail of the distribution, with differences below 0.3 K between the first, second, and third order statistics. The margin introduced by the BEPU analysis with respect to the nominal case is on the order of 7–8 K, indicating a robust response that is well characterized with respect to the uncertainties considered.

The pressure difference between the primary and secondary systems also shows high statistical stability, with a spread of less than 1 bar among the first three order statistics. The increase relative to the base case is moderate (approximately 5 bar), and no non-linear behavior or pronounced tail effects are observed.

The integrated inventory loss through the PORV exhibits a different behavior. The nominal case operates very close to the valve setpoint pressure, resulting only in very brief valve openings at the beginning of the transient and a limited accumulated mass discharge. However, certain unfavorable combinations of uncertain parameters degrade the transient evolution, leading to sustained PORV openings. In these cases, the accumulated discharged mass increases abruptly, reaching values on the order of 150–176 kg. This change of regime explains both the large difference with respect to the base case and the presence of a pronounced upper tail, characterized by a close proximity between the first and second order statistics and a more significant drop at the third order. This behavior is consistent with the system physics and with the proximity of the nominal state to the PORV actuation threshold.

In addition, the parameters having the greatest influence on the evolution of each of the three analyzed variables were studied using a basic neural network approach. For the peak cladding temperature (PCT) (Fig. 5), the most influential parameters, in descending order, are decay heat power, nominal power, and initial secondary-side pressure. In this case, all parameters exhibit a positive correlation. Regarding the pressure difference between the primary and secondary systems (Fig. 6), the most influential parameters are nominal power, initial pressurizer pressure, and decay heat power, all showing positive correlations. In this case, parameters with a relatively high influence but negative correlations include the nucleate boiling heat transfer coefficient, the auxiliary feedwater turbine-driven pump injection temperature, and the liquid-phase heat transfer coefficient. Finally, the loss of primary inventory due to pressurizer PORV opening (Fig. 7) is mainly influenced by decay heat power (positive), PORV setpoint pressure (negative), nominal power, and initial primary pressure (both positive).

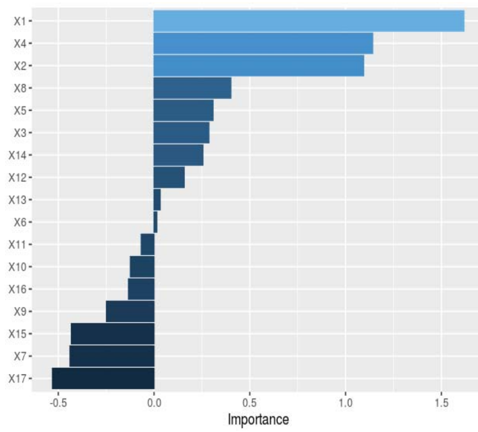

Fig. 5. Importance of input parameters on the PCT

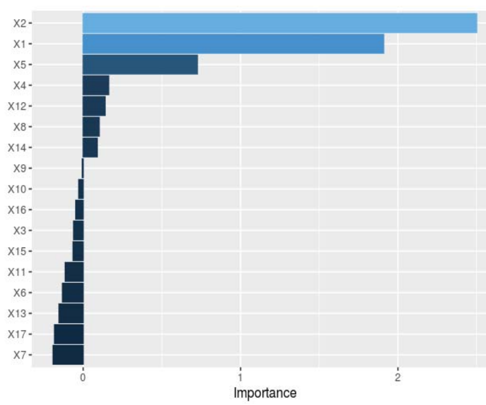

Fig. 6. Importance of input parameters on the Primary–Secondary pressure difference

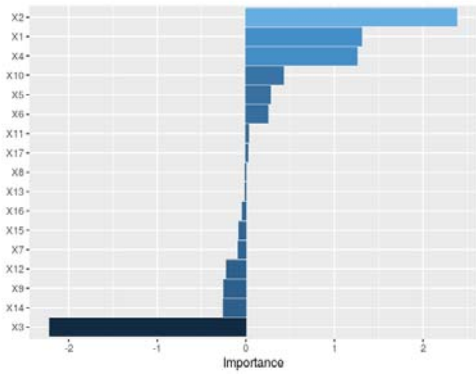

Fig. 7. Importance of input parameters on the loss of inventory through de PSZ PORV

The uncertainty intervals derived from the LEPL (Table 3) were calculated for a 90% confidence level in order to allow comparison with the results obtained from the 124 Wilks-based simulations. For the PCT, the upper bound of the uncertainty interval is 624.2 K, which exceeds the 1st-order Wilks maximum. For the other two figures of merit, the upper bounds of the uncertainty intervals remain below the 3rd-order Wilks maxima.

