Progress in Nuclear Energy 192 (2026) 106142

Contents lists available at ScienceDirect

Progress in Nuclear Energy

journal homepage: www.elsevier.com/locate/pnucene

Review

Sensitivity analysis in severe accident simulations:A historical perspective

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ARTICLE INFO

Keywords:
Sensitivity analysis
Severe accidents
Simulations
Nuclear safety

ABSTRACT

In recent years, the application of Best Estimate Plus Uncertainty methodologies in the frame of Severe Accidents (SAs) has gained significant momentum. Both researchers and regulatory bodies in the field recognize the importance of quantifying the uncertainties associated with SA codes results as well as sensitivity analysis' relevance in understanding the variables driving the calculated uncertainty. In this framework, the current work aims to deliver a thorough overview of the historical evolution of the application of sensitivity analysis techniques within the SA domain over the past five decades, detailing their primary focus, geographical context, main techniques and key documents. Highlighting how sensitivity analysis evolved over the years, the paper underscores its critical role within nuclear safety assessments. This review offers both a detailed historical perspective and insights into future directions for research, emphasizing the need for a balance between computational efficiency and model accuracy, and suggesting the integration of machine learning techniques to enhance future analyses.

Abbreviations

ASAP	Adjoint Sensitivity Analysis Procedure
BEPU	Best Estimate Plus Uncertainty
BDBA	Beyond Design Basis Accident
BWR	Boiling Water Reactor
CANDU	CANadian Deuterium Uranium
CC	Correlation Coefficient
CEC	Commission of European Communities
CRP	Coordinated Research Project
CSAU	Code Scaling, Applicability and Uncertainty
DBA	Design Basis Accidents
DCH	Direct Containment Heating
DEC	Design Extension Condition
EE	Elementary Effect
EURATOM	European Atomic Energy Community
FAST	Fourier Amplitude Sensitivity Test
FSAP	Forward Sensitivity Analysis Procedure
FOM	Figure Of Merit
GSA	Global Sensitivity Analysis
IAEA	International Atomic Energy Agency
LHS	Latin Hypercube Sampling
LSA	Local Sensitivity Analysis
LWR	Light Water Reactor
ML	Machine Learning
MUSA	Management and Uncertainties of Severe Accidents
NPP	Nuclear Power Plant
OAT	One-at-a-Time
PCA	Principal Component Analysis
PCC	Partial Correlation Coefficient
PRA	Probability Risk Analysis
PRCC	Partial Rank Correlation Coefficient
PSA	Probabilistic Safety Assessment
PWR	Pressurized Water Reactor
QUASAR	Quantification and Uncertainty Analysis of Source Terms for Severe Accidents in Light Water Reactors
SA	Severe Accident
SAMG	Severe Accidents Management Guideline
SBO	Station Blackout
SFP	Spent Fuel Pool
SI	Sensitivity Index
SMR	Small Modular Reactor
SOARCA	State-of-the-Art Reactor Consequence Analyses
SRC	Standardized Regression Coefficient
SRRC	Standardized Rank Regression Coefficient
ST	Source Term
STCP	Source Term Code Program
UA	Uncertainty Analysis

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https://doi.org/10.1016/j.pnucene.2025.106142
Received 9 April 2025; Received in revised form 26 October 2025; Accepted 11 November 2025
Available online 17 November 2025

(*continued*)

UASA	Uncertainty and Sensitivity Analysis
U&S	Uncertainty and Sensitivity
UQ	Uncertainty Quantification
USNRC	United States Nuclear Regulatory Commission

1. Introduction

As stated in IAEA Safety Standards Series No. SF-1 (IAEA, 2006), "the fundamental objective of nuclear safety is to protect people and the environment from harmful effects of ionizing radiation". This primary goal pertains to all nuclear facilities and installations, and it remains applicable in all circumstances, covering scenarios from normal operation to accidental events. As for the latter, it seems particularly pertinent in the case of Severe Accidents (SAs).

SAs, also referred to as Beyond Design Basis Accidents (BDBAs) or more recently, as stated in IAEA TECDOC-1791 (IAEA, 2016), Design Extension Condition (DEC) with core melt, in fact, encompass all those scenarios involving partial or complete core degradation. The same scenarios could lead to an impairment of containment integrity and, as a consequence, in a radioactive release to the environment.

In this context, safety analyses appear to be critical for twofold reasons:

- on one side, to assess and understand the behavior of a Nuclear Power Plant (NPP) during a SA (with the aim to decrease the likelihood of such types of accidents);
- on the other side, to assess the potential consequences outside the NPP (with the objective of mitigating them).

The importance of safety analyses involving SAs has been recognized since the beginning of the nuclear era. A serious accident scenario was first postulated in 1950 (USAEC, 1950), and it influenced the development of the initial equations for the definition of the exclusion area around a NPP. Few years later, in 1957 (USAEC, 1957), the possible outcomes of a worst-case accidental scenario were formally evaluated. Similarly, the dimension of the exclusion area as well as the distances from the low population zone and the closest center with a population of 25,000 people was determined on the basis of a "maximum credible accident", which would result in a potential hazard outside the NPP (USNRC, 1962).

The analyses previously mentioned relied on conservative assumptions and were designed to yield conservative safety margins. However, a shift from such conservative approaches towards more realistic ones had already started to emerge in the 1970s, when the United States Nuclear Regulatory Commission (USNRC) Reactor Safety Study (USNRC, 1975) introduced a whole different methodology, namely the Probabilistic Risk Assessment (PRA), as an alternative to the deterministic approach typically used for safety analysis. For the first time, they introduced realistic elements, such as the adoption of fault trees and the assessment of system failure probabilities, alongside the traditional conservative assumptions to better characterize NPP system responses. Nonetheless, it was not until the 1989 that more realistic, best-estimate calculations were formally accepted by the USNRC (USNRC, 1989a, 1989b). Since then, Best Estimate Plus Uncertainty (BEPU) methodologies have been formulated and extensively applied worldwide (Herranz and Gauntt, 2018; IAEA, 2008; Perez et al., 2011; Prošek et al., 2003; Rohatgi and Kaizer, 2020).

