



Integrating best estimate plus uncertainty analysis into model-based systems engineering

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ABSTRACT

The licensing of new nuclear reactors after the Fukushima accident presents significant challenges due to the complexity of nuclear systems and the stringent regulatory requirements involved. Model-based systems engineering (MBSE) has emerged as a useful approach for managing the development of such complex systems, while Best Estimate Plus Uncertainty (BEPU) methodologies have proven valuable within regulatory frameworks for safety evaluation. However, digital models and databases that are needed to provide evidence that the system meets the specified requirements are usually isolated in discipline-specific data repositories. To address this challenge, this article proposes a model breakdown structure (MBS) methodology, using a set of interconnectable models to seamlessly integrate MBSE, computer-aided engineering (CAE) models, and BEPU analysis. The Brazilian Multipurpose Reactor (RMB) served as the system of interest to exemplify the effectiveness of the proposed methodology. A requirement specification was linked to a finite element analysis (FEA) that estimates the peak cladding temperature in a slow loss of flow accident scenario. Additionally, key design factors are identified using design of experiments (DOE) and analysis of variance (ANOVA). Lastly, Wilks' theorem and Monte Carlo simulations are applied for uncertainty quantification. The results indicate that the 95/95 upper tolerance limit of the peak cladding temperature remains below the onset of nucleate boiling. Furthermore, the utilization of Wilks' theorem can reduce computational cost for uncertainty quantification, and the effect of sampling methods is negligible in Monte Carlo simulations with large sample sizes. This approach can enhance the verification and validation (V&V) of regulatory requirements in the licensing process of new reactors.

1. Introduction

Nuclear facilities must undergo a comprehensive licensing process, which establishes various regulatory requirements from site selection to decommissioning. Throughout the entire life cycle, compliance with safety standards is typically demonstrated through simulations—either conservative or best estimate (realistic) models—making integration between modeling and simulation tools particularly valuable. According to D'Auria (2019), the Best Estimate Plus Uncertainty (BEPU) is an approach of particular interest to the licensing process of nuclear power plants (NPPs), which results from an interaction of deterministic safety analysis and probabilistic safety assessment. In the BEPU approach, both

experiments and computational models are applied to provide the best estimate of the technical performance parameter along with an uncertainty analysis.

The BEPU history remounts the United States Nuclear Regulatory Commission (U.S.NRC) pioneering efforts for verification and validation (V&V) of thermal-hydraulic codes (U.S. Nuclear Regulatory Commission, 1989). The concept of design extension conditions (DEC) had been introduced in the early 1990s and was further elaborated and incorporated into the International Atomic Energy Agency (IAEA) Safety Standards after the Fukushima accident in 2011, becoming an important aspect of the regulatory framework of NPPs (Král and Krhounková, 2024). In DEC, methodological procedures for performing safety analyses should be able to cope with a significant level of uncertainty, as

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Nomenclature

ANOVA	analysis of variance	MC	Monte Carlo method
BEPU	Best Estimate Plus Uncertainty	MOE	measure of effectiveness
CAE	computer-aided engineering	MOP	measure of performance
CCD	central composite design	MSOSA	Magic Systems of Systems Architect
CFD	computational fluid dynamics	MTR	material testing reactor
CI	confidence interval	NPP	nuclear power plant
COI	critical operational issue	NTHC1	Neutronics and Thermal Hydraulics Code
ConOps	concept of operations	ONB	onset of nucleate boiling
DBA	design-basis accident	PB	Plackett-Burman
DEC	design extension conditions	PCT	peak cladding temperature
DOE	design of experiments	PIRT	Phenomena Identification and Ranking Table
FEA	finite element analysis	PPF	power peaking factor
FFD	full factorial design	RMB	Brazilian Multipurpose Reactor
IAEA	International Atomic Energy Agency	SCRAM	reactor trip
INCOSE	International Council on Systems Engineering	SE	systems engineering
KPP	key performance parameter	SLOFA	slow loss of flow accident
LHD	Latin hypercube design	SRS	simple random sampling
LHS	Latin hypercube sampling	SysML	Systems Modeling Language
LOCA	loss of coolant accident	TL	tolerance limit
LOFA	loss of flow accident	TPP	technical performance parameter
M&S	modeling and simulation	U.S.NRC	United States Nuclear Regulatory Commission
MBS	model breakdown structure	UTL	upper tolerance limit
MBSE	model-based systems engineering	V&V	verification and validation
		WBS	work breakdown structure

fuel degradation and core melting can happen. For instance, [Matias Avelar et al. \(2023\)](#) applied BEPU analysis to study a critical safety phenomenon of water-cooled nuclear reactors in accident conditions. Thus, regarding safety analysis, either BEPU or conservative approaches may be applied for verification of regulatory requirements at different categories of accident conditions.

It is challenging and expensive to have integrated test facilities that replicate accident conditions for NPPs. Therefore, various regulatory requirements are verified through simulation. In this context, the BEPU approach becomes more important for determining the licensing margin, which is defined as “the difference between the safety limit and the upper bound design or safety analysis result (e.g., peak cladding temperature) for the related physical parameter analyzed” ([Zhang and Schneidesch, 2023](#)). The likelihood of a system meeting its requirements can be improved by revising the design to incorporate additional safety margins. In the context of the BEPU approach, such evaluations depend on the availability of experimental data to support the V&V process. For instance, [Freixa et al. \(2021\)](#) compared the results obtained by the BEPU against experimental data from integral test facility experiments. They observed that 95 % of the output parameters analyzed were inside of the BEPU spectrum, which strengthens confidence in its application to support the licensing process.

Lessons learned from the Fukushima Daiichi accident in 2011 reinforced existing safety requirements. Since then, the development of nuclear systems faces significant challenges during the licensing process, such as prolonged time and high costs ([Corrado, 2025](#); [International Atomic Energy Agency, 2016](#); [Mignacca et al., 2020](#)). However, the current document-based process hinders access to information and extends decision-making cycle times in many countries ([Nuclear Energy Agency, 2021](#)). To address this gap, a digital engineering approach can help inform regulatory authorities whether safety requirements were met.

Digital engineering provides a faster and easier way to collect and analyze data. Digital engineering is defined by the US Department of Defense as “an integrated digital approach that uses authoritative sources of system data and models as a continuum across disciplines to support lifecycle activities from concept through disposal” ([Department](#)

[of Defense, 2018](#)). The use of computational tools in the development of complex systems enables faster decision-making, better risk management, and cost reduction. As complexity increases, these tools help address the challenges of systems analysis, ensuring that systems meet performance and safety requirements. In this context, the US Department of Defense published a digital engineering strategy to change communication from documents to digital models. Within this strategy, the systems engineering (SE) transformation initiative aims to modernize how systems engineers use model-based approaches to specify, develop, and verify systems. Challenges include improving capabilities in different areas such as integration of modeling environments, including those applied to model-based systems engineering (MBSE).

MBSE is defined by the International Council on Systems Engineering (INCOSE) as “the formalized application of modeling to support system requirements, design, analysis, verification, and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases” ([International Council on Systems Engineering, 2023](#)). MBSE has already achieved a level of maturity that is commercially viable, and it is currently applied in many other sectors such defense and aerospace ([Dickerson and Mavris, 2013](#)). Common benefits of MBSE include enhanced management of system complexity and better communication among stakeholders, which is achieved through a system model.