The LEPL uncertainty interval for the PCT is moderate and approximately symmetric around the nominal value. This indicates that, within the considered uncertainty ranges, the PCT response varies in a quasi-linear manner and is not strongly affected by threshold effects or non-linear feedback mechanisms.

A similar behavior is observed for the primary–secondary pressure difference. The LEPL interval remains relatively narrow and centered around the base case value, suggesting limited non-linearity and a smooth dependence on the uncertain parameters.

In contrast, the LEPL results for the integrated inventory loss through the PORV reveal the limitations of the linear approach. Although the LEPL interval predicts a substantial increase of the discharged mass relative to the nominal case, its upper bound remains significantly lower than values obtained through the BEPU analysis. This discrepancy is attributable to the threshold-driven nature of the phenomenon. The nominal operating point lies close to the PORV setpoint pressure, such that small perturbations in uncertain parameters can trigger a transition from brief, intermittent valve openings to sustained relief valve operation. This change of regime leads to an abrupt increase in the accumulated discharged mass, which cannot be adequately represented by a first-order linearization around the nominal point.

Table 3. Base case maximum values and LEPL uncertainty intervals (90%)

	Base case	LEPL uncertainty interval
PCT (K)	613.80	(603.41 624.20)
ΔP (bar)	95.79	(93.04 98.54)
Inventory loss (kg)	13.15	(0 130.58)

An assessment was also performed to determine the existence of linear correlations between the input parameters included in the analysis and the three output variables considered. Table 4 summarizes the representative linear correlation coefficients in each case (for those parameters exhibiting statistically significant correlations), while Fig. 8 through 10 present observed-versus-predicted value plots. Only a limited number of parameters exhibit a clear linear relationship, with nominal power and decay heat power being the most prominent. All three output variables show a positive linear relationship with power. For the PCT (Fig. 8) and the loss of primary inventory due to pressurizer PORV opening (Fig. 10), the linear regression models explain approximately 73% and 82% of the observed variability, respectively, as indicated by their coefficients of determination (R^2). In contrast, for the pressure difference between the primary and secondary systems (Fig. 9), the explained variance is limited to 36%.

Table 4. Linear correlation coefficients

Parameter	PCT	ΔP	Inventory loss
Nominal power	97.30 (0.00)	52.66 (0.00)	1461.75 (0.00)
Decay heat power	23.59 (0.00)	6.48 (0.000)	492.07 (0.00)
PORV setpoint pressure	-	-	-2939.2 (0.00)
Initial PSZ press.	-	22.56 (0.00)	836.06 (0.00)
RCP2 mass flow rate	22.44 (0.00)	-	-
Nucleate boiling model multiplier	-	-	133.02 (0.03)

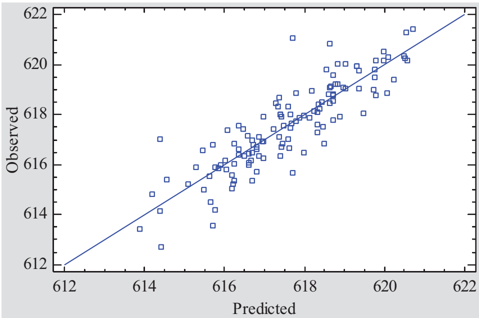

Fig. 8. Observed vs predicted values for the PCT (R^2=73)

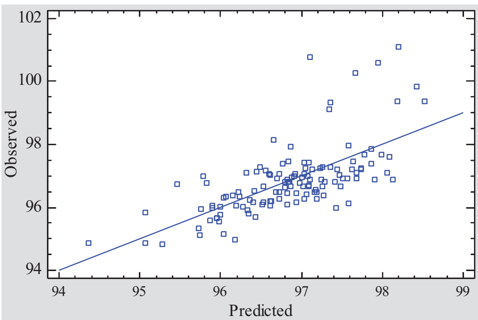

Fig. 9. Observed vs predicted values for the ΔP (R^2=36)

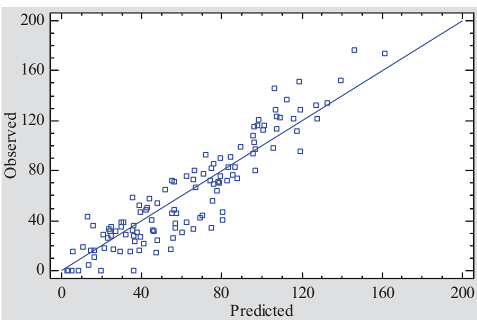

Fig. 10. Observed vs predicted values for the loss of inventory (R^2=82)

4. Conclusions

The results obtained show that, in no case, critical values are reached that could significantly destabilize the system. In addition, the influence of the different parameters on the evolution of each of the three analyzed variables has been studied using a neural network. In general terms, the most influential parameters are the power and the initial pressures of both the primary and secondary circuits.