The employment of BEPU methodologies in the frame of SAs is not as widespread as in thermal-hydraulics or in Design Basis Accidents (DBAs) analysis. However, their application has gained significant momentum in the past two decades: building upon past experience, some recent projects have been devoted to embedding Uncertainty Analysis (UA) methodologies into the safety analysis of SAs. Among these, it is worth mentioning the SOARCA project in the United States (US) (USNRC, 2022), the EURATOM project "Management and Uncertainty of Severe Accidents" (MUSA) (Herranz et al., 2021, 2025) and the IAEA Coordinated Research Project (CRP) I31033 (IAEA, 2024a, 2024b, 2024c, 2023).

While the major focus of these projects was the quantification of the uncertainties stemming from the results yielded by the system codes (MELCOR, ASTEC, MAAP, AC2, …) employed for the safety analysis of SAs scenarios, some (even if limited) efforts were additionally devoted to the identification of the key variables driving the uncertainty itself. In this respect, the important role played by the sensitivity analysis was highlighted and reaffirmed.

In particular, by identifying the variables having the most significant impact on the outcomes of SA codes, sensitivity analysis not only complements the results from UA, but it might also be useful in:

- boosting the understanding of SA dynamics;
- improving results' robustness;
- enhancing codes' optimization;
- providing critical insights into areas for improvement;
- providing the basis for the optimization of safety measures and Severe Accidents Management Guidelines (SAMGs);
- providing direction for future research and experimental campaigns.

In this framework, the current work aims to deliver a thorough review of the application of sensitivity analysis techniques within the context of SAs. While sensitivity analysis is widely applied in various fields, applications outside the domain of SAs fall outside the scope of this paper. Moreover, by focusing specifically on SAs, this work seeks to address a gap in literature. In fact, to date, no review has exclusively addressed sensitivity analysis within this domain, despite its significant peculiarities would make substantial differences with respect to applications of sensitivity analysis in other domains.

This paper traces the development of sensitivity analysis from its initial applications to its current status as an essential tool in nuclear safety assessments. By documenting this evolution, this review not only serves as a valuable resource for established professionals but also offers a foundational knowledge base for students and young researchers entering the field.

It is worth noting that this review is structured to emphasize the historical evolution of sensitivity analysis in the frame of SAs and to highlight the pivotal studies over the past decades.

2. Background

As previously mentioned, this review paper adopts a historical perspective, and it focuses on the evolution of the application of sensitivity analysis techniques in SAs rather than on providing detailed descriptions of the sensitivity analysis techniques per se. Nevertheless, before proceeding with the actual review, it is essential to establish a basic understanding of the concept of sensitivity analysis and of its underlying objectives. To this end, this background section will report definitions of sensitivity analysis as available in the literature, and it will provide an overview of the macro-categories to which the different sensitivity analysis techniques belong to. Moreover, bibliographic references to existing reviews on the sensitivity analysis techniques that have been developed over the years will be also provided.

2.1. Definitions

Various definitions for sensitivity analysis can be found in literature. However, despite slight differences, they generally convey the same concept, that is the evaluation of the impact of input parameters on selected output targets.

In this regard, a selection of sensitivity analysis definitions is proposed in the following:

- Saltelli and Sobol' (1995): they describe sensitivity analysis as aiming "to apportion the output uncertainty to the uncertainty in the input parameters".
- Saltelli and Sobol' (1995): they also differentiate the definition of sensitivity analysis on the basis of different problem settings:
  a) "Parameter screening, where the task is to identify active factors in a system with many parameters";
  b) "Global SA, where the emphasis is on apportioning the output uncertainty to the uncertainty in the input parameters";
  c) "System analysis by way of local sensitivities, where the emphasis is on the impact of the parameters not of the model variance but of the model itself".

This differentiation would be clearer in the following sub-section.

- Homma and Saltelli (1996): they define sensitivity analysis more specifically as the process that "aims to quantify the relative importance of each input model parameter in determining the value of an assigned output variable".
- Saltelli (Saltelli, 2002; Saltelli et al., 2008): sensitivity analysis is described as "the study of how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input". The same definition is also reported by the European Commission ("Sensitivity Analysis: SAMO - European Commission, " n.d.).
- Razavi et al. (2021): a broader definition is provided as "the study of how the 'outputs' of a 'system' are related to, and influenced by, its 'inputs'".
- Razavi et al. (2021): they also note that "To many, sensitivity analysis simply means a process in which one or multiple factors in a problem are changed to evaluate their effects on some outcome or quantity of interest". However, "The modern era of SA has focused on a notion that is commonly referred to as 'Global Sensitivity Analysis (GSA)' (Saltelli et al., 2000), as it attempts to provide a 'global' representation of how the different factors work and interact across the full problem space to influence some function of the system output".

The provided definitions, with their different facets and nuances, disclose the existence of different types of sensitivity analysis techniques. A concise description of three macro-categories is included in the next sub-section.

2.2. Macro-categories

Techniques for sensitivity analysis are broadly categorized into three main macro-classes: screening methods, Local Sensitivity Analysis (LSA) and GSA (Li et al., 2023). A brief overview is reported in the following.

As implied by the name of this macro-class, screening methods are designed to screen out the non-influential variables in a model (Campolongo et al., 2011). Such methods are particularly useful when a large set of variables is considered, and the computational cost is prohibitive. By excluding the unimportant variables from the model, it is possible to pinpoint the variables to be prioritized for a more refined analysis with more (computationally) expensive techniques. In this regard, these methods can be utilized in the initial stage of a sensitivity analysis.