The creation of a system model is a primary goal of MBSE. This model can be understood as an integral part of the system's technical baseline. In a broader development context, the system model exists as an integrating framework. In this approach, changes to the system requirements or to the system design are reflected in the system model and propagated through other models affected by the changes ([Friedenthal et al., 2015](#)). The rise of MBSE introduces a structured approach through interconnected models to attain this objective. The system model describes the system architecture, its concept of operations (ConOps), and its functions. The system requirements are translated into measures of effectiveness (MOEs) and measures of performance (MOPs) that are usually assessed to support decision-making and trade-off analysis. Notwithstanding, most of the data that is needed to calculate these

measures is obtained from external sources.

Modeling and simulation (M&S) approaches, along with computer-aided engineering (CAE) methods, such as finite element analysis (FEA) and computational fluid dynamics (CFD), are useful tools for engineering design. The majority of tools used for these tasks—primarily CAE or multi-physics simulations—are organized within fragmented, discipline-specific silos, leading to widely distributed and isolated sources of information (Khandoker et al., 2022). In fact, existing MBSE methodologies face significant challenges integrating the modeling and simulation of architectures and physical behaviors of complex systems, restricting its application (Gu et al., 2024). Fig. 1 illustrates this gap. Therefore, modern MBSE tools leverage SE but lack the ability to coordinate their models with the engineering disciplines domains, which constrains the ability to analyze the impact of changes across design platforms on system requirements (Gu et al., 2024; Khandoker et al., 2022; Nigischer et al., 2021; Zhang et al., 2022).

Refocusing from documents to models can offer the most accurate and current design data to stakeholders and decision-makers. Thus, MBSE can provide several benefits for the nuclear energy sector (Corrado, 2025). As the licensing process is critical for the development of new reactors, new approaches become necessary. In this sense, the application of an integrated methodology may shorten the cycle time from data gathering to decisions in the licensing process (Mignacca et al., 2020; Nuclear Energy Agency, 2021). According to Zhang et al. (2023), MBSE can provide a streamlined method for BEPU analysis, utilizing some benefits from the preceding methods already established. In addition, MBSE provides a requirements-based philosophy, which is crucial for realization of digital threads (i.e., seamless flow of data between digital models) in complex systems such as NPPs (Mengyan et al., 2024). Moreover, the integration of MBSE with computer-aided design models is a future direction of research (De Florio et al., 2024). When interconnected, these models capture the full complexity of the system. In this context, this paper proposes a novel methodology that aims to support the licensing process of nuclear systems, by using an integrated digital environment to automate the verification of requirements. In this methodology, MBSE is applied to manage requirements, demand, and receive data from an uncertainty analysis and inform safety margin to decision-making. On the other hand, CAE is applied to conduct FEA, identify key factors, and perform uncertainty quantification. To

illustrate the effectiveness of the proposed methodology, a case study is presented using the Brazilian Multipurpose Reactor (RMB) as the system of interest. The novelty of this research lies in integrating multiple methods to provide a holistic understanding of system behavior and streamline the decision-making process. Once the methods are integrated and models validated, uncertainty quantification analysis can be conducted to verify safety compliance and determine safety margins.

2. Methodology

The novel methodology, named Model Breakdown Structure (MBS), is a digital thread based on the integration of MBSE models and CAE models, which supports systems engineers and decision-makers by providing on-demand assessments of design changes and trade space analysis. By integrating MBSE into a systems development environment, multi-physics models may offer automated feedback on whether design changes meet system requirements. After the data can seamlessly flow between models, methods to enhance the requirements verification process, such as the design of experiments (DOE) and uncertainty quantification can be applied.

2.1. Integration of models to enhance the requirements verification process

MBSE is a methodology used by system engineers and technical leadership to support requirements generation and verification processes. The International Council on Systems Engineering (INCOSE) defines the verification process as “evidence is provided that the system, the system elements, and the work products in the life cycle meet the specified requirements.” (International Council on Systems Engineering, 2023). On the other hand, a validation process means that “evidence is provided that the system, the system elements, and the work products in the life cycle will achieve their intended use in the intended operational environment.” (International Council on Systems Engineering, 2023). Thus, the concepts of verification and validation from a systems perspective differ from those applied at the model level in the BEPU methodology (Zhang, 2019). In the MBSE context, the goal of the verification process is to compare the analysis output against a requirement—complementary to model-level V&V, which use both numerical

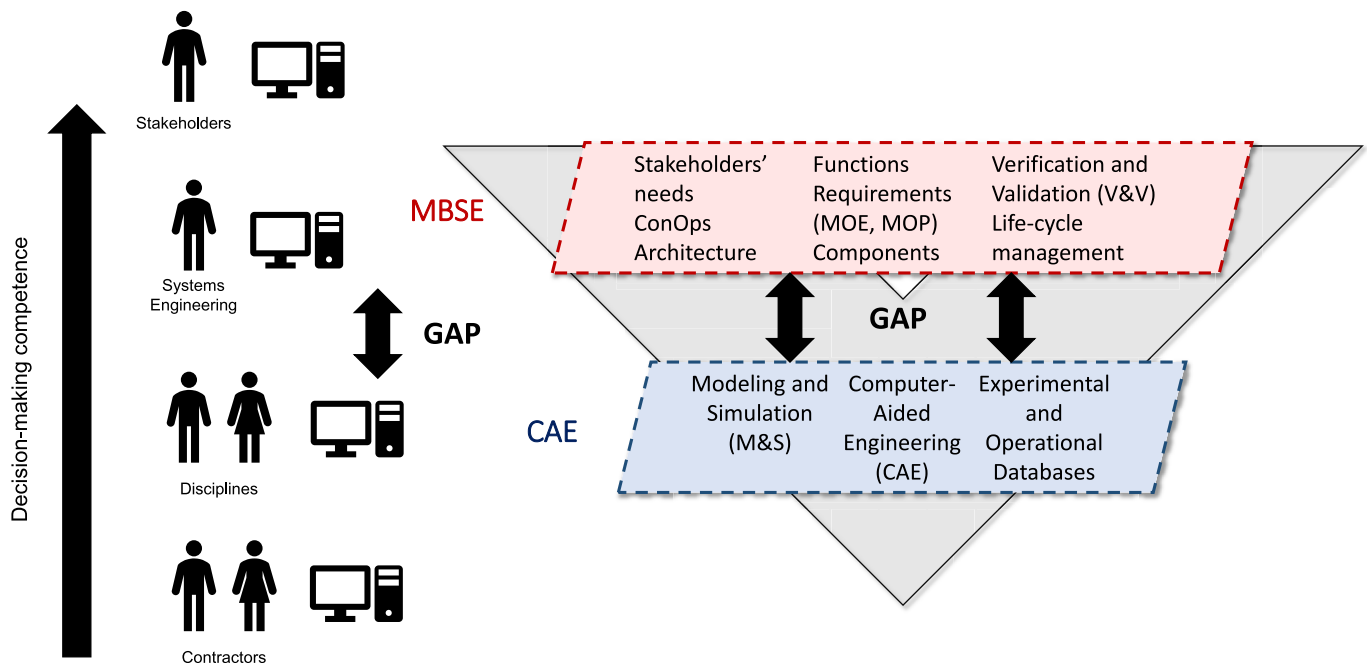


Fig. 1. Gap between MBSE tools and CAE methods bottlenecking data flow for decision-making and overlaid on the SE V-model.

and experimental results, along with scaling techniques, to ensure simulation accuracy.

