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Nuclear safety Enhanced: A Deep dive into current and future RAVEN applications

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ABSTRACT

As the horizon of nuclear energy expands with the advent of small modular reactors, Generation IV reactors, and fusion reactors, there is a growing perspective that the licensing process could benefit from a more comprehensive approach. Moving beyond traditional deterministic and probabilistic risk assessment analyses might pave the way for a novel safety analysis paradigm propelled by the increasing computational power at our disposal.

This paper explores different methodologies that can improve the outcomes of nuclear safety analysis. These range from uncertainty quantification techniques, aimed at enhancing the precision of safety margins, to deploying dynamic event trees by driving system code simulations, capturing the potential evolutions of severe accidents. These methodologies offer a better understanding of the management and consequences of nuclear accident scenarios, significantly improving the accuracy and efficiency of safety predictions compared to traditional methods.

Specific case studies illustrate the practical application of these advanced techniques, demonstrating substantial improvements in predicting and managing the dynamics of severe accidents. These findings underscore the effectiveness of these methodologies in enhancing risk assessment capabilities and informing decision-making processes for nuclear safety management. The paper also emphasizes the importance of adaptability and continuous evolution, a call for action to address emerging nuclear safety concerns and highlights the utility of advanced tools like RAVEN.

1. Introduction

Ensuring high-level nuclear safety standards in fission and fusion reactors remains a pressing concern, driven by the complex phenomena occurring in severe accidents. These phenomena, demanding intensive experimental and modeling efforts, often defy easy laboratory reproduction given the intricate facilities required and the challenges of simulating fuel rod melt. Computational tools engage in the challenge of modeling complex phenomena and fill the gap left by impractical experimental activities, although with some drawbacks. Simplifications and scaling effects directly influence computational modeling accuracy and reliability, introducing inherent epistemic uncertainties into the safety assessment process. Further complicating the model accuracy are the intricate interactions of diverse phenomena and rigorous validation needs.

Historically, the nuclear industry has relied on deterministic analyses for safety evaluations, focusing primarily on hypothetical accident scenarios that could pose the most significant risks to the reactor's structural integrity and the potential dispersion of radionuclides into the external environment (Herranz and Gauntt, 2018; D'Auria et al., 2008). These deterministic approaches have been instrumental in understanding and mitigating known risks. However, they may not fully capture the complexities and epistemic uncertainties inherent in accident scenarios involving severe or unforeseen events (Vesely and Rasmuson, 1984).

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Such deterministic methods often came with significant reactor model simplifications and computational precision trade-offs (Linkov and Burmistrov, 2003). However, the exponential growth in computational power offers an opportunity to rethink foundational safety analysis concepts. Nowadays, deterministic analyses serve as the starting point for other evaluations, establishing a robust foundation for understanding potential threats to nuclear safety.

The best estimate plus uncertainties (BEPU) (D'Auria, 2019; Martin and Petruzzi, April 2021) approach is pivotal in this evolution. As severe accident codes advance, the industry is set to incorporate BEPU fully into accident management tactics. Moving away from the deterministic approach, BEPU avoids excessive conservative assumptions, accurately identifying safety margins (Bucalossi et al., 2010). This method provides a means to determine the probability of specific outcomes, with nuances in these distributions emphasizing the primary uncertainty factors.

In line with this paradigm shift, the Management and Uncertainties of Severe Accidents (MUSA) (Herranz et al., 2021) project, funded in Horizon-H2020, merges Severe Accident codes with state-of-the-art uncertainty quantification (UQ) tools, weaving accident management strategies into SA analyses. In parallel with the MUSA project, in the IAEA framework in a synergic way, the IAEA CRP I31033, "Advancing the state-of-practice in uncertainty and sensitivity methodologies for severe accident analysis in water-cooled reactors", aims at improving the state of practice in severe accident analyses by examining and characterizing the impact of uncertainty on severe accident analyses in water-cooled reactors (Mascari F., Overview of IAEA CRP I3, 2022).

Alongside deterministic analyses, probabilistic risk assessment (PRA) is another fundamental approach used in nuclear safety analysis (Fullwood and Hall, 1988). The primary goal of PRA, like any nuclear safety approach, is to understand and quantify risks to make informed safety decisions. However, the significance of uncertainties extends beyond just BEPU. Also, the PRA and risk-informed decision-making require an in-depth grasp of uncertainties (Smith, 2013; Avramova and Ivanov, 2010). These uncertainties can stem from various sources, including variability in event probabilities, complexity in consequence analysis, and the lack of complete or precise data. Effectively managing these uncertainties is crucial in assessing nuclear risks accurately.

Integrating different analysis methods to provide a comprehensive and integrated nuclear safety assessment is often necessary. However, managing such integration can be complex and may require specialized tools to automate and facilitate processes. The Risk Analysis and Virtual ENviroment (RAVEN) tool developed at Idaho National Laboratory (INL) has been invaluable in this context. RAVEN supports nuclear risk analyses and integrates different methods (Alfonsi et al., 2016; Alfonsi, 2013). It can handle data, perform simulations and uncertainty analyses, and provide a comprehensive framework for nuclear safety.

Initially designed to act as a control logic driver, the RAVEN tool has evolved into an instrumental sensitivity and uncertainty estimation framework in various safety analyses. This tool has been successfully coupled with multiple codes, which has significantly enhanced the outcomes of safety analyses. One such noteworthy integration is with MELCOR. The emphasis of this coupling, as highlighted in (D'Onorio et al., 2022; D'Onorio et al., 2021), is on the best-estimate approach for severe nuclear accidents. Instead of relying on conservative values, the approach underscores the importance of presenting results regarding uncertainty ranges, offering a more refined and nuanced perspective on severe accident scenarios. In parallel, to delve deeper into the dynamic probabilistic risk assessment (DPRA) paradigm, RAVEN has been coupled with the Modular Accident Analysis Program 5 (MAAP5) code (Picoco et al., 2017). This code coupling emphasizes dynamic event trees (DETs), an innovative methodology that breaks away from the conventional static event tree (ET) and fault tree (FT) methodologies. The recent advancements in coupling RAVEN with MELCOR further solidify the potential to simulate intricate DET scenarios, deeply investigating different sequences of a severe accident scenario (Glingler et al., November 2023; D'Onorio et al., April 2022). This coupling allows safety analysts to easily develop detailed DETs for complex scenarios like station blackouts, cyberattacks, etc.

The versatility of RAVEN has allowed it to integrate effectively with RELAP5-3D, the Reactor Excursion and Leak Analysis Program code. As delineated in (Rabiti et al., 2012), this coupling extends the BEPU methodology to Generation IV nuclear reactors. Moving away from traditional conservative metrics, this synergy emphasizes presenting outcomes in terms of uncertainty boundaries, granting a more comprehensive and insightful view of reactor safety dynamics.

The nuclear fusion landscape has unique challenges. The current status of the tokamak design and the not yet fully understood physical model involved during accidents provide fertile ground for analysis to quantify uncertainties and safety margins. To investigate this kind of phenomenon, RAVEN has been coupled with MELCOR version 1.8.6 (Glingler et al., November 2023), with the ASTEC code (Maccari et al., 2021), and with the OSCAR-Fusion code for assessing activated corrosion products (D'Onorio et al., Nov. 2022; Molinari et al., 2023).

Today, RAVEN applications span various areas of nuclear safety analysis, ranging from the automatization of UQ applications to DET analyses. This tool continues to evolve, offering innovative solutions to address the ever-growing challenges associated with nuclear safety. In the context of an integrated approach to nuclear safety, RAVEN plays a key role in helping experts effectively and informatively assess and manage risks. Considering these advancements, this paper aims to explore RAVEN's potential further, delving deeper into its capabilities, integrations, and prospects.

This review article explores various techniques that enhance nuclear safety analysis using state-of-the-art uncertainty quantification and dynamic event tree methodologies executed through system code simulations supported by the RAVEN software. This advanced approach moves beyond traditional static deterministic and probabilistic risk assessments, providing a more detailed insight into the management and consequences of potential accident scenarios. The effectiveness of this integrated approach is underscored by a comprehensive review of case studies where these techniques have been applied. These findings are critical as they show how these advanced techniques can directly contribute to more robust nuclear safety protocols and informed decision-making processes.

2. RAVEN tool

RAVEN, a cutting-edge open-source software tool, was conceived in 2012 at INL (Alfonsi et al., 2016). The tool was developed in response to the need for detailed parametric and probabilistic analyses of outcomes from complex system codes, primarily to quantify the safety margins associated with specific safety–critical incidents. The driving force behind RAVEN's inception was to evaluate, understand, and mitigate risks, embodying the risk-informed safety margin characterization philosophy. This vision is deeply anchored in rigorous software quality assurance protocols, earning RAVEN its esteemed NQ1-Lvl. 2 qualification.

RAVEN stands out as a dedicated platform for probabilistic analysis and UQ, boasting compatibility with a wide range of system codes. Its design emphasizes modularity and plug-and-play features, facilitating effortless integration with various programming languages, including C++ and Python. RAVEN's architecture embodies object-oriented design principles. At its core, it operates through a series of fundamental components, granting users the flexibility to tailor their analysis pipeline. These components include distribution, sampler, model, and reduced-order model (ROM). Among its myriad capabilities, RAVEN in the nuclear engineering field focuses on:

- Risk Assessment: Through methods like uncertainty propagation.
- Deep Risk Insights: Achieved via limit surface determinations, rankings, sensitivity assessments, and data mining techniques.
- Risk Mitigation: Proposing strategies using optimization techniques.

- Exploration: Investigating system responses and input spaces using sampling techniques, such as Monte Carlo, Grid, and Latin Hyper Cube.
- Dynamic Learning: Uncovering crucial system features through advanced dynamic supervised learning methods.
- Plant Control Logic Simulations: Integrating this essential feature ensures adaptability without modifying existing source codes in systems like MELCOR, RELAP5-3D, or MAAP5.

From an end-user perspective, RAVEN emerges as a powerful tool, orchestrating intricate calculation flows and accounting for probabilistic dynamics and uncertainty propagation for accurate risk evaluations. It provides a platform to visualize many simulation outcomes and robust data mining capabilities for a holistic analysis of plant behavior. Moreover, it empowers users to explore potential risk mitigation strategies, offering insightful directions and rapid impact assessments. A schematic representation of RAVEN framework and how it interfaces with other codes is represented in Fig. 1. The following subsections provide an overview of the methodologies present in the RAVEN framework.

2.1. Uncertainty quantification

RAVEN has been developed to handle the challenges of UQ, which is especially crucial in safety analyses across various application domains (e.g., see (Alfonsi, 2017) for an example). It is built on basic building blocks that users can mix and match to create their analysis process.

Central to RAVEN's UQ method is perturbing or changing the input space. Understanding the impact of varying inputs on outputs in the safety analysis is crucial in estimating safety margins and gauging potential risks. To understand the relationship between inputs and outputs, RAVEN needs to be able to change the starting conditions of a system code. These starting conditions, which can be uncertain, are usually described using probability distribution functions (PDFs). RAVEN boasts an extensive library of PDFs, allowing analysts to select distributions aligning with their specific concerns.

Moreover, beyond the standard PDFs, RAVEN also offers n-dimensional probability distributions. These distributions let users examine multiple factors simultaneously and show how they might be linked. Some key examples include the multivariate normal distribution and several distributions based on interpolation.

The sampling is the second step of RAVEN's UQ approach. The samplers in RAVEN use different strategies to change the input space of a system, each taking its path through the uncertain variables and their associated PDFs. Other sampling methods are currently available in RAVEN:

- Forward Samplers: These methods, including Monte Carlo, stratified, and grid-based techniques, explore the input space using traditional methods without relying on previous results. For instance, the Monte Carlo method is a common approach where inputs are changed randomly based on specific rules.
- DET Samplers: This method, which is still being developed for tools like MELCOR, is designed for scenarios that change over time, like accidents.
- Adaptive Samplers: These samplers are a bit more advanced. They use information from earlier runs to make smarter choices, balancing accuracy and speed.