An example of this macro-class is the Morris method (Morris, 1991), which qualitative evaluates the importance of input variables by computing incremental ratios, called Elementary Effects (EEs). Through a statistical analysis of such EEs, variables can be categorized as factors with non-influential effects, factors with linear and/or additive effects, and factors with nonlinear and/or interaction effects. An improvement of the Morris screening method has been presented in (Campolongo et al., 2007).

LSA is the historical approach to sensitivity analysis. It focuses on assessing the impact of minor perturbation in input variables on the output of a model. The process typically examines how variations in one parameter alter the output assuming all other parameters remain unchanged, with a technique called One-at-a-Time (OAT) method. The input parameter is perturbed around a nominal or default value, and its impact on the output is primarily obtained by derivative-based techniques to calculate the corresponding sensitivity coefficient.

The main advantage of LSA techniques is that the resulting sensitivity coefficients are intuitive and straightforward to interpret. However, these methods postulate that the correlations between input and output variables are monotonic and that interactions among parameters are negligible. These assumptions could not be valid in complex systems, where models are often non-linear and the interactions among parameters significantly affect the output, thus limiting the accuracy of the analysis results. Two examples of LSA are the Forward Sensitivity Analysis Procedure (FSAP) and the Adjoint Sensitivity Analysis Procedure (ASAP) proposed by Cacuci (Cacuci, 2003; Cacuci et al., 2005).

To overcome the limitations of LSA methods, GSA has been developed. Moving away from a 'local' approach, GSA methods seek to calculate the impact on the output variables by changing simultaneously all the input parameters. Moreover, the entire input parameter space is covered, and their range of variation is not limited to a small interval around a nominal or default value. From a general view, GSA methods can be subdivided into three main categories:

- regression-based, in which regression techniques are employed to construct a statistical model relating input and output variables. Non-parametric methods using linear regression techniques (such as the Standardized Regression Coefficient (SRC), the Pearson Correlation Coefficient (CC), the Standardized Rank Regression Coefficient (SRRC), the Spearman CC, etc.) can be easily fit in the framework of a Monte Carlo UA (Borgonovo and Plischke, 2016);
- variance-based, which features the decomposition of the output variance. Methods belonging to this category aim at measuring how much each input parameter plays a role in the output variability. The Sobol method, for example, quantifies how much variance in the output can be explained by changes in each input, both individually and through interactions with other inputs, by means of Sensitivity Indices (SIs), namely the total SI (measuring the overall impact of an input parameter on the output variance, considering all interactions with other inputs), the first-order SI (considering only the direct contribution of an input parameter) and higher-order SIs (evaluating the contribution stemming from the interaction among two or more input parameters) (Sobol′, 2001, 1993);
- density-based (or moment-independent methods), in which the aftermath of varying an input parameter is evaluated by analyzing the entire output distribution. In (Borgonovo, 2007), the sensitivity index quantifies the input effect calculating the distance between conditional and unconditional distributions of the output.

In addition to the three macro-categories as discussed above, the past decade has witnessed a significant expansion in the adoption of artificial intelligence and Machine Learning (ML) methods. This growing trend has paved the way for the integration of ML techniques into sensitivity analysis. A twofold direction can be identified: first, the use of ML/data-driven approaches to complement and extend the capabilities of more traditional sensitivity analysis methods; and second, the development of surrogate models that might replace computationally intensive simulations.

The proposed overview offers only a brief introduction. Comprehensive reviews of sensitivity analysis methods already exist in the literature, offering detailed discussions of their theoretical foundations, applications, and limitations (Borgonovo and Plischke, 2016; Cacuci et al., 2005; Helton et al., 2006; Hofer, 1999; Iman et al., 1981; Ionescu-Bujor and Cacuci, 2004; Kleijnen and Helton, 1999; Saltelli et al., 2008; Storlie and Helton, 2008). Some recent reviews includes additional information on the application of Machine Learning (ML) techniques to sensitivity analysis (Razavi et al., 2021; Wei et al., 2015).

3. Historical overview

Within the framework of SAs, sensitivity analysis is exploited in two different ways. On one side, individual sensitivity studies are often developed to address the impact of an input parameter on an output variable. On the other side, most examples found in literature associate sensitivity analysis with UA, with the primary objective being the identification of the parameters predominantly contributing to the output uncertainty as quantified in the UA.

Given that the initial Uncertainty and Sensitivity Analyses (UASAs) emerged in the 1980s, the proposed historical overview will start from that period and extend to the last five decades. For each decade, the review will concentrate on three key aspects: the primary focus of the sensitivity analyses, the most prevalent sensitivity analysis techniques employed, and the main documents published.

3.1. *The 1980s: early development*

The 1980s marked a foundational era for the application of sensitivity analysis within the domain of nuclear safety. During this decade, the conceptual development of sensitivity analysis began to emerge, and some efforts were dedicated to its application for accident consequence analyses. These efforts laid the groundwork for the systematic approaches that would characterize the next decades of research and regulatory practices in the field.

In this framework, the opening act was in 1982, with the publication of the Sandia Siting Study (Sandia National Laboratories, 1982). This study, which was born to provide guidance for new siting criteria, highlighted the beneficial nature of sensitivity analysis in evaluating the potential impact of an accident in a NPP. Specifically, the CRAC2 code (the predecessor of the modern MACCS code) was employed to conduct a large number of calculations to characterize the accident consequences quantified through early fatalities and health effects. These evaluations were based on the parametric variations of input data and model parameters, such as site meteorology and population, source term magnitude and emergency response.