The regulatory authority is a key stakeholder in the development of new reactors. Therefore, regulatory requirements should be mapped as stakeholders' needs to guide the development of the ConOps, which describes the expected system behavior under various conditions. Furthermore, to bridge the gap between SE and other disciplines, relevant acceptance criteria should be allocated to digital engineering assets. Experimental results from test facilities are also used to support model validation. Consequently, before an evaluation model is employed for requirement verification, it must be validated, preferably against experimental data. Therefore, given that one of the primary objectives of MBSE is to analyze performance and aid the verification process, it is interesting to couple MBSE with other computational models, such as CAE, by using an integrated approach that leverages MBSE application to a level where decision makers are able to apply physics-based models to perform in-depth analysis of system behavior. Fig. 2 illustrates the MBS concept, which comprises not only the typical deliverables of SE context but also delves into domain-specific models such as CAE methods, experimental databases, and simulations to provide feedback to test cases (V&V models).

As the capacity to perform the assessment of design changes and trade-space analysis is provided, this comprehensive methodology also supports the utilization of the BEPU analysis to enhance the verification process. To achieve that goal, the MBS consists of six initial steps: (1) selecting the MBSE tool; (2) developing a system model; (3) defining a set of requirements; (4) performing model V&V; (5) verifying requirements using simulation-based tests; and (6) creating an experimental design to provide an assessment of which factors have a significant effect on system requirements. For those factors that are known to have a significant impact on system requirements, three more steps are added: (7) building the MBS, (8) propagating the uncertainties

of key factors in the design, to assess their effect on the system MOEs, and (9) using the uncertainty bands, denominated as BEPU MOE, to enhance the verification process, by providing an automated feedback to the MBSE tool. Thus, the BEPU MOE means an MOE that has been assessed via a realistic code using a BEPU approach. It is worth mentioning that these three last steps are only feasible after the integration of MBSE and CAE models.

MBS concept uses existing Systems Modeling Language (SysML) digital-thread architecture. SysML is a graphical modeling language for specifying, analyzing, designing, and verifying systems (Friedenthal et al., 2015). SysML provides the ability to view the system from distinct perspectives and levels of abstraction. MBSE practitioners use SysML to develop system architecture, functions, and requirements.

A straightforward process is proposed to address the gap between MBSE and CAE. This process encompasses two different levels and aims to provide relevant data to support decision-making in the licensing process. First, in the discipline domain, key design factors are identified, and uncertainty quantification is provided for system MOEs using the BEPU approach. Next, in the systems engineering level, the information from different disciplines is integrated into a holistic digital engineering ecosystem that is able to collect and analyze data from distinct models and databases.

The effectiveness of MBS relies not only on integrating CAE into MBSE but also on applying both DOE and BEPU to assess which factors have a significant impact on the MOEs and to quantify the uncertainties on the MOEs. The first part of the MBS is conducted in a typical MBSE environment, whereas the second part of MBS is conducted in a CAE environment. The final part takes advantage of an integrated MBSE/CAE tool to enhance the verification process, as shown in Fig. 3(a). Furthermore, by the end of this process, a traceability matrix between requirements and model variables is also proposed as a support tool, illustrated in Fig. 3(b). Regulatory requirements and their respective

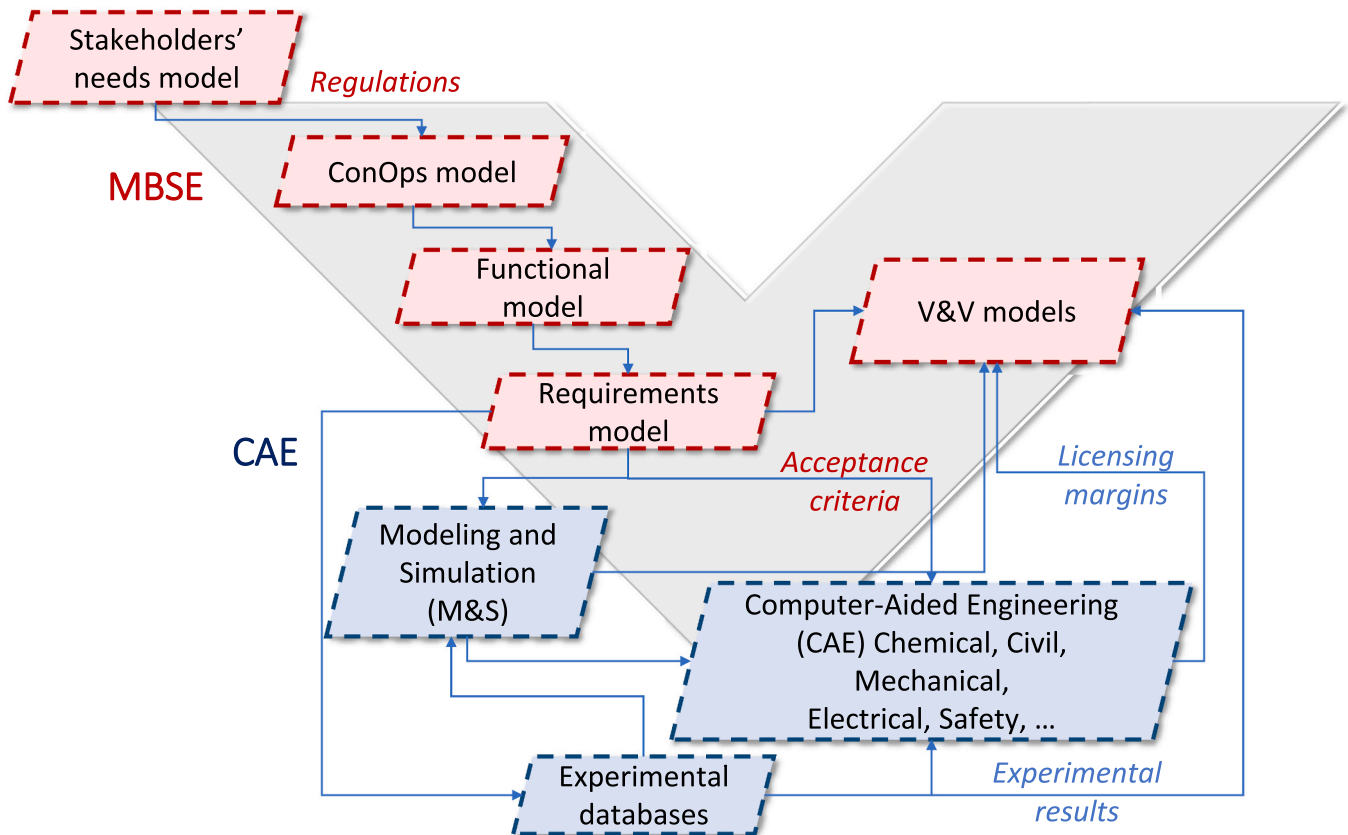


Fig. 2. MBS methodology concept illustrating the typical data flow between MBSE and CAE models.