After all the calculations, RAVEN moves to the postprocessing stage. It uses the HDF5 database system to store and retrieve data when needed. These data are processed in forms like PointSet or HistorySet to help understand the results better. RAVEN has tools like BasicStatistics and ComparisonStatistics, which provide key statistics or compare results to known benchmarks.

The UQ method needs a minimum batch of data based on the type of statistical method adopted. An issue could also arise when analyzing a severe accident sequence when a code crash could occur because of numerical instabilities. For a UQ analysis, the runs that incur crashes should be discarded from the postprocessing statistical analysis. Since code crashes are impossible to predict, UQ analysis should run more parallel simulations than those needed as a minimum requirement for the statistical analysis to be valid. The computational effort and memory required are consequently significantly increased.

2.2. Dynamic event tree

In the PRAs of nuclear power plants, a frequently adopted

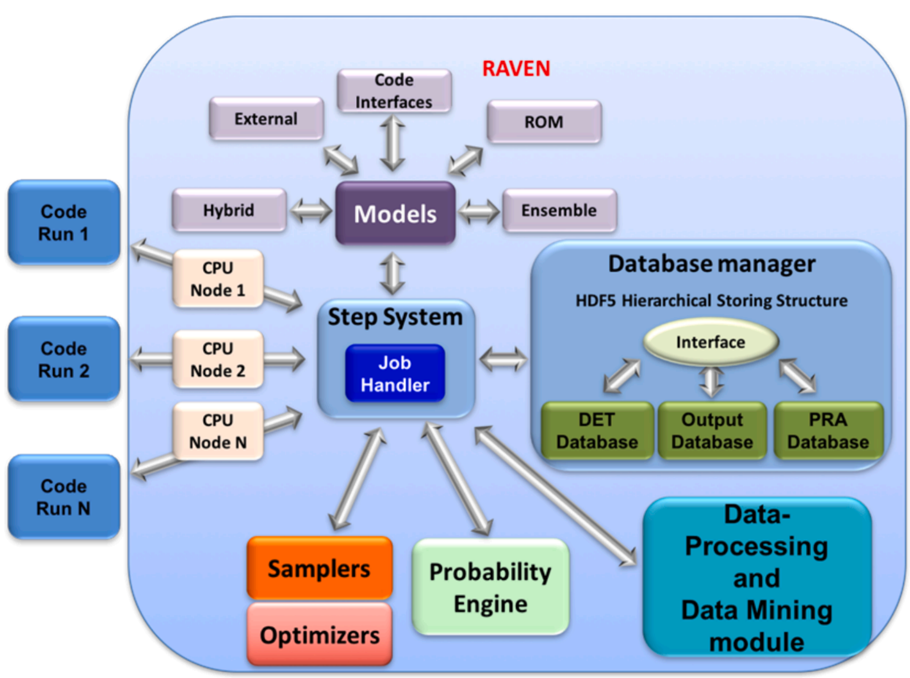

Fig. 1. Schematic representation of the RAVEN software (Alfonsi, 2017).

methodology is ET, which analyzes the impact of the failure or success of safety systems. Starting from a selected postulated initiating event, which brings the system into an altered state, the accident sequence evolves in time. Safety systems are designed to mitigate the accident sequence and get the plant to a safe state, but their intervention could be unsuccessful due to failures. ETs explore the consequences of a postulated initiating event in terms of the failure or success of safety systems. Each failure or success corresponds to an event that creates two parallel branches, one exploring the accident sequence with the system's success while the other exploring the opposite. At the end of the simulation, several branches are created, and for each sequence, a probability is associated based on the failure or success of the events involved, as shown in Fig. 2.

The ET does not analyze the timing or sequencing of the events in the explored accident scenario. Especially when accounting for human operator actions or backup of electricity generation, success depends strongly on the timing of intervention. The DET methodology tries to solve the limitation of standard ET analyses, overseeing the vast spectrum of potential states a nuclear power plant might face. The DET is a PRA method devoted to evaluating the risks and impacts of failures, human actions, and the effectiveness of safety measures during an unexpected event. The creation of two separate stories each time an event is verified follows the same criteria as an ET, although the single event is evaluated at different timings during the progress of the accident sequence. Fig. 3 shows the logical branching condition of a DET analysis.

Theoretically, time sampling of events during an accident sequence could range in a broad interval; therefore, the expert's judgment must decide the correct pruning of the number of timings sampled. The explosion state problem is indeed an issue for DET analysis since the number of simulations could increase exponentially; careful simplifications could solve this issue. Practices like probability truncation methods, adaptive generation, and pruning of sampled values are some approaches to decrease simulations' exponential increase (Maidana et al., 2023).

The DET methodology was integrated into RAVEN in (Alfonsi et al., 2013; Alfonsi et al., 2022) to offer analysts an enhanced and efficient sampling technique for safety-related applications. Adhering to the principles of the DET approach, the DET sampler enables a system code (currently limited to RELAP5-3D, MAAP5, TRACE, and MELCOR) to identify the accident sequence path within a probabilistic context. The Python environment of RAVEN permits an easily accessible platform to couple system code input and output data and utilize the embedded RAVEN DET functionalities. New functionalities have been added to the RAVEN interface with MELCOR to study DETs. Applications have been made on fusion and fission reactors (D'Onorio et al., 2021; Glingler et al., November 2023; D'Onorio et al., April 2022; D'Onorio et al., 2020).

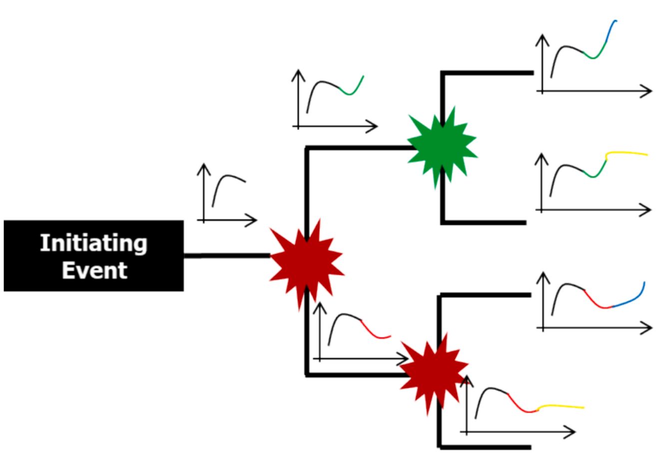

Fig. 2. Event Tree conceptual scheme (Alfonsi et al., 2013; Alfonsi et al., 2022).

A station blackout incident was examined using a basic pressurized-water reactor (PWR) loop model in RELAP5-3D (Alfonsi, 2013). The study focused on identifying the temperature at which the clad failed and the time needed for diesel generators to recover before leading the sequence to clad failure. Another application involved simulating a VVER-1000 reactor in RELAP5-3D to analyze a station blackout scenario using the RAVEN DET methodology. This involved integrating safety system failures and operator recovery actions to assess accident scenarios and estimate core damage frequency metrics (Amirsoltani, 2024). RAVEN was also used in conjunction with the MAAP5 severe accident code. It was applied to analyze a power disruption event in a PWR, accounting for potential failures in the auxiliary feedwater system and the diesel generator as the accident unfolded (Picoco et al., 2017). RAVEN was integrated with TRACE to analyze a scenario involving the depletion of a spent fuel pool (SFP) (Boniface, 2024).

2.3. Optimization algorithms

Optimization algorithms aim to find the best value of a goal function by exploring various combinations of input parameters within specific boundaries. These optimization techniques can be either deterministic or stochastic (Faramarzi et al., 2020).

Deterministic methods typically rely on local gradient calculations and advance the search of optima, minimizing the gradient within the objective function's domain (Luenberger, 1984; Boyd and Vandenberghe, 2004). While effective in linear spaces, they may get stuck at local optima in nonlinear problems (Faramarzi and Afshar, 2014; Faramarzi and Afshar, 2012). On the other hand, stochastic methods explore the objective function globally by introducing randomness into the process. They do not rely on derivative information and are advantageous for nonlinear problems as they avoid getting trapped at local optima. Stochastic algorithms are adaptable to a wide range of problems and are independent of the mathematical properties of the objective function (Mirjalili et al., 2014).

Hybrid algorithms combine deterministic and stochastic methods to exploit their respective strengths. They begin with global exploration using stochastic methods to escape local optima and identify optimal candidates (Faramarzi and Afshar, 2012). Then, deterministic methods are applied to precisely search the microdomain around these candidates, enhancing the accuracy of the results. Hybrid algorithms provide a comprehensive and detailed approach to optimizing goal functions, overcoming the limitations of purely deterministic or stochastic methods.

RAVEN provides different methods to approach optimization problems based on classical approaches like the gradient descent method and metaheuristic approaches like the simulated annealing or genetic algorithm. The gradient descent algorithm calculates the local gradient and endeavors to move in the opposite direction of the gradient (if minimizing or the reverse if maximizing). It is considered converged once it finds the lowest point during its iterative gradient search. It is important to note that gradient descent algorithms are susceptible to becoming stuck in local minima. Consequently, multiple paths may be required to attain the global solution depending on the model.

The other two approaches try to solve the optimization problem of large design spaces, avoiding being stuck in local minima. The simulated annealing algorithm is inspired by the homonymous metallurgy techniques that rely on altering the physical properties of a material and controlling the coolability to increase the mechanical properties. The cooling control is interpreted as a slow control in the probability of reaching an optimized state, casually varying the input space. This technique can avoid entrapment in local minima but has a lower precision in finding optimal values. Another metaheuristic approach embedded in the RAVEN framework is based on genetic algorithms. The input space search algorithm follows genetic operations like crossover and mutation. At each step, the survival of the proposed candidate point tends to enhance the prevailing characteristics that optimize the goal

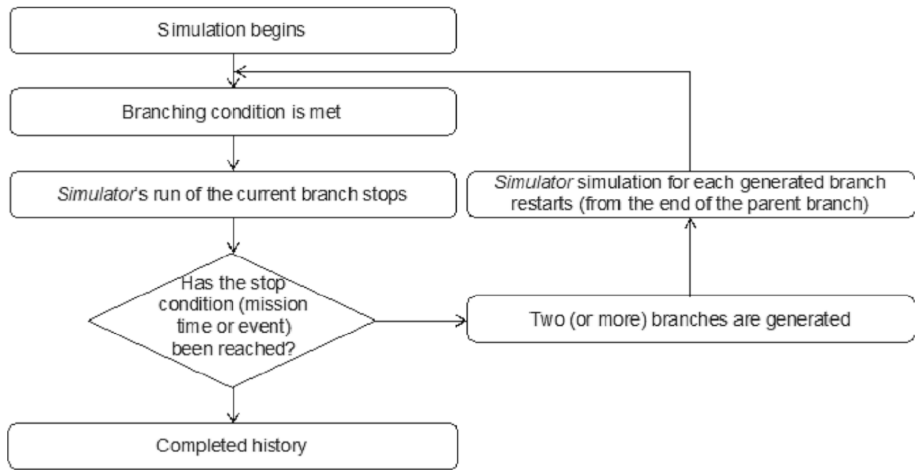

Fig. 3. Logical branching condition.

function selected.

2.4. Limit surface research with support vector Machine

Identifying boundaries that classify the safe operation of a nuclear plant and potential failures is useful in finding possible cliff-edge effects. This boundary, often referred to as a limit surface (LS), allows the separation of the regions where the plant is in a controlled state to states that could entail unforeseen risks. The use of DETs or Monte Carlo methods in sampling the input space can raise issues either on the accuracy of the LS delineation, or on the computational effort needed to efficiently explore the input space and outline this surface with enhanced precision. A solution to the limit of DET and Monte Carlo methods could be adaptive sampling in RAVEN that relies on machine learning algorithm, such as the support vector machine (SVM).