A few years later, in 1985 and 1987, the same CRAC2 code was used for two distinct sensitivity analyses, this time in combination with an uncertainty evaluation. In (Alpert et al., 1985), the authors performed a demonstration UASA focusing on accident consequences and considering 17 input variables. The variability observed in the outcomes was considered as an indicator of potential uncertainty linked to the calculation. Moreover, the sensitivity analysis, carried out by means of stepwise regression and SRCs, pointed out the need to concentrate research efforts on the parameters that contributed most to the uncertainty of the results. In (Benjamin et al., 1987), an analysis was carried out to evaluate, for the Surry 1 Pressurized Water Reactor (PWR), the uncertainty in the risk connected to several SA-related concerns. Alongside the uncertainty evaluation, rank regression was selected to explore the extent to which several specific issues impact the overall variance of the results. Once identified Direct Containment Heating (DCH) as the major contributor, a second analysis was performed to determine the relevance of other issues when excluding DCH from the calculations.

In 1986, a pioneering contribution to the field was offered by Khatib-Rahbar et al., within the frame of the "Quantification and Uncertainty Analysis of Source Terms for Severe Accidents in Light Water Reactors" (QUASAR) (Khatib-rahbar et al., 1986). In this document, the authors described a methodology for UASA of SA sequences in Light Water Reactors (LWRs) with the Source Term Code Program (STCP). For the first time, the UASA focus was directed towards the actual assessment of the Source Term (ST) rather than the consequences of its release to the environment. The methodology foresaw a sensitivity and importance analysis by means of regression techniques. An application of this methodology is provided in (Khatib-Rahbar et al., 1989).

In 1988, Iman and Helton (1988) investigated UASA techniques for three different computer models for complex processes: PATHWAYS (describing radionuclides transport in the environment), MAEROS (modeling aerosol dynamics involving multiple components), and DNET (analyzing salt dissolution in bedded salt deposits). In this study, SRCs were compared to normalized coefficients, SRRCs and Partial Rank Correlation Coefficients (PRCCs). In addition, the authors suggested the use of scatterplots as a great visualization aid for detecting input-output relationships.

In 1989, an Uncertainty and Sensitivity (U&S) investigation for a Station Blackout (SBO) scenario at a Mark I Boiling Water Reactor (BWR) was carried out (Helton and Johnson, 1989). The analysis, performed with the simplified ST model RELTRAC, addressed the impact of various input parameters on the cumulative release fractions of Iodine and Strontium to the environment. To this end, the STEP program was employed to perform stepwise regressions with both raw and rank data, and to calculate the corresponding standardized coefficients.

In 1989, the publication of the Code Scaling, Applicability and Uncertainty (CSAU) methodology (USNRC, 1989b) further affirmed the role of sensitivity analysis within the accepted framework for safety studies. The CSAU methodology, in fact, specified a set of 14 steps to prepare for and conduct an uncertainty evaluation. Notably, step 12 was related to sensitivity analysis, requiring sensitivity studies to analyze the effect of variability in specific parameters on the safety response of the system. Although originally developed for thermal-hydraulic codes, the report also indicated a potential application of the CSAU methodology across other areas, including SAs.

During the same period, there was significant focus also in Europe on assessing the radiation-related implications of an accident, particularly in Federal Republic of Germany with the development of the UFOMOD code (Ehrhardt et al., 1988). The code was structured in a way to allow straightforward retrieval of parameter quantities and the outputs of the

Table 1
Summary of the 1980s - early development of sensitivity analysis in SAs.

Research Focus	First UASAs, mostly related to accident consequence modeling.
Typical Methods	Regression-based approaches (stepwise regression, SRC, PRCC); exploratory parametric variations.
Key Contributions	Sandia Siting Study (1982); QUASAR (1986); CSAU (1989).
Main Insights	Established the methodological foundation for quantitative sensitivity analysis and its integration with early uncertainty assessments in nuclear safety.

different sub-models, thereby facilitating UASAs. Some outcomes of U&S studies using the UFOMOD code are reported in (Ehrhardt and Fischer, 1989; Fischer et al., 1990).

Table 1 provides an overview of the main research focus and key findings covered in this section.

3.2. The 1990s: systematic evolution

Following on from the early applications of the previous decade, the 1990s witnessed a continuation of UASAs for assessing reactor accident consequences. This period marked an increased adoption of the more recent MACCS code.

In 1990, USNRC published the NUREG-1150 (USNRC, n.d.), as a follow-up to the Reactor Safety Study (USNRC, 1975) and Reactor Siting Study (Sandia National Laboratories, 1982). The report, which summarized the re-assessment of SAs-related risk for five commercial NPPs in the US, included a number of sensitivities studies to better characterize the accident progression and to address the impact of emergency actions on the accident consequences. Furthermore, references were made to the use of regression-based sensitivity analysis and PRCC for risk mean value and risk complementary cumulative distribution function, respectively.

In 1992, Helton et al. performed an exploratory sensitivity analysis with the MACCS code (Helton et al., 1992). Stepwise regressions, along with SRCs, were employed to determine a subset of important parameter (out of the 56 initially considered) to be used as a reference for subsequent UASAs with MACCS.

Building on the results obtained in (Helton et al., 1992), Helton et al. published a series of papers in 1995, covering distinct offsite consequences associated with a SA in a NPP. In particular, UASAs were carried out to address early exposure (Helton et al., 1995a, 1995b), food pathways (Helton et al., 1995c) and chronic exposure (Helton et al., 1995d). All the referred works employed several methods for sensitivity analysis, namely stepwise regression, related SRCs (with raw, rank-transformed and log-transformed data), and PRCCs.

The 1990s additionally marked the beginning of a collaboration between the Commission of European Communities (CEC) and the USNRC. This partnership primarily focused on a joint project addressing UA of probabilistic accident consequence codes for nuclear applications (USNRC, 1998; 1997a; 1997b; 1995a; 1995b). Although the main emphasis was devoted to the uncertainties in the results as calculated by the MACCS and COSYMA (the successor of UFOMOD) codes, sensitivity analyses were also conducted. In this case, sensitivity studies were performed prior to the uncertainty step, with the main aim being the identification of the code input parameters to be included in the actual UA.

Table 2 provides an overview of the main research focus and key findings covered in this section.