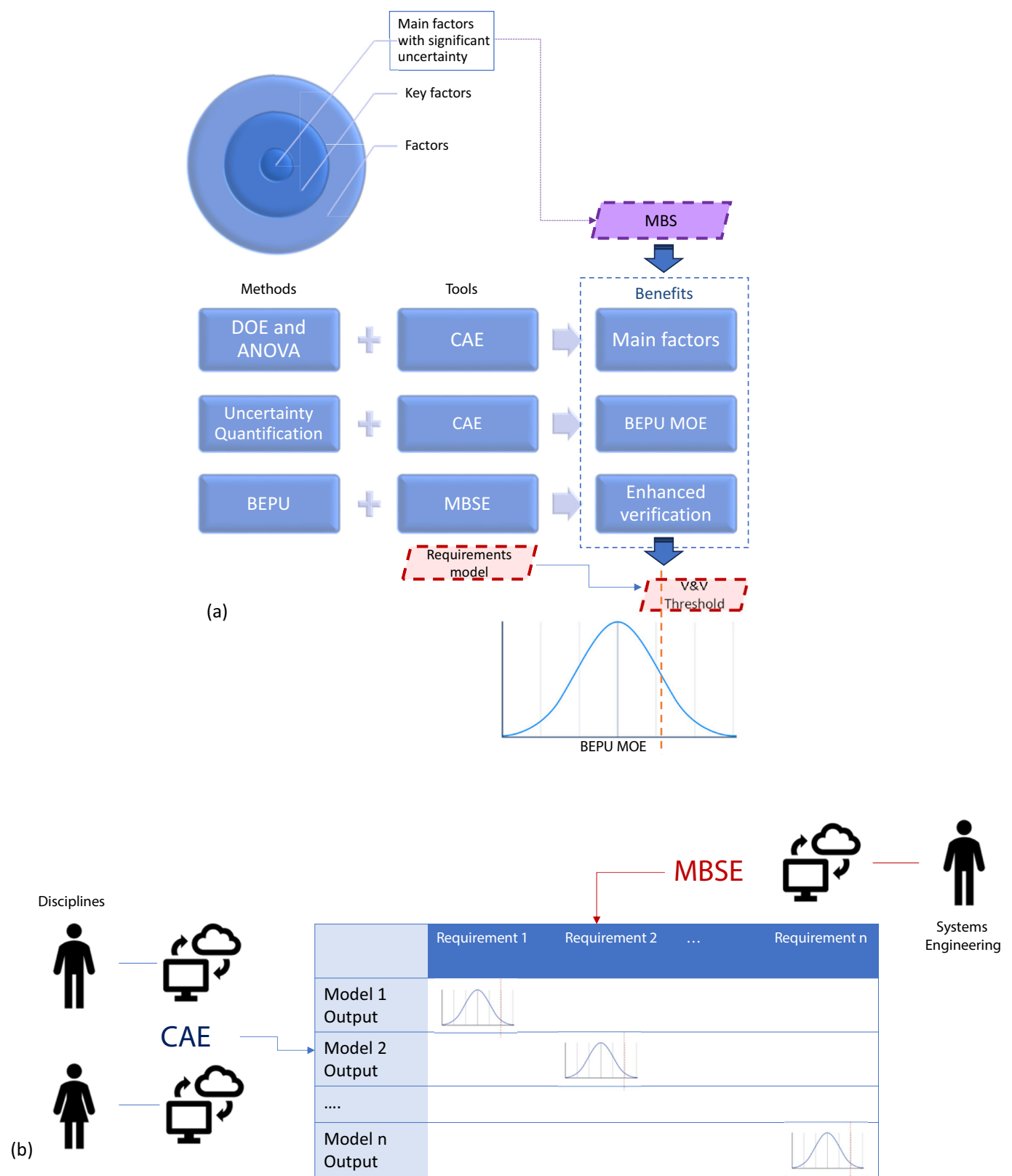


Fig. 3. MBS methodology applied to main factors with significant uncertainties to (a) enhance the verification process and (b) provide traceability between measures and models.

acceptance criteria are identified and linked to evaluation models. Therefore, this methodology helps identify which factors the design team should prioritize to improve licensing margins. Given a specific scenario and the probability distribution functions of key factors, it

defines the uncertainty bands of the MOEs, showing the expected range of system responses.

To effectively integrate MBSE into a CAE tool, it might be interesting to use a single environment that performs both capabilities. Therefore,

as previously discussed, this paper presents a result of using the MathWorks' System Composer MBSE tool as a natural extension to the MATLAB and Simulink environments enabling creation, linkage and testing system requirements within the same simulation continuum. Notably, this approach allows not only full seamless integration but also utilization of a broad variety of specific engineering domain tools developed by MathWorks' and widely used by engineers. Additionally, it also illustrates the same process by integrating Magic System of Systems Architect (MSOSA) and MATLAB, to demonstrate that other tools can also be applied. In both cases, data exchange is automated and bi-directional. Specifically, the simulation within the MBSE tool, which contains the requirements model, provides the input data, executes the Simulink model, receives the simulation results, and evaluates the licensing margin, as it can interpret acceptance criteria derived from textual requirements. This paper does not endorse one specific tool or modeling language, because MBSE practitioners might select other tools that meet their specific needs. However, the authors selected MATLAB to be applied in this paper because it provides a broad applicability to diverse types of engineering applications, including its capacity to integrate with different MBSE tools.

2.2. Modeling and simulation

The RMB is an open-core pool materials testing reactor (MTR), whose main functions are to test materials under a high neutron flux and to produce radioisotopes. Research reactors, also known as non-power reactors, are mainly utilized for purposes such as research, training, and the advancement of various nuclear technologies. They support a wide range of fields, including nuclear medicine and multidisciplinary scientific research in areas like physics, chemistry, and biology. Although they serve research objectives, these reactors must still adhere to stringent safety protocols. Safety functions must be categorized based on their safety significance. As emphasized by the IAEA, it is essential to identify all safety-related functions early in the design phase of nuclear facilities (International Atomic Energy Agency, 2022).

RMB functional requirements are defined in a specification which is part of the system specification. The scope of the functional specification is to identify and define all system functions and their safety categorization. This study considered the first level of safety functions, e.g., reactivity control, cooling, and confinement of radioactive products. Other process-related functions, instrumentation, and control functions may not be identified at an early phase of the design process. However, it is possible to repeat the process of identification and categorization of safety and non-safety related functions throughout the design stage. Conversely, it is advisable to structure functional requirements specification process in stages so that system engineers can deliver important inputs to the domain engineers (International Atomic Energy Agency, 2022).

Safety-related functional requirements are assessed by regulatory authorities in safety analysis reports throughout the licensing process. The accidents list for the RMB reactor considers typical research reactors postulated initiating events, i.e., initiators of fault sequences, which have the potential to challenge the safety limits of the reactor. The credible accidents that are part of the design-basis accidents (DBA) include among other the following scenarios: loss of electric power supplies; insertion of excess reactivity; loss of flow; loss of heat sink; and loss of coolant in the primary cooling system (Soares et al., 2014). It is worth mentioning that DEC scenarios, such as a station blackout for 10 days, can also be part of the safety report for plant behavior assessment, depending on the regulatory framework. To exemplify the application of the MBS methodology, the slow loss of flow accident (SLOFA) scenario was selected due to the availability of simulation data for code-to-code comparison (Ribeiro et al., 2020). Based on this scenario, Table 1 presents a technical measures profile, which describes the entire spectrum of measures, from a required operational capability up to a specific key performance parameter (KPP) and its associated criterion. The peak

Table 1

Example of a technical measure profile of RMB.