RAVEN adopts an iterative procedure for solving the LS research problem (Alfonsi et al., 2016). As a first step, a cartesian N-D grid is defined in the input domain on which the LS has to be identified (see Fig. 4). After a first random sampling on the grid, the research process is accelerated by means of a predicting method that can be set up thanks to a supervised machine learning (ML) model of type classifier (taking only the integer output, for example, 0–1), constituting a ROM of the code response. In this way, the trained ROM prediction is combined with criteria to choose the next nodes in the N-D grid that need to be explored using the code to efficiently improve the knowledge of the LS location. The iterative process is repeated until the prediction of the ML algorithm does not improve by further increasing the training set (under a particular metric).

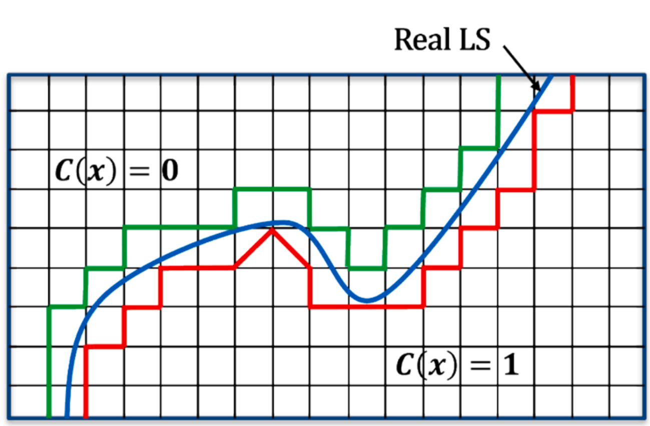

Fig. 4. Example of LS identification in a grid defined in a 2D domain.

One of the ML models most suitable for the application of the LS search method is the SVM for binary classification, with an "RBF" (exponential) type kernel. The SVM is a robust supervised ML method that aims to determine the optimal separation hyperplane between data sets with different labels. For its application, RAVEN relies on the Scikit-learn library of Python. In addition, the RAVEN iterative process for LS search can be accelerated with an adaptive refined multigrid approach (Alfonsi et al., 2016). A more comprehensive description of the method is reported in the RAVEN manual (Alfonsi et al., 2016).

The Limit Surface method of RAVEN is dynamic and iterative, unlike static methodologies that rely on predefined sample points. This methodology offers several advantages. Firstly, since the adaptative sampling is not random but rather driven by an objective (i.e., the LS research), it ensures a more efficient exploration of the input parameters space. Given the computational effort required to simulate accidental transients, this efficiency significantly saves time and resources. Secondly, by dynamically refining the sapling strategy, RAVEN ensures that the identified limit surfaces are more accurate and comprehensive, capturing even the smallest transitions between safe and unsafe operational states.

3. Current RAVEN applications in nuclear safety and risk analysis

This section provides the applications of RAVEN as the main tool for risk-informed analyses divided between MELCOR, ASTEC and OSCAR applications. Deterministic analysis evaluating thermal–hydraulic transients or radionuclide transport are enhanced to gain a wider look into the uncertainties that could arise from standalone simulation. UQ, DPRA, and optimization are the problems presented for fusion and fission applications.

3.1. MELCOR

In design but also licensing process accident sequences are studied to evaluate that design basis accident (DBA) sequences do not have consequences to the environment and the public and that, beyond DBA, satisfies a list of requirements to reduce the risk of damage to the external environment. One of the tools adopted to study severe accident sequences for nuclear reactor licensing is MELCOR. Developed at Sandia National Laboratories, MELCOR is an integrated system code that evaluates the complex phenomena of a nuclear reactor (Humphries, 2024a; Humphries, 2024b). Models that estimate heat and mass transfer, core degradation, hydrogen production and explosion, and radionuclide transport are some of the physics involved during an accident sequence integrated into MELCOR.

The following sections provide enhanced methodologies coupled with MELCOR, increasing the risk assessment insights of a nuclear power plant.

3.1.1. Spent fuel pool Loss-of-Cooling uncertainty quantification

In the MUSA project (Herranz et al., 2021), a dedicated activity involved quantifying uncertainties of an accident sequence in an SFP of a boiling-water reactor (BWR) (D'Onorio et al., 2177; Coindreau, 2023). The complexity of the physical phenomena during a severe accident underscores the significance of recognizing and dealing with the inherent unpredictability and variations that can impact the results. This endeavor encompassed assessing potential benefits that may arise when quantifying uncertainties, aiming to mitigate radiological consequences.

A SFP model has been implemented in MELCOR to quantify the effects of a loss-of-cooling accident with the aggravating scenario of a station blackout. Different types of fuel assemblies are considered in the SFP for a total of 1,535 fuel assemblies (FAs) divided between hot (548 FAs), cold (783 FAs), and fresh (204 FAs). The total decay heat power at the start of the simulation is 2.4 MW, separated between 1.9 MW for hot FAs and 0.5 MW for cold FAs.

Since the system is characterized by a low decay power and a large water inventory, the accident sequence would result in a large time-consuming process. Consequently, the reference case has an initial liquid level of the pool just above the racks to reduce the computational time. Nevertheless, a preliminary analysis estimated that the time needed for the water evaporation from the top of the SFP to the rack levels is 10 days. The following results should be shifted with 10 days added time. The main outcomes of the reference case are represented in Table 1.

RAVEN acts as the main driver to propagate the uncertainties of 29 input parameters characterizing convective and radiative heat transfer, oxidation phenomena, aerosol transport and core degradation. The uncertain input parameters for this analysis have been selected from a database (Herranz et al., 2021), mostly described by a uniform or triangular probability density function (PDF) and sampled from RAVEN with a random Monte Carlo sampling method. The minimum number of runs required to reach satisfying results is 93, a value computed with the Wilks confidence formula. Due to numerical instabilities, some MELCOR simulations crash therefore, the performed runs are 121 higher than the minimum amount required. The main objective of the analysis is to estimate the impact of the uncertain input parameters on a set of figures of merit (FoM) parameters that describe the release of radionuclides:

- Cs, Ru, Sr release into the environment from the SFP building [% of i. i.];
- Ru release in gaseous form into the environment [% of i.i.];
- Onset time of Fission Product release from fuel [h];
- RCs, Ru, Sr release from fuel [% of i.i.];
- RC metric: Dose due to isotopes with the most significant radiological impact (i.e., Sr90, Cs137, Cs134, Ru106, Ce144, Sr89, Ba137m, Ru103) relative to that of the total release of Cs137 [-].

For each of the above-mentioned FoMs, the uncertainty analysis focuses on the following statistical parameters: minimum value, maximum value, mean, median, quantile 5, quantile 95, standard deviation, coefficient of variation, variance, skewness, kurtosis, and cumulative distribution function. The relation between the input uncertainty parameters and the FoMs is characterized by Spearman's and Pearson's correlation coefficients for both simple correlation and partial correlation, linear regression parameters, and scatter plots of FoMs.

The main results in terms of Cs, Ru, and Sr release are represented in Fig. 5, Fig. 6, and Fig. 7 in terms of the statistical parameters selected for this analysis. Table 1 shows the main values of the analysis. To have an accurate statistic near the end of the transient, all the MELCOR simulations have a common end time of 154.36 h. Simulation time is adopted as the pivotal parameter for the UQ analysis.

The Pearson's and Spearman's correlation coefficients, included in the interval between 0.0 and 1.0, indicate the strength of the correlation between the sensitivity coefficient and FoM. A value between 0.4 and 0.69 implies a strong correlation, while a value higher than 0.7 implies a robust correlation. Fig. 8 and Fig. 9 show Pearson's and Spearman's coefficients for the Cs release to the environment with a simple correlation.

The sensitivity analysis workflow starts with evaluating Pearson's and Spearman's coefficients. When a strong correlation is observed, it highlights a correlation between a FoM and the observed sensitivity coefficient. An example of an observed correlation is shown in Fig. 10 and Fig. 11 regarding the sensitivity coefficient of the gap release temperature, labeled as RN1_GAP00_CLFAIL. These figures show the scatter plot for Cs release to the environment and gap failure temperature at the time of maximum Pearson's coefficient and Spearman's coefficient, respectively.

This section has provided the preliminary overview of a UQ, and sensitivity analysis conducted with RAVEN as the driver code for the perturbation of uncertain parameters and MELCOR as the system code

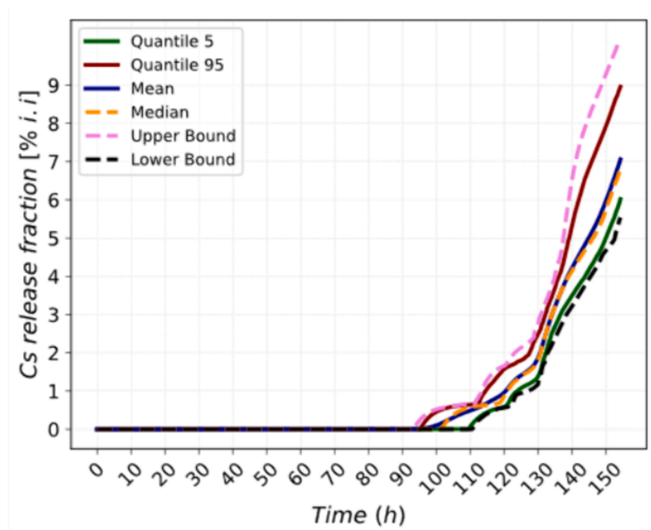

Fig. 5. Time-dependent statistics for Cs release into the environment.

Table 1
Results of the reference computation.

Maximum cladding T° at (h)				1% reloc. fuel (h)	Mass of water in the SFP at (h)				
500 K	**1000 K**	**1500 K**	**2000 K**	**End of the sim.**	**400 t**	**300 t**	**200 t**	**100 t**	**50 t**
34.19	91.38	123.19	172.52	194.2	18.97	45.77	76.25	131.8	165.0
Start of (h)									
H_2 Prod°	**Gap release**	**Mass relocation**	**Collapsed Water Level (m)**	**H_2 prod° (kg)**	**Magma / debris (kg)**	**Release from fuel (% i.i.)**			
						Cs	**Ru**	**Sr**	
54.72	102.36	119.71	0.17	2317.	72165	53%	0.185%	0.275%	

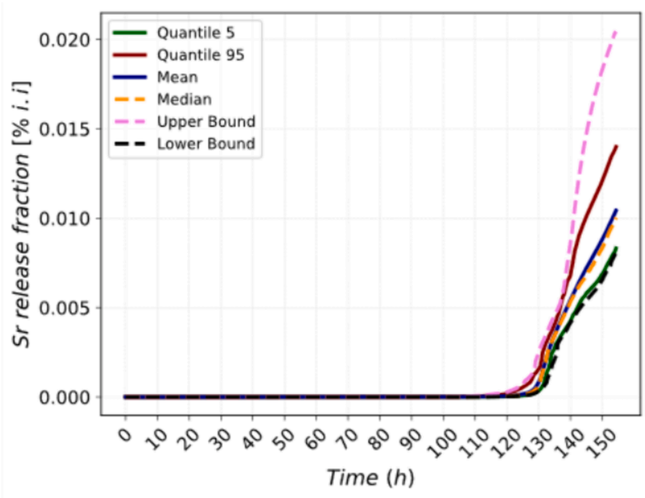

Fig. 6. Time-dependent statistics for Sr release into the environment.

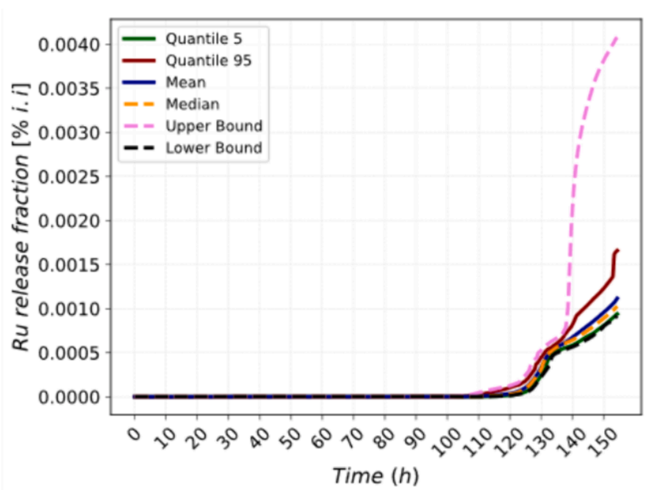

Fig. 7. Time-dependent statistics for Ru release into the environment.