3.3. The 2000s: advancements with integral codes

The 2000s experienced a slight slowdown in the publication of research related to sensitivity analysis in the context of SAs. However, this decade was marked by two significant developments: the expansion of the UASA applicability domain to more complex and integrated codes, such as the MELCOR code, and its potential application to Probabilistic Safety Assessment (PSA) level 2.

As for the former, in 2005, Gauntt proposed a study to demonstrate the potentialities of a probabilistic approach to achieve a more precise assessment of safety margins, highlighting the effectiveness of probabilistic methods as a viable alternative to the more traditional deterministic approaches and as a valuable tool in support to risk-informed regulation (Gauntt, 2005a). This study integrated the use of the MELCOR 1.8.5 SA code with UASA into two distinct applications: the first aiming at estimating the hydrogen amount that may be expected to be produced under SBO conditions in the Sequoyah NPP (Gauntt, 2005b); the second focusing on the aerosol deposition within the AP1000 containment (Gauntt, 2004). Both applications relied on regression-based methods to investigate the parameters most responsible for the variance in the results, utilizing the coefficient of determination (R-squared) as an indicator of parameters' influence.

As for the latter, Devictor discussed the use of UASA within the framework of SA studies and PSA level 2 analyses (Devictor, 2004; Devictor and Bolado-Lavín, 2005). Together with reporting UA techniques suitable for PSA level 2, the studies reviewed various sensitivity analysis methods highlighting their limitations:

- On one side, sensitivity measures (such as SRC, PRCC, Pearson and Spearman CCs) can be easily calculated during the post-processing phase of UA results. However, the reliability of their outcomes is closely tied to the underlying assumptions of linearity and monotonicity;
- On the other hand, more complex methods, such as Sobol or FAST, require extensive computational resources due to the significant amount of computations involved, which challenge their practical application to a full PSA level 2.

Regardless of these shortcomings, the critical role of sensitivity analysis in informing decision-making processes was underscored, affirming its significance in enhancing the robustness of safety assessments.

In addition to what reported above, it is worth mentioning the work proposed by Iooss et al., in 2009 (Iooss et al., 2009). The paper described the functionalities of the LEONARD fast-running software, with a particular focus on its dedicated UASA toolbox. Specifically, the sensitivity analysis, carried out by means of SRCs, assessed the influence of different input parameters on the corium mass within the reactor pit for two different scenarios: one considering the injection of water in the reactor cavity, one without any injection. Furthermore, scatterplots were recommended to corroborate or detect anomalies in the results.

Table 2
Summary of the 1990s - systematic evolution and international cooperation.

Research Focus	Formalization of UASAs for reactor accident consequences; start of collaborative programs.
Typical Methods	Regression-based approaches (stepwise regression, SRC, PRCC); exploratory parametric variations.
Key Contributions	NUREG-1150 (1990); Helton et al. (1992, 1995); USNRC-CEC collaboration series (1995–1998).
Main Insights	Standardized statistical sensitivity techniques and promoted US-EU collaboration.

Table 3
Summary of the 2000s - expansion to integral codes.

Research Focus	Application of UASA methodologies with integral SA codes and PSA Level 2 studies.
Typical Methods	Regression-based measures (SRC, PRCC, R-squared).
Key Contributions	Gauntt (2004, Gauntt, 2005a); Devictor (2004); Devictor and Bolado-Lavín (2005); Iooss et al. (2009); Glaeser (2008).
Main Insights	Demonstrated feasibility of integrating probabilistic and best-estimate approaches with UQ studies, highlighting the need to balance accuracy and computational cost.

Lastly, the 2000s saw the birth and development of the so-called GRS method (Glaeser, 2008). This method required a lower number of calculations to obtain a 95 % probability and 95 % confidence levels in the outcomes obtained by the UA, and it featured the possibility to evaluate sensitivity measures through the evaluation of SRRCs, rank CCs and correlation ratios. Although not directly linked to SA analyses, the GRS method represents a pivotal document, since it influenced many of the SA-related UASAs carried out in subsequent years.

Table 3 provides an overview of the main research focus and key findings covered in this section.

3.4. The 2010s: the dawn of SOARCA

The 2010s were defined by the State-of-the-Art Reactor Consequence Analyses (SOARCA) project, a significant initiative by USNRC. Leveraging decades of research, the SOARCA project aimed at providing a more realistic comprehension of the possible outcomes and the impact on the public health resulting from a postulated SA. To this end, updated plant information as well as optimized data for emergency plans and response were included. In addition, the analysis was carried out by using two state-of-the-art computer codes, namely the MELCOR code to analyze the accident progression and the MACCS2 code to assess offsite consequences.

The initial phase of the SOARCA project dealt with the integrated analysis of two NPPs, namely the Peach Bottom BWR and the Surry PWR (USNRC, 2013a, 2013b). The selected NPPs have been the subjects of previous studies (Sandia National Laboratories, 1982), which allowed for meaningful comparisons and continuity in research. Furthermore, a large number of sensitivity studies were conducted to assess different scenarios and to examine key issues related to accident progression, accident mitigation, and offsite consequences.

The series of sensitivity assessments performed in the first part of the SOARCA project laid the foundation for its second phase, which aimed at supplementing the previous studies by incorporating the results from UASAs. In particular, the outcomes of such analyses were detailed in three separate reports, each dedicated to one of the considered NPP: Peach Bottom (U.S. NRC, 2016), Surry (U.S. NRC, 2022) and Sequoyah (USNRC, 2019). A fourth report (USNRC, 2022) summarized the results and collected the main findings from the three aforementioned UASAs. Additionally, project's insights and methodologies were published in a series of conference and journal papers (Bixler et al., 2018, 2020; Ghosh et al., 2017, 2021; Mattie et al., 2017), thus contributing to expanding the body of knowledge in the field.