Technical measure	Description
Required Operational Capability	Provide cooling
Critical Operational Issue (COI)	Can the RMB provide safe shutdown after SLOFA?
Measure of Effectiveness (MOE)	The ability to remove heat from a 30-MW core during and after SLOFA
Measure of Performance (MOP) / Key Performance Parameter (KPP)	The core temperature shall be conducted to and maintained at an acceptably low value for an extended period, avoiding the occurrence of onset of nucleate boiling (ONB)
Technical Performance Parameter (TPP)	Cladding temperature
Acceptance Criterion	Peak Cladding Temperature (PCT) < 391.15 K

cladding temperature (PCT) shall be less than 391.15 K in order to avoid coolant nucleate boiling at cladding surface. This requirement is an illustrative threshold, i.e., an example of acceptance criterion for pool-type MTR (Akhal et al., 2023).

Cooling is one of the most important functions in any nuclear reactor design, especially in the case of a loss of flow accident (LOFA). The critical operational issue is stated in an interrogative form to doubt if the RMB can provide safe shutdown during and following this accident. A direct engineering measure of cooling, i.e., the basis for describing the cooling performance, is the heat transfer rate from the fuel system to the primary circuit. Nonetheless, a more usual measure of performance is the temperature at important interfaces such as the fuel-cladding outer surface. This interface temperature is critical due to other important phenomena that can take place, e.g., onset of nucleate boiling, departure of nucleate boiling, or even metal-water reaction in more severe scenarios (Matias Avelar et al., 2023). The approach shown so far has no major differences from traditional MBSE methods. The stakeholder needs are translated into a concept of operations and a functional analysis, leading to the development of MOEs, MOPs, along with requirement specification. The key benefit of the MBS approach lies in its integration with the system development environment. In this setup, requirements are directly tied to variables, realized through multi-physics models, and evaluated using V&V models.

The RMB core is designed to generate 30 MWth. Table 2 presents the RMB core data. Similar to other nuclear reactors, during its licensing process a significant number of studies have to be conducted using M&S in order to ensure the compliance with safety requirements under

Table 2

RMB core specification and dimensions (Ribeiro et al., 2020; Soares et al., 2014).

Specification	
Type	MTR
Fuel meat	U ₃ Si ₂ -Al enriched at 19.75 %
Coolant/ Moderator	Light water
Reflectors	Heavy water & Beryllium
Flow direction	Upwards
Number of control rods/ Material	6/ Hafnium
Number of fuel assemblies	23
Number of fuel plates per fuel assembly	21
Dimensions	
Core (cm)	44.35 × 41.70
Internal chimney (cm)	46.35 × 71.75
Chimney thickness (cm)	0.4
Central control rod support (cm)	9 × 10.8
Peripheric control rod support (cm)	9 × 13.27
Control rod support thickness (cm)	0.5
Fuel plate (mm)	1.35 × 75 × 655
Lateral support plate (mm)	5.0 × 80.5 × 890
Plate meat (mm)	0.61 × 65 × 615
Channel (mm)	70.5 × 2.45 × 655
Cadmium wire diameter (cm)	0.1016

different accident scenarios (Akhal et al., 2023; Ribeiro et al., 2020; Soares et al., 2014).

Usually, multi-physics models are obtained by applying fundamental physical laws which govern the behavior of the system (i.e., transition between states). In this study, FEA was used as a representative CAE method. When experimental data is not available, code-to-code comparison emerges as an alternative for model validation. This approach involves comparing the results of the numerical model against those obtained from an established or alternative computational code that employs similar methodologies. To study the core behavior during SLOFA, FEA was employed using the partial differential equation toolbox in MATLAB. Fuel and cladding were considered as the main components that play a role in this scenario. The three phases were investigated: steady state, SLOFA transient, and cold shutdown. Fig. 4 presents a schematic of the RMB. Fig. 4(a) shows the primary coolant inlet and outlet, and Fig. 4(b) shows the reactor core and the reflector tank. Fig. 4(c) shows a schematic of the cross section of some RMB fuel plates. The dashed-line box represents the two physical domains, F1 for fuel and F2 for cladding of the hottest subchannel shown in Fig. 4(d). A triangular mesh shown in Fig. 4(e), typically used in 2D analysis, was generated using the MATLAB toolbox with an approximate upper bound on the mesh edge lengths of half fuel thickness. A mesh sensitivity test

was also performed.

The temperature distribution in both domains is obtained by solving the heat equation:

$$\rho c_p \frac{\partial T(t, x, z)}{\partial t} = k \nabla^2 T(t, x, z) + Q(t, z) \quad (1)$$

where ρ is density, c_p is specific heat, T is temperature, t is time, k is thermal conductivity, and Q is the volumetric heat generation rate in the fuel, which is directly proportional to the reactor power and assumes a chopped cosine function in the axial direction of the fuel plate.

The heat equation was solved for each finite element using the MATLAB toolbox. Code-to-code comparison was performed against the Neutronics and Thermal Hydraulics Code (NTHC1) results published by Ribeiro et al. (2020). To provide code capability to perform efficient and reliable calculations, solver options were set to a relative tolerance of 10^{-5} . Additionally, to solve the SLOFA transient, the following boundary conditions were applied:

$$\frac{\partial T_f}{\partial x} = 0, \text{ at } x = 0 \quad (2)$$

$$-k_c \frac{\partial T_c}{\partial x} = h(T_c - T_w), \text{ at } x = x_{co} \quad (3)$$