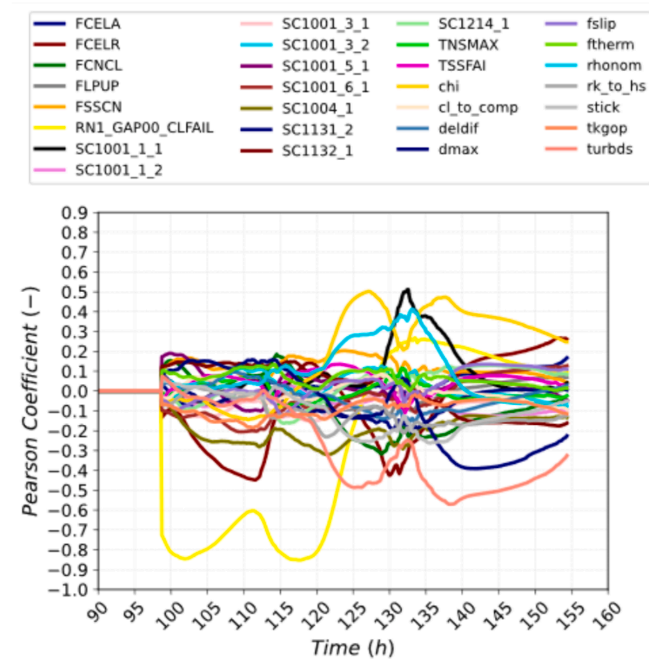

Fig. 8. Time-based Pearson's coefficient for Cs release to environment (simple correlation).

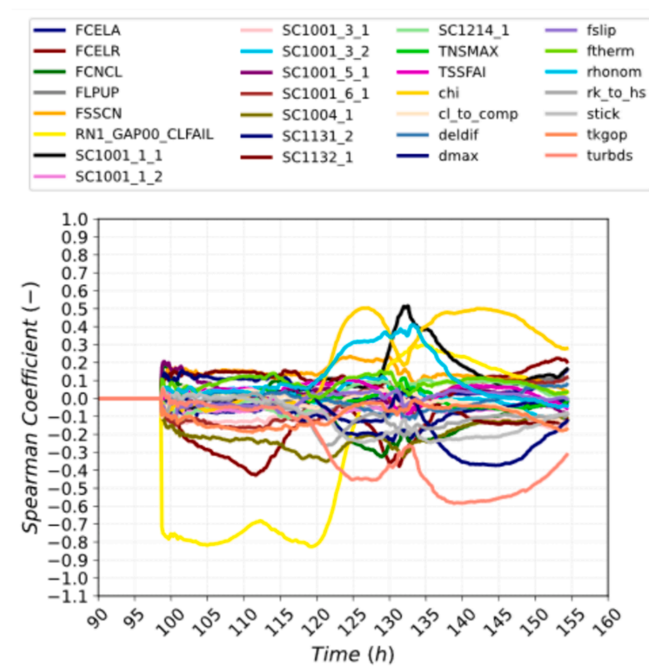

Fig. 9. Time-based Spearman's coefficient for Cs release to environment (simple correlation).

evaluating the progress of an accident sequence in an SFP. Future work will provide a more in-depth description of the results of this assessment.

3.1.2. Cyberattack of the I&C of BWR disabling the intervention of ECCS

A first application of the RAVEN and MELCOR interface for DET analysis is presented in (Glingler et al., November 2023). The analyzed scenario involves a cyberattack targeting the instrumentation and control (I&C) system of a BWR/3 with MARK I containment while the reactor is in the hot shutdown phase. The cyberattack manipulates the recorded liquid level readings of the reactor, bypassing the standard cooling system interventions and posing a potential risk to the integrity of the physical barriers designed to prevent the release of radioactive materials.

The DET analysis explores two events during the hot shutdown: the timing of the cyberattack and the duration required for the operator to restore the proper functioning of the I&C system (referred to as the recovery time). The operator's intervention triggers the emergency core cooling system (ECCS) and refloods the reactor core, bringing the plant to a safe state. The events are sampled at discrete intervals based on uniform distributions and a grid-based forward sampler. At the end of the analysis, 178 scenarios are simulated by MELCOR. Fig. 12 and Fig. 13 show the temperature and pressure transient for the MELCOR simulation, where the operator's intervention activates the ECCS and restores the plant in a safe state.

The input space is defined by the sampled values of the events selected and is discretized based on the peak cladding temperature (PCT). An accident scenario is recovered successfully if the maximum temperature reached by the cladding is below the threshold value of 1477.0 K (USA, 2024). The discretization based on the PCT delineates two regions of the input space separated by an LS, as shown in Fig. 14.

The recovery time limit delineates the PCT region from the recovery of the plant-safe functionalities. This limit depends on the liquid level

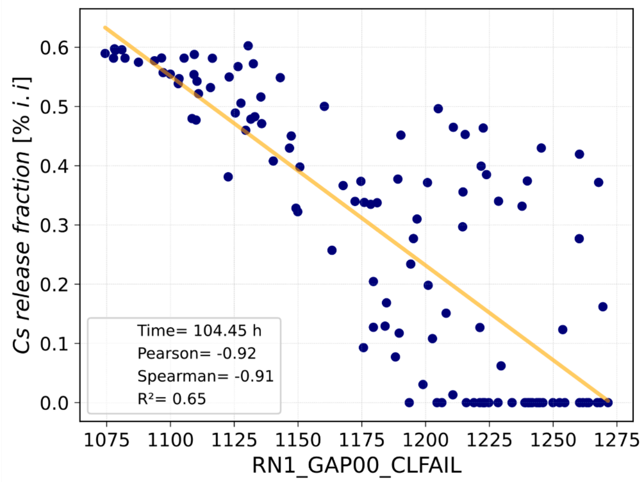

Fig. 10. Scatter plot for Cs release to environment and gap failure temperature at the time of maximum Pearson's coefficient.

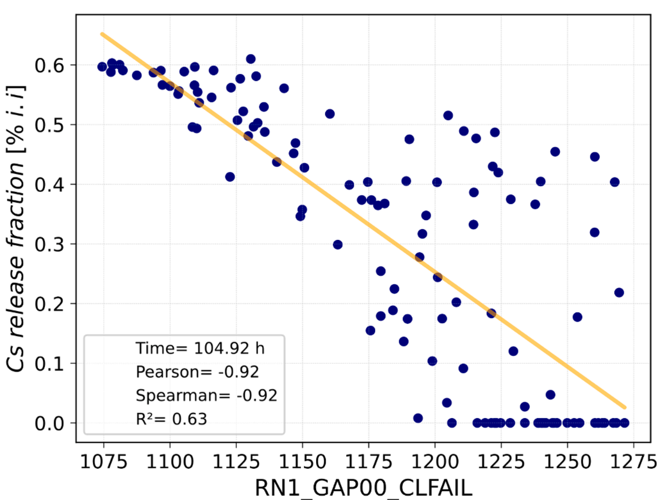

Fig. 11. Scatter plot for Cs release to environment and gap failure temperature at the time of maximum Spearman's coefficient.

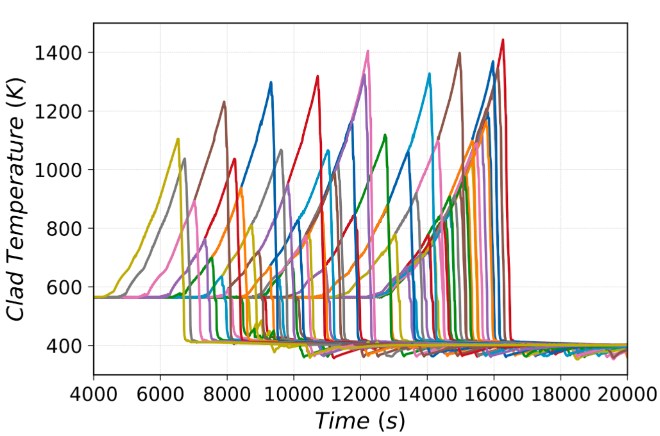

Fig. 12. Temperature transient.

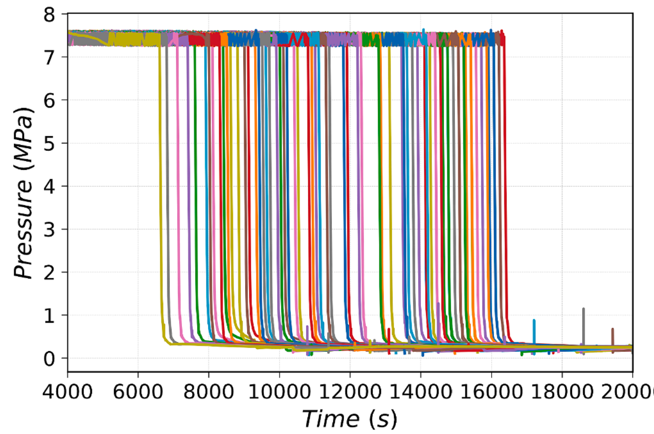

Fig. 13. Pressure transient.

inside the reactor at the time of the cyberattack. In a BWR, during a hot shutdown phase, the liquid level decreases due to evaporation caused by decay heat. When a liquid level set-point is reached, the reactor core isolation cooling (RCIC) system refloods the reactor. Consequently, the liquid level has a periodical trend with an increasing period since decay heat decreases in time after the shutdown. The cyberattack event occurring at the peak value of the periodic liquid level trend directly influences the recovery time limit. For such a case, the recovery time limit would be greater than in a different accident scenario where the cyberattack occurred at a lower liquid level of the reactor. Fig. 14 shows that the recovery time limit follows a similar periodical trend of the liquid level. The second curve has higher values for the recovery time since the decay heat is lower but also because the mean temperature of the coolant in the reactor is lower due to the previous activation of the RCIC.

3.1.3. Thermal-Hydraulic optimization of the EU-DEMO vacuum vessel pressure suppression system

Ongoing activities for the EU-DEMOnstration power plant Water-Cooled Lithium Lead (WCLL) Breeding Blanket (BB) concept (Del Nevo, 2019) are currently focused on the design of the Vacuum Vessel Pressure Suppression System (VVPSS). The primary function of the VVPSS is to mitigate in-vessel leaks that would compromise the integrity of the vacuum vessel, the first barrier against the release of radiological materials from tokamak fusion devices (Pinna et al., 2019; D'Onorio et al., 2023). The design requirement for the maximum allowable pressure in the vacuum vessel is equal to 2.0 bar abs (Ciattaglia et al., 2019). The preliminary analysis, also based on constraints regarding limited space available in the EU-DEMO building, suggests installing six suppression tanks, one of which is designed for small leaks, Fig. 15 shows the current layout.

This design has demonstrated the correct mitigation of in-vessel loss-of-cooling accident (LOCA) scenarios with a pressure peak lower than

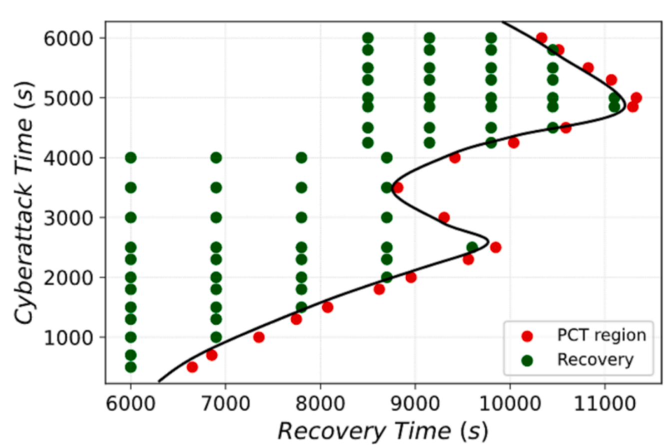

Fig. 14. Limit Surface.