In all the UASAs conducted within the framework of the SOARCA project, sensitivity analysis was employed in two distinct manners: on one side, it was integrated within the UA; on the other side, it was also conducted in terms of separate sensitivity studies. In the integrated approach, various advanced techniques were utilized, including rank stepwise regression, quadratic regression, recursive partitioning tree, and multivariate adaptive regression splines. Conversely, in the separate studies, the OAT method was applied, allowing for the examination of specific issues. In addition (Ghosh et al., 2017), also referred to a graphical approach to sensitivity analysis, indicating scatterplots as a valid qualitative way to visualize input-output relationships and 3d contour plots as a valuable alternative to scatterplots when two parameters guide the sensitivity analysis.

The SOARCA UASAs represented a significant advancement in nuclear safety analysis. Nonetheless, throughout the decade, the growing interest in applying U&S techniques was further evidenced by a variety of additional contributions:

- In 2012, a UASA of the TMI2 accident was conducted using the SCDAP/RELAP5 code (Rao et al., 2012). SRRCs and PRCCs were used to determine the sensitivity/relevance of input parameters in relation to the key output variables, also denoted as Figures Of Merit (FOMs);
- In 2015, a Bayesian nonparametric approach was employed to construct a surrogate model to replace the computationally expensive MELCOR model for the estimation of the ST during a SA in a BWR. The employment of a surrogate model allowed the calculation of Sobol' SIs for both total and first-order effects. Pearson and Spearman CC were also determined (Zheng et al., 2015);
- In 2015, an ensemble-based sensitivity analysis for SA modeling is proposed (Hoseyni et al., 2015). In this work, three different sensitivity measures, namely the input saliency, the Hellinger distance and the Kullback-Leibler divergence, are calculated and then aggregated to obtain the final sensitivity ranking;
- In 2016, an integrated approach for a UASA of the ST in a Fukushima-like scenario was proposed (Zheng et al., 2016). First, a screening method using EE was employed to screen out less important parameters. Second, the actual UA was performed with the MELCOR code. Third, a Bayesian surrogate model is created and employed to carry out a sensitivity analysis following the Sobol' theory;
- In 2017, a UASA for a SA in a VVER-1200 was carried out following the GRS methodology (Gasparov et al., 2017). A total of 93 calculations with SOCRAT/B1 code was employed for both UA and subsequent sensitivity assessment. Sensitivity results were reported in terms of the Kendall's rank CC;
- In 2018, uncertainties on the heat removal from the molten core during the ex-vessel phase of a SA for a APR-1400 were assessed using the Korean COOLAP-I code (Hwang et al., 2018). SRCs, Partial Correlation Coefficients (PCCs), Pearson and Spearman CCs were selected as importance indices.

Table 4 provides an overview of the main research focus and key findings covered in this section.

Table 4
Summary of the 2010s – SOARCA paving the way for large-scale UASAs.

Research Focus	Large-scale implementation of BEPU and UASA within the SOARCA program and related initiatives.
Typical Methods	Regression-based techniques (SRC, PRCC, multivariate adaptive regression splines); OAT studies; graphical approaches (scatterplots, contour plots). First applications of CCs, variance-based and screening methods.
Key Contributions	SOARCA series (2013–2020); Zheng et al. (2015, 2016); Hwang et al. (2018).
Main Insights	Marked a turning point toward integrated BEPU frameworks, combining deterministic and probabilistic evaluations in SA modeling.

3.5. The 2020s: collaborative frontiers

The 2020s saw an exponential increase in the number of works devoted to UASA of SA scenarios. This surge originated from both the impetus coming from the previous decade and the collaborative projects that unfolded during the period. By fostering international collaboration, these projects, such as the EURATOM MUSA project (Herranz et al., 2021, 2025) and the IAEA CRP I31033 (IAEA, 2024c, 2024b, 2024a, 2023), played a pivotal role in advancing the application of UASA to SAs.

As for the MUSA project, its main objective was to quantify the uncertainties associated to SA codes predictions when modeling SA scenarios, with particular focus on the radiological ST. Within the project, 28 organizations from three continents worked together to review existing Uncertainty Quantification (UQ) methodologies, to establish a database of system code input parameters, and to conduct UASAs at two distinct levels: first targeting a simplified yet representative SA scenario as a training exercise (Angelucci et al., 2022, 2024a; Angelucci and Paci, 2023; Mascari et al., 2022; Mascari et al., 2024a,b; Tiborcz and Beck, 2024) and then addressing reactor (Angelucci et al., 2024a, 2025; Brumm et al., 2023, 2025; Iglesias et al., 2024; Mascari et al., 2024a; Tiborcz and Beck, 2025) and spent fuel pool scenarios (Coindreau et al., 2023; Garcia et al., 2024). In most cases, sensitivity analysis was limited to Pearson and Spearman CCs, addressing only linear or monotonic relationships. However, in (Angelucci et al., 2022, 2025; Angelucci et al., 2024a,b), regression-based Feature Selection (FS) techniques were applied. Specifically, forward and backward stepwise regressions, together with the LASSO regularization (backed up by cross-validation), were implemented alongside the more commonly used Pearson and Spearman CCs.

Similarly to the MUSA project, the IAEA CRP I31033 established an international framework where experts from all over the world joined efforts to advance the characterization and quantification of uncertainties in simulations' results from SAs codes. As a result, a number of journal papers (Ahn, 2024; Ahn et al., 2024; Ahn and Park, 2022; Choi et al., 2022) and 4 technical documents were published, with applications related to PWRs and Small Modular Reactors (SMRs) (IAEA, 2023), CANDU reactors (IAEA, 2024c), BWRs (IAEA, 2024a) and the QUENCH-06 test (IAEA, 2024b). Depending on the application domain, different sensitivity analysis techniques were employed:

- For PWRs and SMRs, a number of techniques were chosen featuring both commonly used regression-based coefficients (Pearson CC, Spearman CC, Kendal CC, PCC, PRCC, SRRC) and more advanced techniques (such as generalized perturbation theory and Principal Component Analysis (PCA));
- For CANDU reactors, only Pearson and Spearman CCs were evaluated;
- For BWRs, most organizations limited the analysis to Pearson and Spearman CCs. However, one organization went a bit further using a Monte Carlo filtering technique;
- For the QUENCH-06 application, Pearson and Spearman CCs were employed as sensitivity measure by all the organizations. One partner, however, was able to calculate Sobol SIs, for both total and first-order effects.