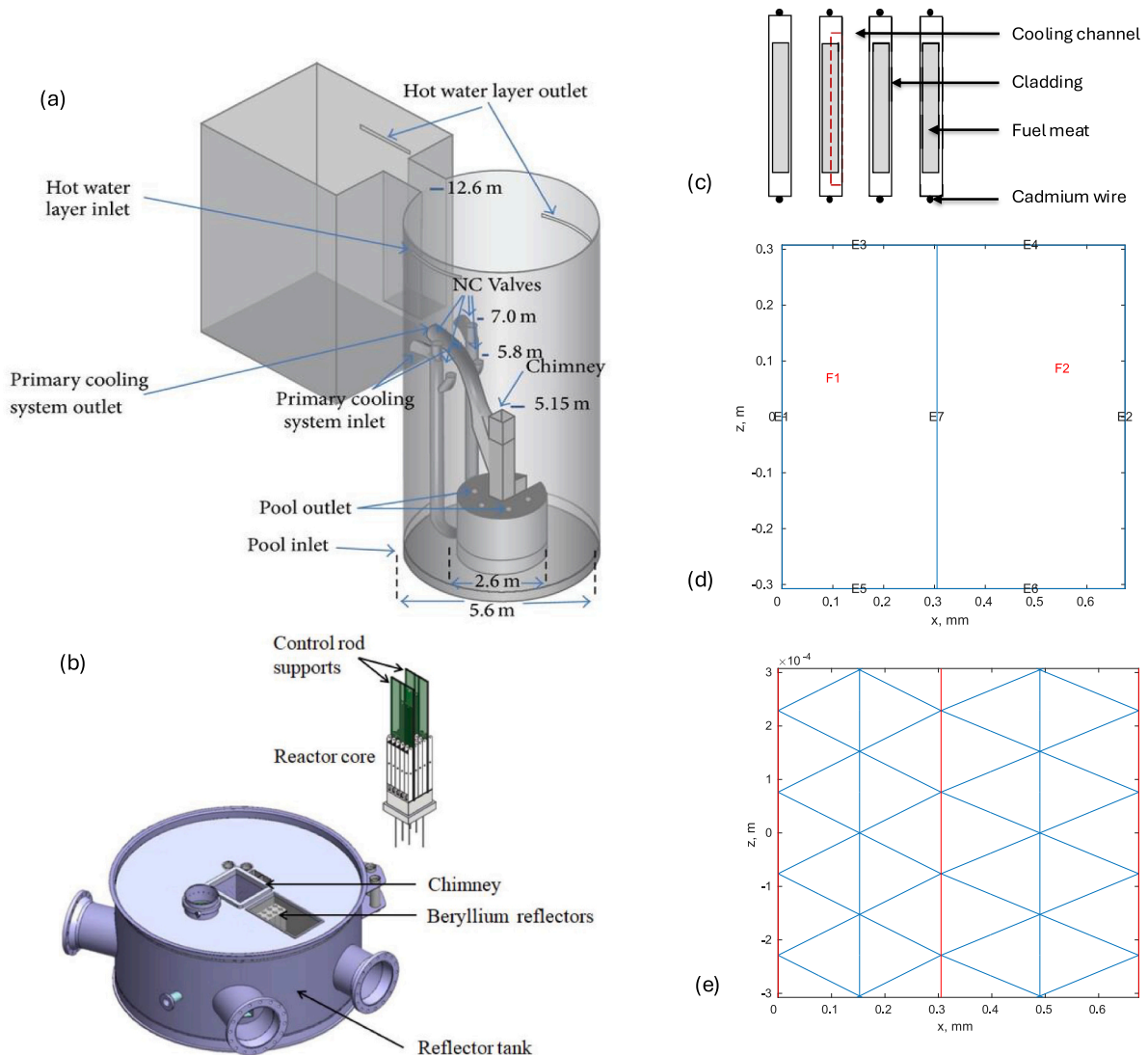


Fig. 4. RMB design showing: (a) overall configuration, (b) reflector tank and reactor core, (c) fuel plate components, highlighting in red (d) the heat transfer analysis area for the fuel (F1) and cladding (F2), and (e) the computational mesh (Ribeiro et al., 2020; Soares et al., 2014). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$k_c \frac{\partial T_c}{\partial x} = k_f \frac{\partial T_f}{\partial x}, \text{ at } x = x_f \quad (4)$$

$$\frac{\partial T_f}{\partial z} = 0 \text{ and } \frac{\partial T_c}{\partial z} = 0, \text{ at } z = \pm L/2 \quad (5)$$

In Eqs. (2)–(5), subscripts *f* and *c* refer to fuel and cladding, respectively, and *L* is active fuel length. Boundaries are addressed in the *x* coordinate as *x_f* and *x_{co}* for the fuel-cladding and cladding-coolant interfaces, respectively. Additionally, *T_w* is the coolant temperature and *h* is the convective heat transfer coefficient of the coolant, which was calculated using the Dittus-Boelter correlation for turbulent flow given by

$$h = 0.023 Re^{0.8} Pr^{0.4} k_w / D_h \quad (6)$$

where *Re* is the Reynolds number, *Pr* is the Prandtl number, *k_w* is the water thermal conductivity, and *D_h* is the hydraulic diameter (Ribeiro et al., 2020). The conditions for the validity of this correlation, such as *Re* > 10,000 and 0.6 ≤ *Pr* ≤ 160, were checked. The volumetric heat generation rate in the fuel domain *Q* is given by

$$Q = PPF \frac{P(t)}{V} \cos\left(\frac{\pi z}{L_e}\right) \quad (7)$$

where *PPF* is the power peaking factor, *P(t)* is the decay heat power, *V* is the volume of the core, and *L_e* is the extrapolated height of the fuel plate. The decay heat power generated in the fuel after shutdown was calculated using the Wigner-Way formula;

$$P(t) = 0.0622 P_0 \left(t^{-0.2} - (t_0 + t)^{-0.2} \right) \quad (8)$$

where *P₀* is the thermal power before the reactor shutdown, *t* is the time elapsed since the reactor shutdown, and *t₀* is the operating time before the shutdown. The coolant flow rate *m(t)* decreases exponentially, with a time constant of 25 s, according to

$$m(t) = 849.92 e^{\left(-\frac{t}{25}\right)} \quad (9)$$

No delay is considered for the reactor trip (SCRAM), i.e., once the shutdown reactivity insertion occurs and the decay heat function is applied to determine the volumetric heat generation throughout the fuel.

2.3. Methods for design of experiments and uncertainty quantification

The third part of the MBS methodology focuses on design space exploration and uncertainty propagation. Design space exploration can be conducted using DOE and analysis of variance (ANOVA). Different types of experimental designs can be applied for distinct purposes. For instance, in a full factorial design (FFD), all combinations of factor levels are tested to understand how each factor and their interactions affect the output. Additionally, ANOVA is used to determine which factors contribute most significantly to the observed variation. For experiments with many factors, two-level full factorial designs can lead to a substantial number of runs. To reduce the number of experiments, screening designs such as Plackett-Burman (PB) are recommended. However, in PB designs, the main effects are heavily confounded with two-factor interactions. For response surface modeling and space-filling, central composite designs (CCD) and Latin hypercube designs (LHDs) can be applied, respectively. Although LHDs have already proven to be a valuable method for DOE, especially when exploring high dimensional computational models, they lack the structured layering of levels needed to resolve interactions or curvature (Chen et al., 2023; Hernandez et al., 2012; Ye, 1998).

In this study, an FFD experimental design and ANOVA were conducted using MATLAB to assess whether hypothetical material properties and reactor power could have a significant effect on the accident

progression. Thus, seven factors were selected. These factors represent the material properties of both physical domains under analysis and reactor power. Hence, typical ranges for fuel and cladding material properties were applied, as shown in Table 3 (International Atomic Energy Agency, 1997; Ribeiro et al., 2020). In addition, the ANOVA assumptions, such as normality and homoscedasticity, were checked.

Uncertainty quantification can be conducted using Monte Carlo (MC) simulations. However, the MC method demands a significant number of runs. On the other hand, the main advantage of the Wilks' theorem is that the number of runs is not affected by the number of uncertainty factors (Lee et al., 2014; Matias Avelar et al., 2023; Wilks, 1941). The use of Wilks' theorem in nuclear safety analysis was pioneered by Gesellschaft für Anlagen- und Reaktorsicherheit (GRS) (Rohatgi and Kaizer, 2020). Since then, it has been widely used in BEPU analysis as it also allows an effective uncertainty quantification using a limited number of simulation cases, mitigating the amount of computational effort compared to MC simulations (D'Auria, 2019; Lee et al., 2014; Zhang and Schneidesch, 2023). A common practice is to use a 95 % confidence level and 95 % probability. For instance, according to the 1st-order Wilks' theorem, the 95 % /95 % one-side tolerance limit (TL) is the highest value within 59 sample data (Lee et al., 2014; Wilks, 1941). The input deck for uncertainty quantification using Wilks' theorem is based on simple random sampling (SRS) from probability distribution functions of uncertainty factors within their uncertainty ranges (Lee et al., 2014). For instance, for normal distributions, the boundaries were truncated within the interval given by the mean ± 1.96σ, for a 95 % probability range. As the use of low-order statistics can lead to conservative estimates of the TL, it is highly recommended to increase the order of statistics to increase accuracy, i.e., avoid conservatism and substantial variability (Kang, 2021). As in many engineering applications, like CFD simulations, solving the full model is computationally expensive; it might be useful to reduce the number of runs for uncertainty quantification. Conversely, the utilization of MC simulations may also avoid the degree of conservatism that results from Wilks' theorem application (Chen et al., 2023; Kang, 2021; Song et al., 2023).