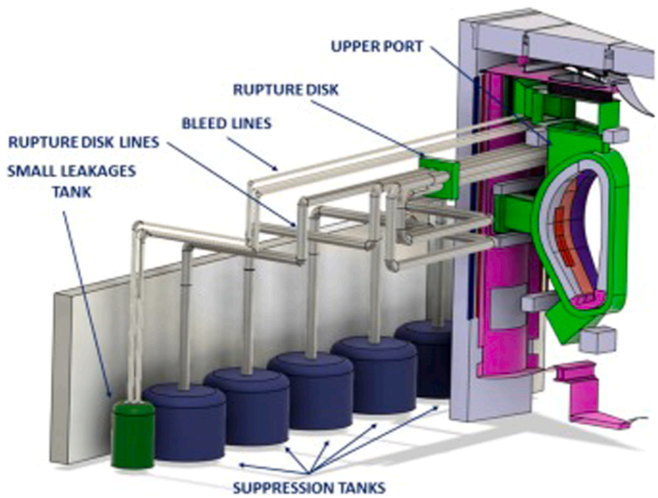

Fig. 15. Current VVPSS layout.

the design limit (Caruso, 2016; D'Onorio and Caruso, 2021). A challenge arising from this system is mitigating a hydrogen explosion in the suppression tanks or in the bleeding and rupture lines of the VVPSS. As seen in Fig. 16 a proposed solution is installing two expansion tanks connected to the suppression tanks designed for hydrogen recombination in a passive autocatalytic recombiner (PAR) (D'Onorio et al., 2023).

The EU-DEMO reactor based on the (WCLL) concept has been modeled in MELCOR to study the DBA evaluating thermal–hydraulic transient and tritiated water (HTO) transport (Glingler et al., September 2023). To test the effectiveness of the VVPSS design with integrated PARs, an in-vessel LOCA has been simulated from 10 out-board first wall channels. Since some of the geometrical and set-point parameters of the rupture disk and bleeding lines have not been optimized, the RAVEN gradient-based method searches the optimal configuration in terms of the amount of hydrogen recombined.

The parameters selected for the optimization of the amount of hydrogen recombined by the PAR are:

- Bleeding line opening set-point;
- Rupture disk opening set-point;
- Initial liquid level in Suppression Tank A;
- Initial liquid level in Suppression Tank B;
- The volume of expansion tanks where PARs are installed.

The parameters have been sampled within a limited range of variability, complying with the physical nature of the problem. Since the input space is characterized by a multimodal function, entrapment in local minima could weaken the optimization. For this reason, the search for optimum is initialized with parallel trajectories, and the values have been grid sampled from a uniform distribution.

The RAVEN MELCOR coupling workflow starts from the trajectory initialization. The values sampled are written in the MELCOR input deck, and the simulation starts. At the end of the MELCOR simulation, the final amount of hydrogen recombined is evaluated. The RAVEN gradient descent algorithm evaluates the local gradient of the objective function with a central difference approximation. For this case, the objective function is the amount of hydrogen recombined at the end of the MELCOR run. RAVEN samples new values for each trajectory based on the acceptance criteria selected. The objective function is evaluated and compared with the previous result. If the absolute value of the local gradient is below a threshold value, the optimization is satisfied, and the optimization search for that trajectory is terminated. Other parameters

Table 2
Final amount of H2 and the corresponding trajectory.

Trajectory	Final amount of H_2 estimated by the optimization algorithm (kg)
0	1.091
1	1.090
2	1.128
3	1.132
4	1.111
5	1.054
6	1.115
7	1.137
8	1.125
9	1.137

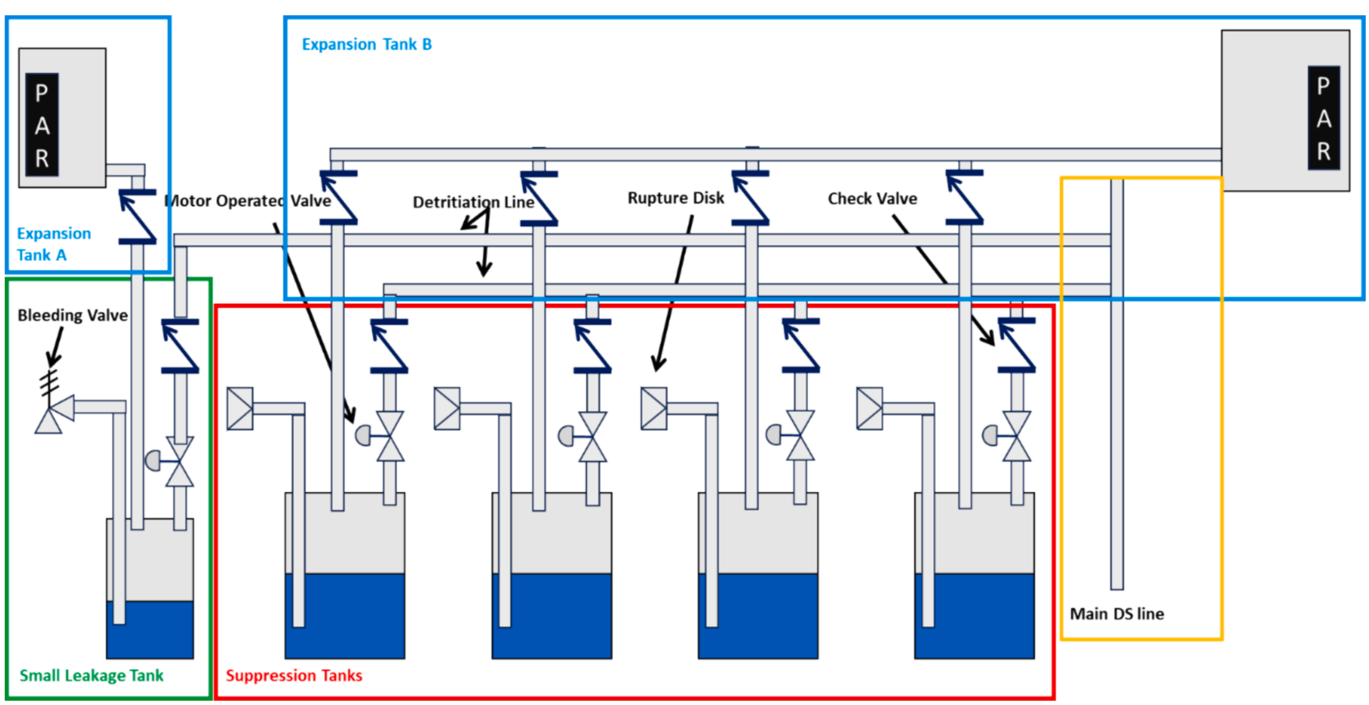

Fig. 16. VVPSS layout with PARs.

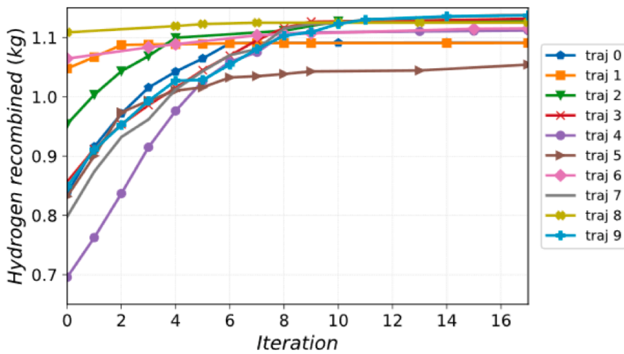

Fig. 17. Final H_2 recombined during each successful iteration.

used to terminate the optimization search are based on the persistence of a trajectory that reaches convergence and the maximum number of iterations. The main limitation of this method, especially for multimodal objective function, is associated with the entrapment in a local minima without reaching the maximum value of the objective function. A solution to this limitation is partly overcome by initializing more than one trajectory, but to completely resolve this problem, a hybrid method should be implemented based on both deterministic and stochastic search of the input space.

The main outcomes are presented in Table 2, showing the final amount of hydrogen recombined for each trajectory, and in Fig. 17, showing the optimization progress for each trajectory.

This study demonstrates the capabilities of RAVEN when tasked with optimizing a general objective function. The employment of the gradient descent method brings precision in estimating optimal values. However, it's worth noting that this method tends to get stuck in local maxima or minima, especially when dealing with complex multimodal objective functions. To mitigate this issue, initializing the search with multiple parallel trajectories proves beneficial in circumventing local entrapment. Nevertheless, it's essential to acknowledge that this approach does not entirely resolve the inherent limitations of the algorithm when confronting multimodal problems. Future advancements in this approach could explore integrating a stochastic search within the input space alongside the gradient descent method, which can be applied selectively to the most promising runs. This envisioned hybrid algorithm would aim to harness the strengths of both methods while effectively overcoming their respective inherent drawbacks.

3.2. ASTEC

The ASTEC code, developed by the French Institut de Radioprotection et de Sûreté Nucléaire (Chatelard et al., 2016), is designed for the integral simulation of severe accident sequences in water-cooled nuclear power plants. The code covers the phenomena occurring from the initiating event to the release of source terms to the environment. ASTEC employs a modular structure, where each module simulates specific physical phenomena or reactor zones. The main modules are CESAR for the thermal-hydraulics of the coolant circuit, ICARE for modeling the reactor core geometry and degradation, CPA for the containment thermal-hydraulics, and SOPHAEROS for the assessment of fission products transport.

3.2.1. ASTEC–RAVEN coupling

For those codes for which RAVEN does not have a specific interface, such as ASTEC, the coupling can be done through a generic interface already embedded in the RAVEN framework. Alternatively, users can develop a specific Python interface to be included in the source code. Following this last approach, a new interface was created to connect RAVEN with ASTEC. One of the key features present in the coupled interface includes the capability of RAVEN to read the output file of an ASTEC calculation and understand if the simulation was successful or failed. This is a significant advantage in the case of UQ analysis, where the results of failed simulations must be discarded from the statistics. Another key feature is the modification of the ASTEC input file with data and parameters processed by RAVEN or set in the RAVEN XML file. The code coupling was implemented for analysis on a single node and multinode cluster platforms (Maccari et al., 2021).

3.2.2. Review of ASTEC–RAVEN UQ analyses

The ASTEC–RAVEN is conceived for UQ analyses in safety BEPU studies (Maccari, 2024). Most of the performed UQ analyses are based on the probabilistic propagation of input uncertainties method (D'Auria, 2019; Bersano, 2024). This envisages the selection of uncertain parameters for input, characterized by a PDF. RAVEN performs a random sampling of the input uncertain parameters; the sampled parameters are then propagated in the ASTEC input file. The results of ASTEC are then collected for statistical analysis. For example, a sensitivity analysis can be performed to characterize the importance of each input uncertainty parameter in propagating the uncertainty to each output. The ASTEC–RAVEN coupling workflow for UQ analyses is represented in Fig. 18.