The existence of linear correlations between the different parameters included in the analysis and the three output variables considered has also been evaluated. Only a limited number of parameters exhibit such relationships, with nominal power and residual power standing out in all three cases, together with the initial pressures of the primary and secondary circuits. In the case of the PCT and the inventory loss due to the opening of the pressurizer PORV, the linear regression models explain 75% and 84% of the observed behavior, respectively, as indicated by their coefficients of determination (R2). However, for the pressure difference between the primary and secondary circuits, the obtained R2 value is too low (38%) for the linear regression model to be considered truly representative.

The results obtained using the Linear Error Propagation method (LEPL) show good consistency with the BEPU analysis for the Peak Cladding Temperature (PCT) and the primary–secondary pressure difference figures of merit. The values obtained through the BEPU approach lie within or slightly above the LEPL uncertainty intervals, reflecting the capability of BEPU to capture unfavorable combinations of parameters that cannot be represented through a local linear approximation.

In contrast, the inventory loss through the pressurizer relief valve (PORV) exhibits a significant discrepancy between the two approaches. Although the LEPL interval predicts a substantial increase relative to the base case, its upper bound remains below the values obtained from the BEPU analysis. Because the nominal case operates very close to this threshold, small perturbations can induce a regime change toward sustained valve openings, resulting in an abrupt increase in the accumulated discharged mass. This type of behavior cannot be adequately captured by a linear approximation, whereas the BEPU analysis is able to represent it explicitly and in a physically consistent manner.

Acknowledgement

This work was carried out under a cooperation agreement between the Universitat Politècnica de València (UPV) and the Spanish Nuclear Safety Council (CSN), within the framework of the contract

Advanced Simulation and Analysis Methods in the Field of Nuclear Safety, Part II (MASA-2; BOE-A-2020-6227).

References

CSN (2015), Instrucción IS-37: Análisis de accidentes base de diseño en centrales nucleares.

D'Auria, F., C. Camargo and O. Mazzantini (2012). The Best Estimate Plus Uncertainty (BEPU) approach in licensing of current nuclear reactors. Nucl Eng Des 248:317–28.

Devictor, N. and R. Bolado-Lavin, Uncertainty and sensitivity methods in support of PSA level 2. CSNI Workshop on Evaluation of Uncertainties in Relation to Severe Accidents and Level 2 PSA. Aix-en-Provence, November 7-9, 2005.

Framatome (2020), PKL IIIi 4.2: Cool-Down in NC Mode under ELAP Conditions. Test Report, Rev. A. OECD/PKL Phase 4.

Gorham, E. D., et al. (1993). Evaluation of Severe Accident Risks: Methodology for the Containment, Source Term, Consequence, and Risk Integration Analyses. NUREG/CR-4551, SAND86-1309.

IAEA (2008a). Best estimate safety analysis for nuclear power plants: Uncertainty evaluation Safety Reports Series No. 52. Viena.

IAEA (2008b). Evaluating the reliability of predictions made using environmental transfer models Safety Reports Series No. 57. Viena.

IAEA (2009), SSG-2- Specific Safety Guide : Deterministic safety analysis for nuclear power plant. Viena.

Mendizábal R. (2023). Ley de propagación lineal de errores. Propuesta de estudio dentro del proyecto MASA-2.CSN. Madrid.

Tran, CH. and Aya Diab (2025). Uncertainty-aware prediction of Peak Cladding Temperature during extended station blackout using Transformer-based machine learning. Nuclear Engineering and Design 437 113984.

Unal, C., B. Williams, F. Hemez, SH. Atamturktur and P. McClure (2011). Improved best estimate plus uncertainty methodology, including advanced validation concepts, to license evolving nuclear reactors. Nucl Eng Des 241:1813–33.

Wilks, SS. (1941). Determination of sample sizes for setting tolerance límits. Ann Math Stat 12(1):91–6.

Wilsom, EG. (2013). Historical insights in the development of best estimate plus uncertainty safety analysis. Ann Nucl Energy 52:2–9.