In addition to the considerable work done within the aforementioned reports, a large number of studies were produced in the same years. Various SAs codes (MELCOR, MAAP, SCDAP/RELAP5, ASYST, ASTEC, SOCRAT, AC2, …) and several topics were included in the analyses, as can be noticed in (Chen and Wang, 2023; D'Onorio et al., 2022, 2021; Darnowski et al., 2021; EPRI, 2021; Gharari et al., 2021; Guo et al., 2021; Malicki and Lind, 2023; Morreale et al., 2023; Nistor-Vlad et al., 2023, 2024; Ryzhov et al., 2023; Sadek et al., 2021; Stakhanova et al., 2023a, 2023b; Wang et al., 2022; Yang et al., 2024).

To conclude the section, it is worth mentioning three other works in which less common sensitivity analysis techniques were used. For example, in (Amidu et al., 2022) the application of the Sobol method is supplemented by the Cotter Indices methods, which "permits the ranking of the input parameters and applies to any situation irrespective of the dependence between the input variables". In (Nicoulaud-Gouin et al., 2022), instead, three different techniques are employed (namely Spearman CC, Morris and Sobol methods), exploiting regression-based, variance-based and screening methods for sensitivity analysis. Lastly, in (Song et al., 2023), the authors introduced the Grey CC, a method already used in fault diagnosis, in the attempt to take into account the variation of parameters' impact with the accident progression.

Table 5 provides an overview of the main research focus and key findings covered in this section.

Table 5
Summary of the 2020s - collaborative frontiers and data-driven methodologies.

Research Focus	International collaboration and methodological innovation in SA-related UASA.
Typical Methods	CCs; Regression coefficients (PRCC); feature-selection techniques (LASSO, stepwise regression); Sobol- and Morris-based GSA; ML-assisted methods.
Key Contributions	MUSA project; IAEA CRP I31033.
Main Insights	Characterized by extensive international cooperation, broader code applications, and the first integration of machine-learning approaches into SA sensitivity frameworks.

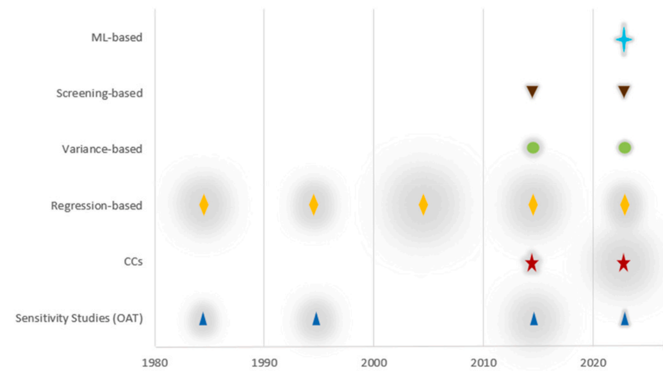

Fig. 1. Evolution of sensitivity analysis techniques applied to SA studies in the past five decades (1980–2020). Early decades were dominated by OAT and regression-based approaches, while more recent years have seen the introduction of correlation-, variance- and screening-based methods, as well as ML applications. The relative frequency of each technique's use is qualitatively represented by the size of the halo surrounding each marker.

4. Discussion & future directions

This review paper traces the historical evolution of the application of sensitivity analysis techniques to the SA domain over the past five decades. Coherently with its main objective, this review specifically excludes applications of sensitivity analysis outside the addressed domain. By restricting the field and narrowing the scope, it provides a comprehensive examination of significant developments and pivotal documents[1] that have shaped the current practice, additionally offering insights for future advancements.

Reflecting its historical perspective, the paper outlines the sensitivity analyses conducted in each decade, starting from the 1980s. For each period, several aspects are explored: the primary focus of the analyses themselves, the different codes employed for their unfolding, the main

[1] It is important to acknowledge that data availability and accessibility did often present challenges, particularly concerning older projects.

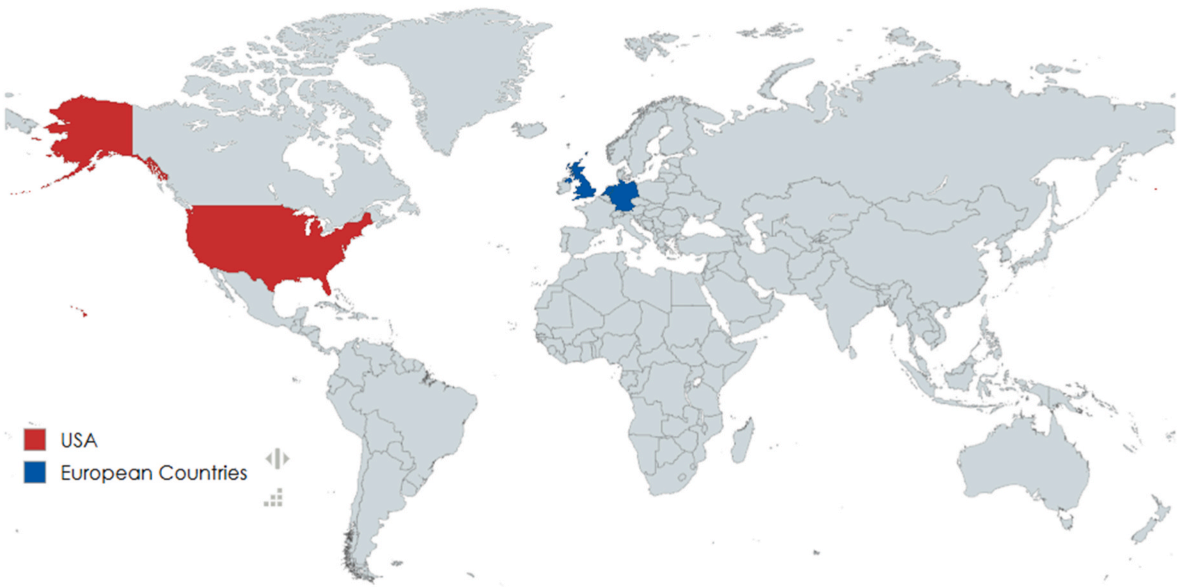

Fig. 2. Geographical distribution of sensitivity analysis contributions within the SA field - before year 2000. During the formative decades of SA research, sensitivity analysis applications were largely confined to United States and Western Europe.