The first exploratory safety study of the RAVEN-ASTEC framework on a multinode cluster platform was performed in (Maccari et al., 2021). This work investigates the uncertainty affecting the ASTEC simulation of a LOCA event in an experimental facility. Another BEPU application of the RAVEN-ASTEC coupling was developed in the framework of the MUSA project (Herranz et al., 2021). This UQ application analyzes a severe accident sequence in a SFP (Coindreau, 2023). A comprehensive BEPU study performed with RAVEN-ASTEC coupling was reported in (Maccari, 2024). The study explores the application of accuracy evaluation and UQ methods to the simulation of the QUENCH test-06 experimental campaign in the framework of severe accident phenomena studies. This activity was performed in the framework of the IAEA CRP I31033 "Advancing the State-of-Practice in Uncertainty and Sensitivity Methodologies for Severe Accident Analysis in Water-Cooled Reactors" (Mascari F., Overview of IAEA CRP I3, 2022). Another plant application is presented in (Maccari et al., November 2021). This activity assessed the uncertainty affecting the thermal–hydraulic

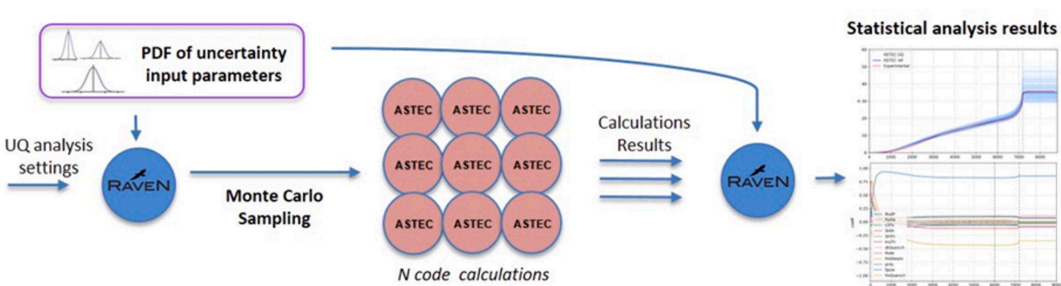

Fig. 18. RAVEN-ASTEC coupling workflow for UQ analyses (Maccari et al., 2021).

parameters embedded in the ASTEC code by studying a Design Basis Accident (DBA) sequence in a passively mitigated small modular reactor (SMR).

3.2.3. Application of limit surface search algorithm

In the framework of the NUGENIA ASCOM project (Chatelard, 2018), a DBA simulation of a small-break LOCA in an IRIS-like SMR was developed with the ASTEC code (Maccari et al., 2021). In a more recent study, a UQ was applied to the same DBA to assess the uncertainty affecting the SMR's passive safety systems (Maccari et al., November 2021). One of the FoMs considered in the UQ was the maximum containment pressure, which has a safety limit (1.35 MPa) that was never reached in the analysis.

An application of the LS search method is the identification of the boundary between a system's safe and unsafe conditions (see Section 2.4). Within this purpose, following the UQ study conducted in (Maccari et al., November 2021), a more restrictive safety condition is considered, such that the new limit falls inside the uncertainty band obtained in the performed UQ analysis. The new maximum allowable containment pressure is considered to be 1.10 MPa; as seen in Fig. 19, some UQ calculations fall above this safety limit.

In this situation, the RAVEN LS search algorithm was used to identify those input conditions leading the system to a safe state and find the boundary that divides the safe state from the unsafe conditions. To reduce the computational effort, the dimension of the input domain was reduced by selecting the most important input parameters according to the sensitivity analysis conducted in the reference study (Maccari et al., November 2021). Two parameters were chosen: decay heat power factor (FpPower) and the heat-transfer surface of the emergency heat removal exchanger (SEhrs), within the respective uncertain domains of variation.

The algorithm chosen to train the ROM is an SVM; the desired number of parallel calculations was 10, and the number of consecutive converging loops to determine the end of the search process was selected to be eight. The adaptive multigrid approach of RAVEN for convergence acceleration was also activated, and the LS search algorithm converged at 230 simulations. In Fig. 20, the results of the LS search problem are reported in terms of input values of each executed calculation in the two-dimensional input domain. The maximum pressure reached in each simulation is visualized in a scale of color.

Fig. 20 represents the combination of the two input variable values, giving rise to a maximum calculated pressure of Pmax ~ 1.10 MPa (i.e., the LS location). On the left of the LS, input value combinations leading to Pmax > 1.10 MPa (unsafe conditions) can be found; on the right, input values leading to Pmax < 1.10 MPa (safe conditions) can be found. The convergence evolution of the algorithm is well described by the scatterplot in Fig. 21, reporting the maximum containment pressure on the y-axis and the submission number of each calculation on the x-axis. It can be observed that the algorithm must first find a first guess for the

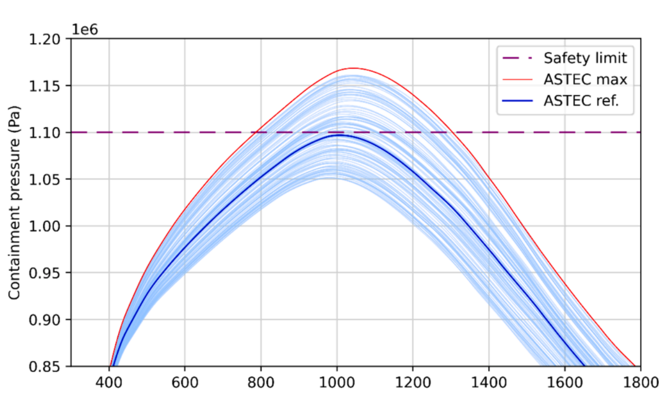

Fig. 19. Peak in containment pressure, dispersion band obtained in the UQ analysis, and new safety limit of 1.10 Pa.

LS line location and then persist on it to draw down the whole line in the input domain until convergence is reached.

3.3. Oscar-fusion

The tOol for Simulating ContAmination in Reactors (OSCAR) code is a system code developed by the Commissariat à l'énergies atomique et aux énergies alternatives (CEA) in collaboration with Framatome and Electricité de France for the estimation of activities and masses inventory of the Activated Corrosion Products (ACPs) for cooling circuits of PWRs (Harrington et al., 2019; Rafique, 2010; Daquait et al., 2017). OSCAR has been modified in OSCAR-Fusion to simulate water-cooled circuits of fusion reactors. The lumped model is based on a zero-dimensional closed method and requires several characteristics of the loop to be considered, such as geometry, thermal–hydraulic parameters, neutronic, water chemistry composition, materials, corrosion parameters, and release rates of materials.

Safety analyses of nuclear reactors also rely on evaluating ACPs produced and mobilized inside the cooling circuits of fission or fusion facilities (Zubair et al., July 2022; Terranova and Di Pace, 2021). Wet corrosion, erosion, and release phenomena mobilize activated materials throughout the working fluid, reaching regions of the cooling system accessible by worker personnel. Predicting and optimizing the contaminant transport in tokamak cooling circuits may benefit radiation exposure assessment, source terms identification, design optimization, and maintenance plan definition.

One of the latest applications of the OSCAR-Fusion V1.3 code is coupling with RAVEN (D'Onorio et al., Nov. 2022). The RAVEN OSCAR-Fusion coupling interface allows perturbation of the parameters in the OSCAR input deck. The interface is based on a Python script that takes the processed input parameters from the RAVEN framework and overwrites the data to the OSCAR-Fusion input deck. A comma-separated value file is created to write down each perturbed parameter.

The RAVEN OSCAR-Fusion possible applications are explained in (D'Onorio et al., Nov. 2022). In this paper, the EU-DEMO Cassette Body (CB) Primary Heat Transfer System (PHTS) is studied in terms of ACP transport, while in (Molinari et al., 2023), the EU-DEMO Plasma Facing Units PHTS is analyzed. Both analyses have considered a continuous activation scenario of 1888 days, with an efficiency of 99 % of the ion exchange resins and mechanical filters.

3.3.1. Uncertainty quantification for EU-DEMO Divertor Cassette Body

The first application on the EU-DEMO CB PHTS is shown in Fig. 22 with the OSCAR-Fusion model. Two different parameters have been perturbed: the corrosion rates with uniform distribution and the nuclear reaction rates with normal distribution. A case study has been carried out for each of the perturbed parameters. Case Study 1 considers as FoM, the Co-60 activity trapped in the ion exchange resin filters and the perturbed parameters are the iron-based alloys corrosion rates, the Short-Term Corrosion Rate (STCR) and Long-Term Corrosion Rate (LTCR). The code uses the STCR and LTCR to evaluate the corrosion rate depending on the simulation time. Case Study 2 considers the total activity trapped in the ion exchange resin filters as FoM, and the perturbed parameters are several nuclear reaction rates.

A total of 100 runs of the OSCAR-Fusion code are needed for each study to reach a 95 % confidence. For Case Study 1, an uncertainty of ± 50 % has been proposed for the corrosion rate perturbation due to the lack of experimental data; for Case Study 2, it has been considered ± 3σ for each of the 15 nuclear reactions. The perturbed parameters used for both case studies are summarized in Table 3 and Table 4.

Fig. 23 and Fig. 24 show the Co-60 activity and the total activity. In both cases, the activity is referred to the one trapped in ion exchange resins as time progresses. In both case studies, the buildup of the activity trapped in the filtering zone of the PHTS is clearly visible. Two factors cause the buildup: the activation scenario considered (which is not pulsed but continuous) and the half-life of the Co-60 or most active

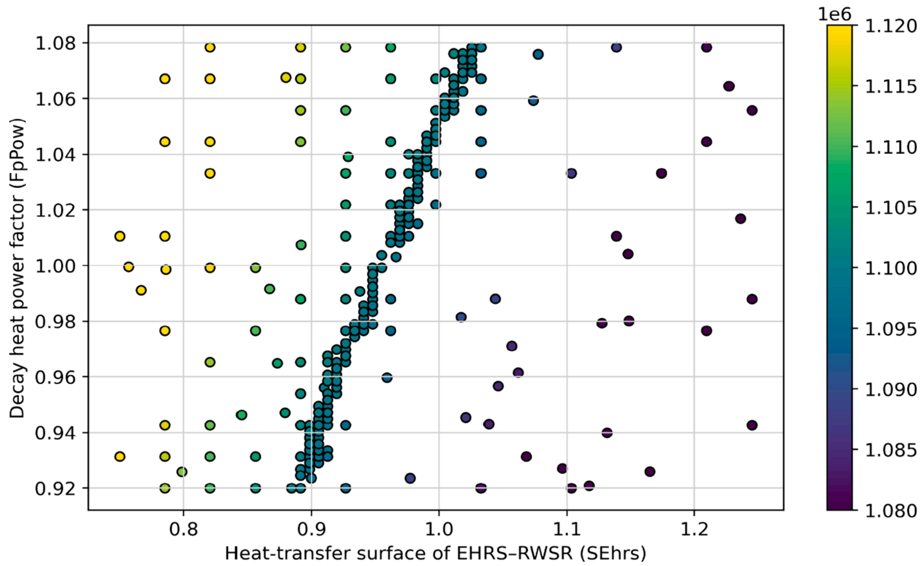

Fig. 20. LS research results in terms of input values (normalized) and corresponding value of output P_{max} (Pa).

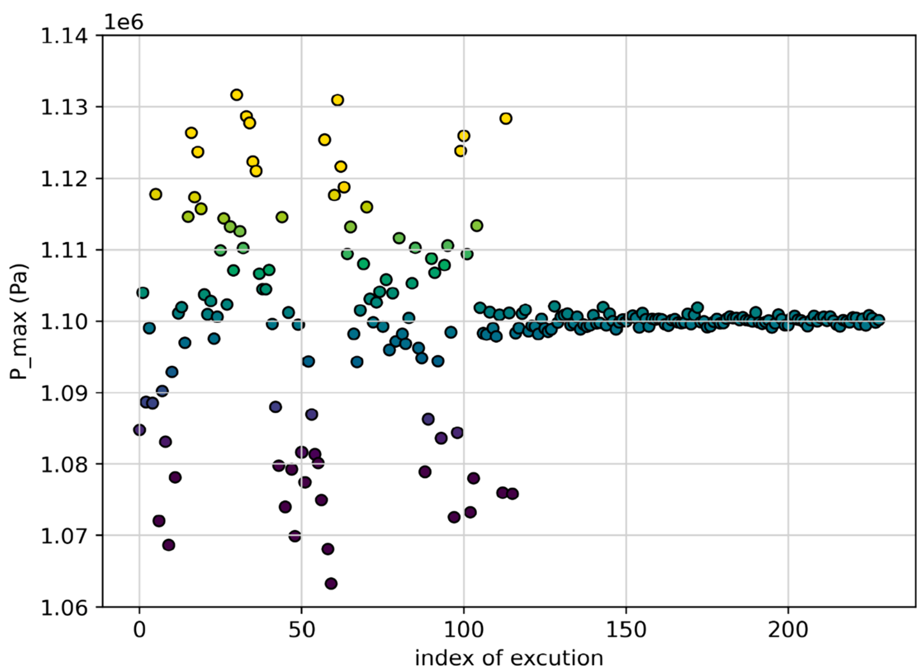

Fig. 21. Calculations executed in the LS search in terms of submission index and output Pmax (Pa).

isotopes, which can be higher with respect to the duration of the entire activation scenario.