In this paper, both approaches were considered. First, DOE and ANOVA were applied to identify key design factors and two-way interactions. Additionally, different orders of the Wilks' theorem were applied to determine the 95/95 TL for PCT. Alternatively, MC simulations using Latin hypercube sampling (LHS) and SRS were applied to estimate the 95 % confidence interval (CI) of the 95-percentile PCT, which can be expressed as following (Kang, 2021);

$$CI_{PCT95,0.95} = PCT95 \pm 2 \bullet SE_{Q0.95} \approx PCT95 \pm 2 \bullet 2.11 \bullet \frac{s}{\sqrt{n}} \quad (10)$$

where *PCT95* is the 95-percentile peak cladding temperature, *SE_{Q0.95}* is the standard error of 95 percentile, *s* is the peak cladding temperature standard deviation, and *n* is the sample size. Therefore, the 95-percentile Monte Carlo estimator is roughly twice as uncertain as the mean estimator (Kang, 2021). In this rule of thumb, PCT95 is assumed to be normally distributed (Szilard et al., 2015). Noticeably, the effect of even larger sample sizes can narrow the CI. The results of MC method were compared with those of Wilks' theorem for PCT95/95. Table 4 presents the uncertainty parameters and their probability distribution functions.

Table 3
Factors' range for experimental designs.

Factor	Units	Minimum	Maximum
Fuel density	kg m ⁻³	4700	10,970
Fuel specific heat	J kg ⁻¹ K ⁻¹	237	330
Fuel thermal conductivity	W m ⁻¹ K ⁻¹	8	40
Cladding density	kg m ⁻³	2700	7930
Cladding specific heat	J kg ⁻¹ K ⁻¹	490	892
Cladding thermal conductivity	W m ⁻¹ K ⁻¹	15	165
Thermal power	MW	25.5	34.5

Table 4
Uncertainty parameters.

Factor	Distribution	Mean	Uncertainty*
Fuel density	Uniform	7835	3135
Fuel specific heat	Uniform	283.5	46.5
Fuel thermal conductivity	Uniform	24	16
Cladding density	Uniform	5315	2615
Cladding specific heat	Uniform	691	201
Cladding thermal conductivity	Uniform	90	75
Thermal power	Normal	30.000	2.296

* Standard deviation for normal distribution and one-side variation for uniform distribution.

3. Results and discussion

The implementation of MBS using the RMB as a case study was conducted using MATLAB and MSOSA as MBSE tools. In both cases, a heat transfer model was developed in MATLAB using FEA to simulate core behavior during a SLOFA scenario. After the integration of models, an automated analysis capability allowed the identification of main factors through DOE. Additionally, the uncertainty quantification of the PCT was performed using different methods. MBSE usage showed that it can significantly help the system development process, specifically due to the automated simulation feedback (Beery, 2016; Nigischer et al., 2021; Zhang et al., 2023). Furthermore, the exploration of design space and the presentation of uncertainty bands allowed a deeper understanding of the system behavior and improved the requirement verification process (D'Auria, 2017).

3.1. Finite element analysis

The simulation is set to start (at $t = 0$ s) with all nodes from cladding and core at 300 K. The reactor's thermal power is set at nominal value (30 MWth). The steady state is rapidly achieved, and the system is kept with constant attributes up $t = 50$ s, where the loss of flow starts to happen. The accident scenario (SLOFA) sequence occurs as follows: the reactor operating at its nominal power when the loss of flow occurs, the reactor SCRAM (shutdown) happens at approximately 4 s after the loss of flow, the decay heat is removed with the remaining flow rate. The solution of the partial differential equations and boundary conditions allows the assessment of temperature profile throughout the entire fuel and cladding domains, as shown in Fig. 5.

To conduct the accident analysis, several simplifications were considered on the MATLAB model compared to the NTHC1 model (Ribeiro et al., 2020). First, the authors found that the volumetric heat generation rate in the fuel can be modeled using a chopped cosine shape

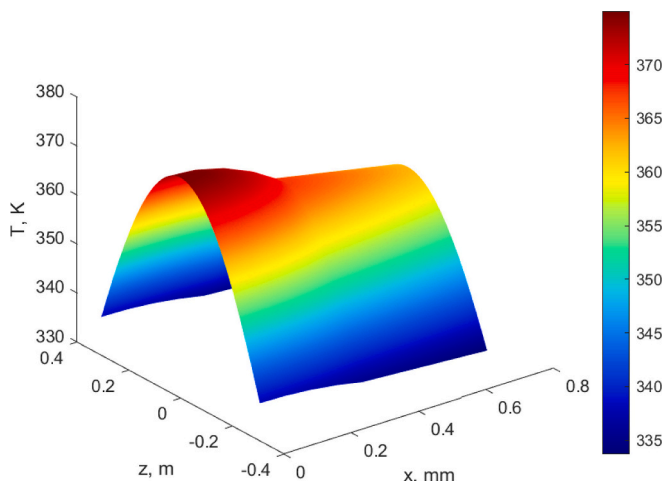


Fig. 5. Steady state temperature distribution.

function in the axial direction of the fuel plate, which provided good results compared to the SERPENT code simulation. Conversely, the overall decay of the core over a certain period was estimated using the Wigner-Way formula to simplify the need to couple heat transfer partial differential equations with a system of seven ordinary differential equations responsible for the neutron point kinetics. A third important simplification is a constant average coolant temperature, i.e., axially averaged value, applied as a boundary condition for the cladding domain. Fig. 6 shows RMB power and coolant flow rate during SLOFA.

During the SLOFA, fuel and cladding temperatures increase due to the lack of effective cooling. A typical criterion that defines the acceptable level of performance of the reactor coolant system is based on the PCT, which in this case shall be less than 391.15 K to avoid the possibility of onset of nucleate boiling (ONB) (Akhal et al., 2023). Likewise, it is possible to establish a similar framework for evaluating system behavior for each postulated accident. It is worth mentioning that simplified modeling alone is not sufficient to support decision-making in the licensing process. However, the MBS approach aims to improve communication among stakeholders throughout the entire life cycle, and simplified modeling remains particularly useful in early design phases.

3.2. Peak cladding temperature requirement verification

In the SE context, requirements can be verified using inspections, demonstrations, analysis, and tests (International Council on Systems Engineering, 2023). In the nuclear engineering context, the PCT requirement in a DBA analysis (e.g., SLOFA) can be calculated by two different approaches: BEPU or conservative (D'Auria, 2019). The BEPU approach is based on the nominal calculation, i.e., PCT calculated using variables at their design-specified values plus other calculations that take the inputs probability distribution functions into account. On the other hand, the conservative approach uses a combination of maximum deviation of the input variables from their design-specified values and conservative boundary and initial conditions (Todreas and Kazimi, 2011).