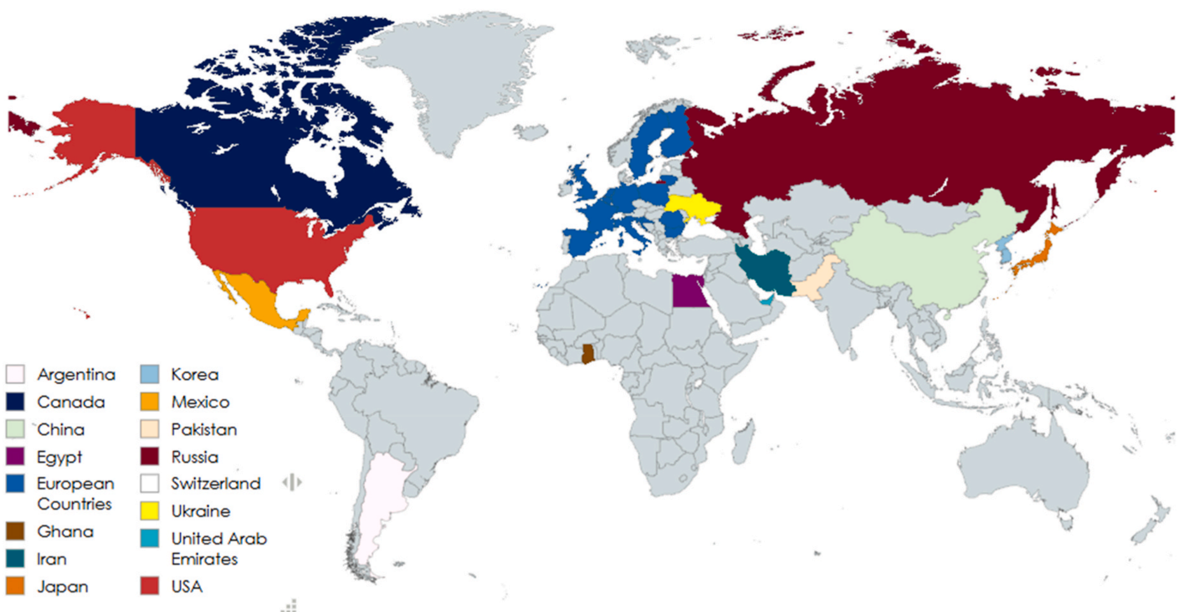

Fig. 3. Geographical distribution of sensitivity analysis contributions within the SA field - post year 2000. In contrast with the earlier period, sensitivity analysis – related research expanded worldwide, with an increasing participation from Asian countries and a broader set of European partners.

documents published, and the sensitivity analysis methods employed.

In this regard, as the large amount of information provided might be misleading to some extent, a visual summary of the techniques employed through each decade is included in Fig. 1. Moreover, Fig. 1 additionally offers a visualization of the relative use of each group of techniques across the decades, using the size of the halo around the markers to qualitatively indicate their frequency of use.

Fig. 1 clearly illustrates significant progress made in the past 15 years, with the integration of more advanced techniques (such as SIs, ML and data driven methodologies) into sensitivity analyses. These advancements address the limitation of simpler methods, which often cannot accommodate the complex, non-linear nature of nuclear systems and SA phenomenology. However, despite the progress, many recent applications still rely on CCs and regression-based techniques, due to the ease of computing them and their lower computational demands. This underscores the need for a balance between computational cost and model accuracy.

Figs. 2 and 3 illustrates the geographical distribution of the different contributions to sensitivity analysis in the SA field on a world map, allowing for a comparison among the eras pre- and post- 2000. These visuals clearly depict a shift from a predominant contribution from the US and Europe to a more globally distributed participation after the year 2000, highlighting the increasing international engagement in this research area.

Building upon the foundation laid by the present individual and shared expertise, there is considerable potential for further progress, by availing the work performed in other domains and integrating advanced techniques, such as (but not limited to) ML data-driven methodologies.

By doing so, it will be possible to efficiently explore high-dimensional parameter spaces, identify complex and non-linear dependencies between inputs and outputs, and enhance the overall robustness of the analysis. Furthermore, by exploiting ML to implement less computationally demanding models, the resulting reduction in computational cost might promote the use of the more demanding techniques and a more accurate application on ML-based sensitivity analysis approaches.

Future research could leverage the momentum stemming from existing international collaborations to develop more comprehensive benchmarks and, eventually, guidelines for a systematic and standardized application of sensitivity analysis within the SA field.

CRediT authorship contribution statement

Michela Angelucci: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Salvatore A. Cancemi:** Writing – review & editing. **Sandro Paci:** Writing – review & editing, Supervision. **Luis E. Herranz:** Writing – review & editing, Supervision.

Funding

This research received no external funding.

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.

Acknowledgements

The authors would like to acknowledge the valuable insights provided by the MUSA (grant agreement no. 847441) and SEAKNOT (grant agreement no. 101060327) projects, which contributed to establishing the essential background and context for the development of the present study.

Data availability

No data was used for the research described in the article.

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