An interesting use of the UQ results is the analysis of the possible correlation between the perturbed variables and FoMs. The quantification used Pearson's and Spearman's coefficients; the coefficients can be used to check whether there is a correlation between the FoM and the perturbed parameter. The following three figures show examples of this type of analysis. In Fig. 25, the high correlation before 300 days means a higher corrosion rate is caused by the high corrosion tendency of iron-based alloys during the initial exposition to a water environment, as in a pipeline. The high correlation, which starts from about 1,200 days, means that long-term corrosion entails a buildup of Co-60 into the filtering zone of the PHTS.

Fig. 26 and Fig. 27 show a strong correlation of the Fe-54 (n,p) and the Mn 54 (n,p) reaction for the entire activation scenario. This strong correlation is caused by iron in the material as an alloy base element. The Mn-54 is not the most active isotope in the coolant but is the one with the longest half-life, which entails a higher buildup into the PHTS filtering zone.

3.3.2. *Uncertainty quantification of EU-DEMO Divertor Plasma Facing unit*

Considering the evaluated high impact of Mn-54 on activity buildup into the PHTS filtering zone (Molinari et al., 2023), the second UQ studies the Mn-54 build-up in the EU-DEMO Plasma Facing Units PHTS loop. Two different parameters have been perturbed: the lithium concentration in the coolant, and the corrosion rates of stainless steel and copper-based alloys. In both cases, a uniform distribution was chosen, following the data available in the literature. The OSCAR-Fusion model for the DEMO Divertor PFU is shown in Fig. 28.

Looking at a single FoM for each case study, 100 runs of the OSCAR-

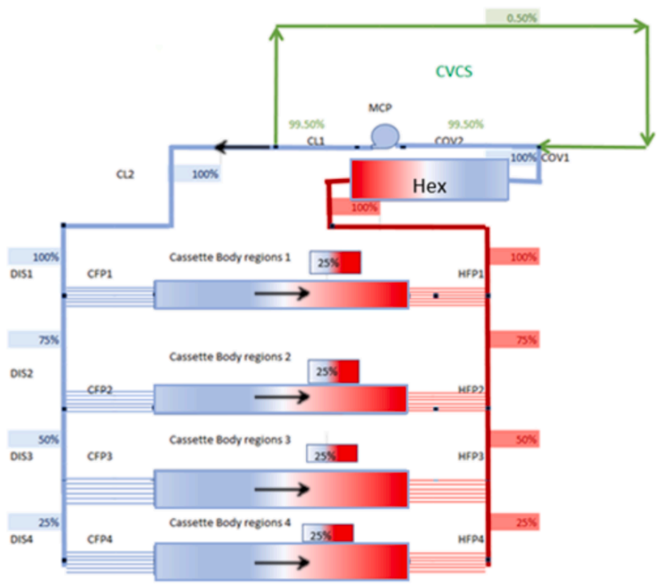

Fig. 22. DEMO Divertor Cassette PHTS nodalization.

Table 3
Perturbed parameters for Case Study 1.

Corrosion rates (Uniform distribution) [g/s/m^2]		
Parameter	Lower Bound	Upper Bound
Moorea law STCR	8.0E-7	2.4E-6
Moorea law LTCR	2.3E-7	6.9E-7

Table 4
Perturbed parameters for Case Study 2.

Nuclear reaction rates (Normal distribution) [1/s]				
Parameter	Mean	Sigma	Lower Bound	Upper Bound
Co-59(n,g) Co-60 *m*	6.26E-10	1.15E-11	5.34E-10	7.18E-10
Cr-50(n,g) Cr-51	2.75E-10	4.86E-12	2.36E-10	3.14E-10
Cr-52(n,2n) Cr-51	3.47E-12	1.73E-13	2.08E-12	4.86E-12
Cr-52(n,p) V-52	1.45E-12	8.19E-14	7.95E-13	2.11E-12
Fe-54(n,a) Cr-51	1.33E-12	1.14E-13	4.15E-13	2.25E-12
Fe-54(n,g) Fe-55	4.14E-11	1.12E-12	3.24E-11	5.04E-11
Fe-54(n,np) Mn-53	8.03E-12	4.69E-13	4.27E-12	1.18E-11
Fe-54(n,p) Mn-54	7.74E-12	3.28E-13	5.11E-12	1.03E-11
Fe-56(n,2n) Fe-55	5.90E-12	4.48E-13	2.31E-12	9.48E-12
Fe-56(n,p) Mn-56	1.74E-12	7.09E-14	1.17E-12	2.30E-12
Fe-57(n,g) Fe-58	4.76E-11	2.29E-12	2.92E-11	6.59E-11
Fe-58(n,g) Fe-59	2.72E-11	4.20E-13	2.38E-11	3.05E11
Mn-53(n,g) Mn-54	1.68E-09	1.91E-10	1.47E-10	3.21E-09
Mn-55(n,2n) Mn-54	9.74E-12	5.40E-13	5.41E-12	1.40E-11
Mn-55(n,g) Mn-56	2.72E-10	6.14E-12	2.22E-10	3.21E-10

Fusion code are necessary to reach a 95 % confidence. The FoM selected is the Mn-54 activity on the deposit and outer oxide layer. Table 5 and Table 6 show the main statistical parameters for Case Studies 1 and 2, respectively. In both cases, an increasing trend is caused by the continuous activation scenario considered instead of a pulsed one.

In Case Study 1, the Mn-54 decay is not visible despite the half-life of about 312 days, and this happens because a change in the chemical composition of the working fluid implies a change in pH. The corrosion rate has a direct dependence on pH values, so perturbing the pH causes a perturbation of the corrosion rate. This can lead to a different buildup of the Mn-54 on the outer oxide layer of a pipeline, resulting in lost visibility of the isotope decay because in the same intervals in which the isotope decays more Mn-54 is deposited. Instead, in Case Study 2, there is a direct corrosion rate perturbation. For this reason, a decreasing trend starting from about 1000 days of the simulated activation scenario is shown in Fig. 29 and Fig. 30.

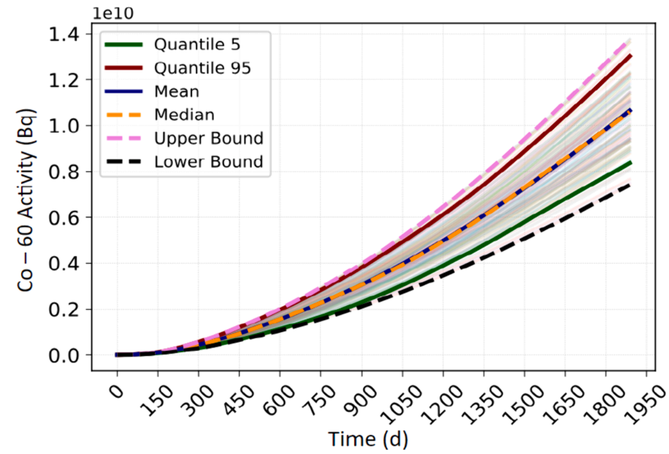

Fig. 23. Main statistical parameters evaluated during the simulation for Co-60 activity in resins (Case Study 1).

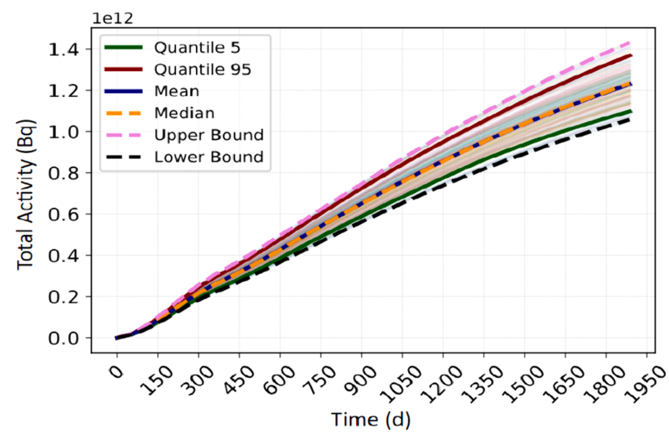

Fig. 24. Main statistical parameters evaluated during the simulation for total activity in resins (Case Study 2).

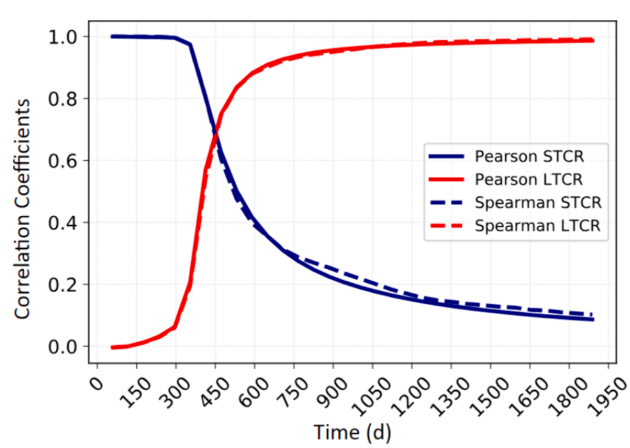

Fig. 25. Pearson's and Spearman's coefficients for Case Study 1.

According to the UQ performed with OSCAR-Fusion, a perturbation in the corrosion rate of different materials or all the parameters on which the corrosion rates depend can significantly affect the activity at the end of the activation scenario considered or during maintenance operation.

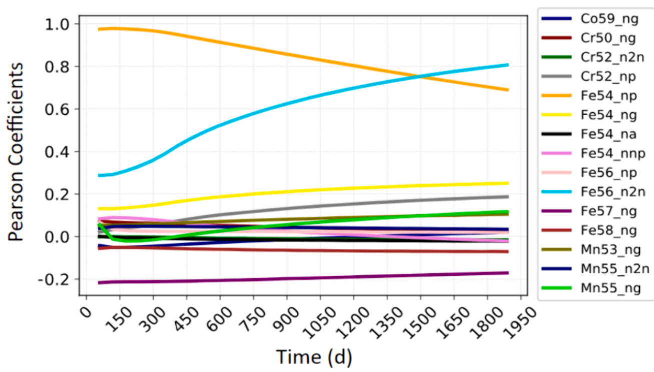

Fig. 26. Pearson's Coefficient for Case Study 2.

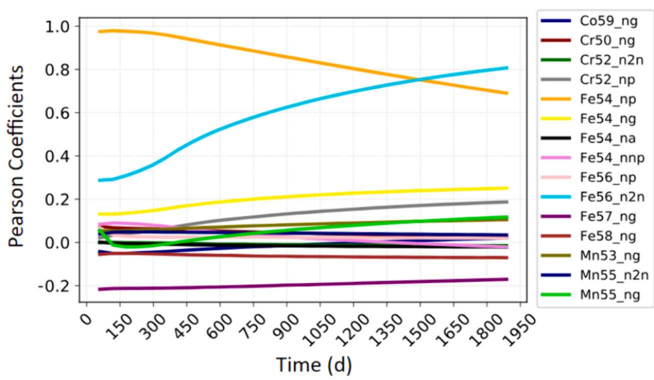

Fig. 27. Spearman's coefficient for Case Study 2.

4. Conclusions, future Developments, and applications

The industry's dedication to embracing new approaches underscores its commitment to ensure robust nuclear safety in an era of technological advancements and increased computational capabilities. Combining advanced tools like RAVEN and innovative methodologies moves the nuclear industry toward more meticulous and expansive safety approaches. RAVEN offers an open computational environment for adopting advanced statistical modeling techniques coupled with standard nuclear codes, enhancing the outcomes of nuclear safety analyses. Applications vary from standard PRA techniques to UQ methodology and optimization strategies. The Python environment, which is the foundation of RAVEN, helps analysts develop code-to-code interfaces specific to the analyst goals.

The phenomena occurring during accidental sequences of a nuclear reactor are complex, and their modeling relies on assumptions and simplifications to reduce the computational burden. At the same time, heat and mass transfer correlations, for example, rely on uncertain parameters. The variability of such parameters could significantly influence simulation.

This paper highlights a consolidated overview of recent achievements in improving safety analysis outcomes thanks to interfaces between RAVEN and safety codes like MELCOR, ASTEC, and OSCAR. An SFP scenario modeled in MELCOR, guided by RAVEN's UQ via Monte Carlo sampling, reveals significant correlations between input parameters and radionuclide release. Likewise, enhanced by RAVEN's input management, OSCAR-Fusion simulations of the EU-DEMO reactor components provide insights into isotope inventories during activation scenarios, with key correlations outlined through statistical analysis. Further, integrating RAVEN with DET methodology expands the horizon of PRA, mapping out the impact of varying accident sequence events, including cyberattack simulations, on reactor safety. This approach successfully defines an LS, indicating safe and unsafe operational conditions. ASTEC code interactions demonstrate how knowledge of this boundary can optimize safety margins and assess system probabilities within these thresholds. Overall, the results endorse RAVEN's capability to significantly refine the predictive accuracy of nuclear safety assessments.

The insights from these analyses establish a strong foundation for future developments and applications in nuclear safety and risk assessment, setting the stage for the next frontier in predictive safety modeling. State-of-practice PRA approaches commonly used by regulators and industry for nuclear systems use the ET/FT methodology, which often relies on simplified system representation and employs somewhat static Boolean logic to depict failure propagation and accident progression. While numerous dynamic PRA methodologies have been proposed to address these shortcomings of the traditional ET/FT methodology, the standalone plant-level applications of the dynamic PRA methodologies are still difficult due to their computational requirements. Furthermore, only a small portion of the plant ET/FT may involve the types of dynamic interactions or epistemic uncertainties that challenge the ET/FT methodology. In that respect, using dynamic PRAs in practice is often limited to those aspects of the system that pose challenges for traditional PRA. Verifying the resulting traditional and dynamic PRA models is particularly important when digital control systems and plant dynamics are heavily coupled. In such cases, an extensive number of modeling assumptions are introduced to accommodate model complexity with reliability models (e.g., FTs and ETs) as much as possible.

The research presented in (Mandelli et al., 2020; Mandelli et al., 2020) tackles these issues by proposing methods designed to reduce and automatize the linking of classical PRA with dynamic PRA by presenting several algorithms designed to construct ETs automatically from dynamic PRA methods. In more detail, by sampling the timing and sequencing of events through a DPRA methodology, a set of simulation runs is generated, and the simulation model output is collected at the end of each run. The presented algorithm relies on clustering methods to identify patterns in the simulation data set. Clustering algorithms are data mining methods designed to identify groups of data points (i.e., clusters) that are close to each other based on a predefined distance metric.

When applied to time series (i.e., accident sequences), clustering methods can identify groups of scenarios with "similar" temporal behaviors. These methods iteratively partition the dynamic PRA data scenarios into clusters, each of which contains scenarios with similar temporal behavior. Each clustering partition generates a branch in the ET; the corresponding branching rule is determined by looking at the differences in the sampled values of each cluster. In other words, the output data is partitioned into clusters where scenarios in each cluster have similar dynamics; then, the algorithm identifies differences in the input space that cause the separation between clusters (e.g., successful or failed system activation).

In the context of advanced reactor systems, the classical PRA approach might not apply, given the architectural design of such systems. Classical PRA approaches have been originally designed around the architecture and dynamics of light-water reactor systems and consist of three analysis levels. The first level analyzes accident sequences that might lead to core damage. The second level considers the portion of the obtained sequences that might lead to the release of radioactive material outside the boundaries of the plant (e.g., the containment). Finally, the third level estimates the consequences in terms of injury to the public and damage to the environment. Usually, these three analysis levels are performed sequentially. Advanced reactors are systems that are architecturally very different from light-water reactors in terms of nuclear fuel, heat extraction, or safety barriers that heavily rely on passive (i.e., physics-based) features. Thus, when analyzing advanced reactors, such a sequence of analysis steps might be condensed into one single analysis, which directly determines a set of accident sequences (with estimated consequences in terms of radioactive release) for each initiating event.

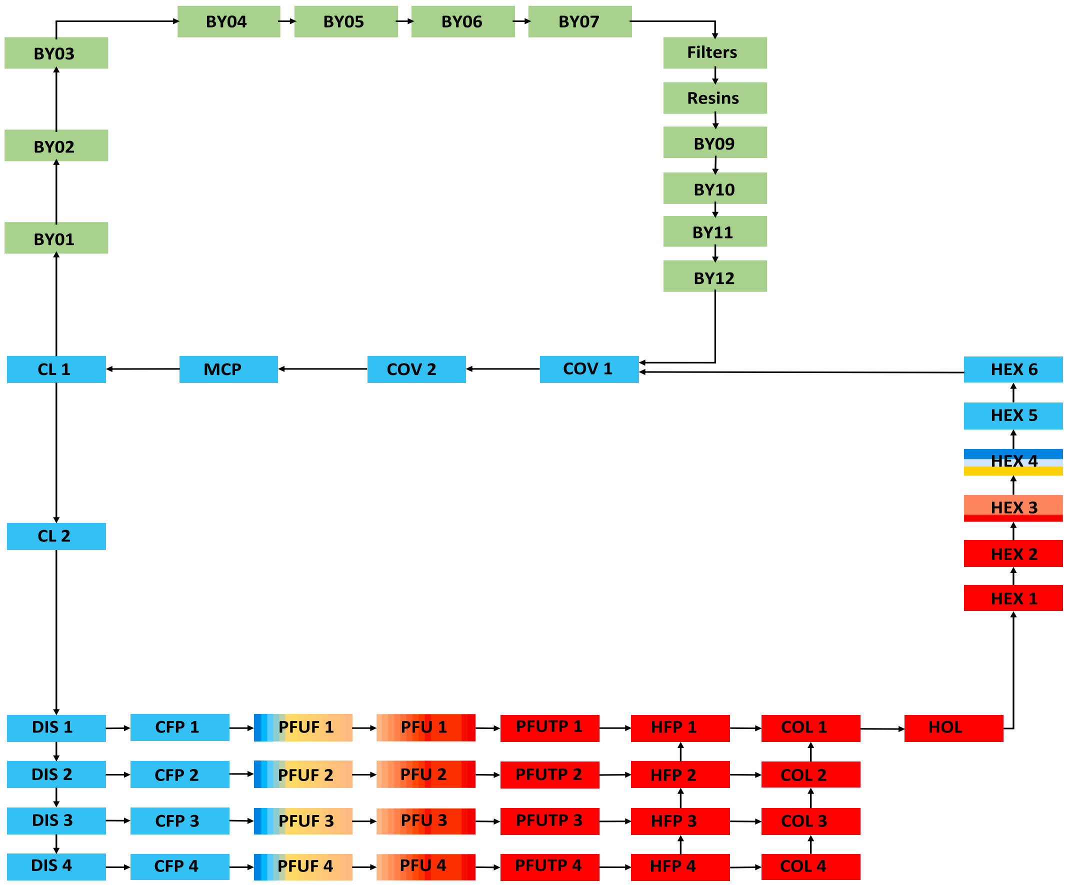

Fig. 28. DEMO Divertor PFU nodalization.

Table 5
Perturbed parameter for Case Study 1.

Lithium concentration (Uniform distribution) [ppm]	
Lower Bound (LB)	Upper Bound (UB)
0.0	1.5[1]

[1] Maximum value allowed in OSCAR-Fusion V1.3.

Table 6
Perturbed parameters for Case Study 2.

Standardised coefficients for corrosion rates (Uniform distribution) [g/m^2/s]		
Coefficient	UB	LB
Copper based alloy	1.22E-05	7.67E-06
Stainless Steel STCR	5E-06	5E-07
Stainless Steel LTCR	1E-06	1E-07

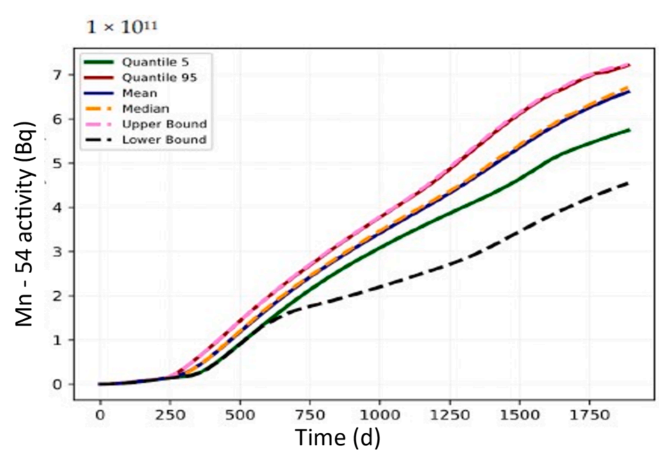

Fig. 29. Main statistical parameters evaluated after lithium concentration perturbation.

Dynamic PRA methods offer a practical solution to analyze complex accident sequences where simulation is the key to capturing system performance under abnormal (i.e., accident) conditions. In such settings, dynamic PRA methods can be used to precisely simulate the plant response to an initiating event and evaluate the consequences of radioactive release (i.e., one single-level risk analysis).

One final application of the RAVEN code currently being pursued is its use within the reliability and integrity management (RIM) program for advanced reactors; see (Lawrence et al., 2022; Mandelli et al., 2023). The objective of the RIM program is to define, evaluate, and implement strategies to ensure that performance requirements for systems, structures, and components (SSCs) are defined, achieved, and maintained throughout the plant's lifetime. The RIM program can benefit the industry by reducing implementation costs and providing consistency in implementation for users. More specifically, RAVEN is employed as a data analytics tool designed to support the RIM program for advanced reactors and targets two research directions: SSC reliability target allocations and RIM strategy identification and evaluation. Here, RAVEN determines the SSC reliability value that satisfies regulatory constraints and minimizes operation and maintenance costs. This is accomplished by employing RAVEN optimization methods (e.g., genetic algorithms and multiobjective optimization methods) coupled with the plant PRA model (i.e., the minimal cut sets generated by the plant PRA model). The

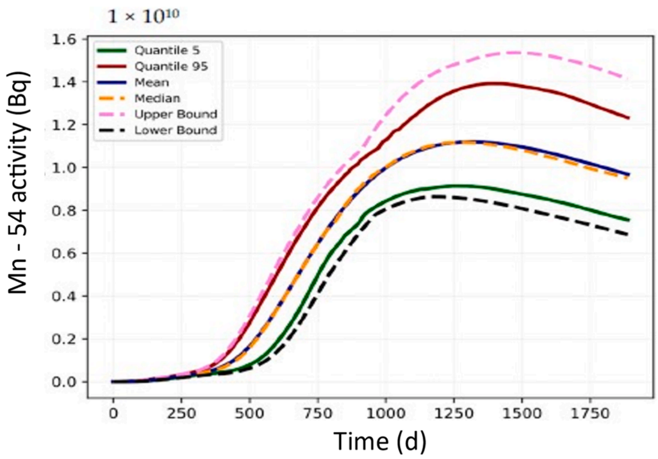

Fig. 30. Main statistical parameter evaluated after corrosion rate perturbation.

goal is to determine the optimal reliability target for each SSC queried in the plant PRA (through basic events in the set of minimal cut sets) such that:

- The operation and maintenance costs associated with the SSC reliability targets are minimized, and
- The frequency of the considered accident sequences modeled in the plant PRA model is below the regulatory requirements.

CRediT authorship contribution statement

Matteo D'Onorio: Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Tommaso Glingler:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Martina Molinari:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Pietro Maccari:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Fulvio Mascari:** Writing – original draft, Supervision, Methodology. **Diego Mandelli:** Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Andrea Alfonsi:** Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Gianfranco Caruso:** Writing – review & editing, Writing – original draft, Supervision, Resources, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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