The main advantage of the integration of models is that FEA results can be directly applied into the requirement verification process. For instance, Fig. 7 shows an example of a requirements diagram where a value property, which is the output of a MATLAB model is applied to satisfy the requirement verification in MSOSA. In this approach, the MATLAB model runs a series of SLOFA simulations to verify the PCT requirement, which may be either conservative or BEPU, depending on the selected approach. The SLOFA model, described in section 2.2, gets

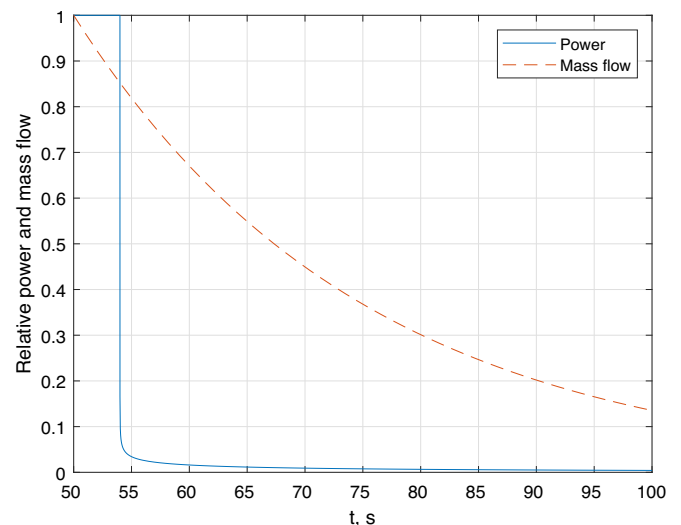


Fig. 6. Relative power and mass flow profiles in the RMB reactor core.

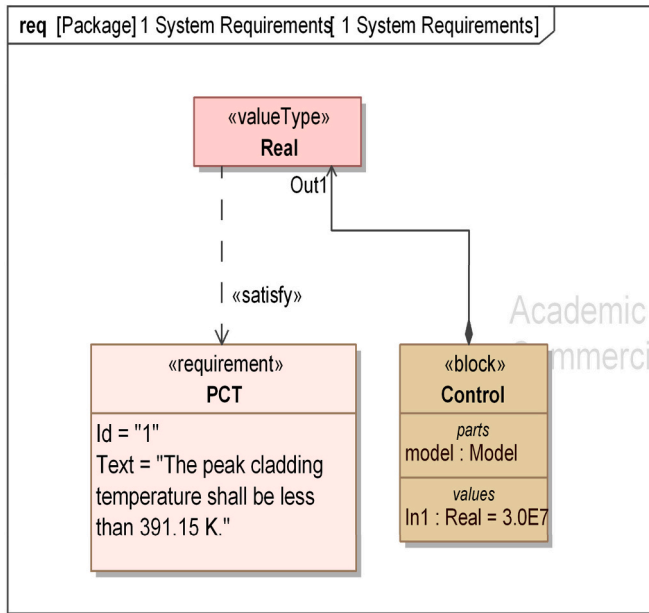


Fig. 7. System requirement linked to a MATLAB model for co-simulation in MSOSA.

the PCT result throughout the entire simulation time. Additionally, a test model controls the number of simulations that are needed, based on the uncertainty quantification strategy described in section 2.3. Lastly, the PCT requirement in the MBSE tool is linked to that specific test model, which allows tracking the requirement verification status.

3.3. Code-to-code comparison

Code-to-code comparison was applied to assist model validation as experimental data was not available. The PCT observed in the hot sub-channel obtained from NTHC1 considering nominal conditions was 369.53 K (Ribeiro et al., 2020). For a conservative calculation, it was assumed that the reactor was operating at its maximum overpower level (15 %) when the loss-of-flow occurred. The same RMB model on NTHC1 was revisited and the same calculations were performed using the partial differential equation toolbox on MATLAB. As shown in Table 5, an excellent agreement was obtained. The PCT computed for this transient is far below the ONB temperature of the cladding (391.15 K). Therefore, throughout the transient after the failure of both pump motors, the coolant did not reach the saturation temperature.

Similarly to NTHC1, the MATLAB model using FEA demonstrated to be a useful tool for MTR research reactors analysis, providing an accurate estimate of the core behavior. Both fuel and cladding temperatures increased due to the lack of effective cooling. The MATLAB implementation facilitated a significant reduction in computational time, thereby supporting efficient design space exploration in the initial phases of system development. Coupled neutronics and thermal hydraulics codes and other types of FEA, such as CFD are usually applied to verify regulatory requirements in the licensing of new reactors.

3.4. Identification of key factors

Design space exploration considered a total of seven factors defined

Table 5
Code validation against NTHC1 for slow loss of flow accident (SLOFA) of RMB.

Result	The current study	NTHC1 (Ribeiro et al., 2020)
PCT, K (nominal)	368.1	369.5
PCT, K (conservative)	375.3	375.7

in the MATLAB model. Thus, running an FFD with two levels per factor created 128 computational cases. ANOVA indicated the most relevant factors for PCT. Factors with a p -value (shown in the last column of Table 6) lower than 0.05 were considered relevant, ensuring at least 95 % confidence that the factor has a real effect on the dependent variable. Of the initial seven factors, six were identified as key design factors, namely fuel density and specific heat; cladding density, specific heat and thermal conductivity; and thermal power.

Further analysis added all two-way interactions for the six design factors. Thirteen interactions had a negligible effect and could be easily excluded from the model. On the other hand, within the studied ranges, two interactions were identified as significant, e.g., cladding density and cladding specific heat. Table 6 summarizes the ANOVA results. Thermal power is the factor with the highest F-value, which is strong evidence that this is a key factor for PCT. This type of exploratory analysis can be used in the early design phase. The results are not intuitive and can provide valuable insights.

3.5. Uncertainty quantification

The use of higher order statistics, e.g. second or third order statistics, involves an increase in the sample size. Notwithstanding, the lower the order statistics, the more conservative the estimate is. (Martorell et al., 2017; Trivedi and Novog, 2023). As demonstrated in Table 7, the first and second orders of Wilks' theorem yielded a more conservative estimate of the 95/95 PCT upper tolerance limit (UTL). As the order of Wilks' theorem increases, the degree of conservatism in results tends to decrease, leading to improved statistical accuracy.

Most regulatory-approved BEPU for nuclear systems approaches for verifying safety criteria rely on propagating input uncertainties through models implemented in computational codes using Wilks' criteria to determine how many safety output calculations are needed to meet standard tolerance levels (typically 95/95) (Jyrkama and Pandey, 2017; Shockling, 2015; Zhang et al., 2023). These approaches often focus on upper or lower TLs based on first order statistics, which can be calculated with a small sample size, usually requiring 59 runs (Lee et al., 2014; Zhang et al., 2023). This method is advantageous because it yields conservative results with fewer simulations, reducing the high computational costs associated with running complex models.

In practice, achieving a precise 95/95 estimate might be challenging with high-dimensional design spaces. Fig. 8 shows the PCT results for 1st-order Wilks' theorem. For the 2nd-order, the UTL did not change significantly and, consequently, the licensing margin. In fact, both results are in agreement with the estimate given by the conservative analysis. Therefore, to improve BEPU analysis accuracy, the use of higher order statistics is recommended. Nonetheless, in this case, the BEPU analysis demonstrates that there is a significant licensing margin (approximately 17 K) between the 95/95 UTL and the ONB requirement.

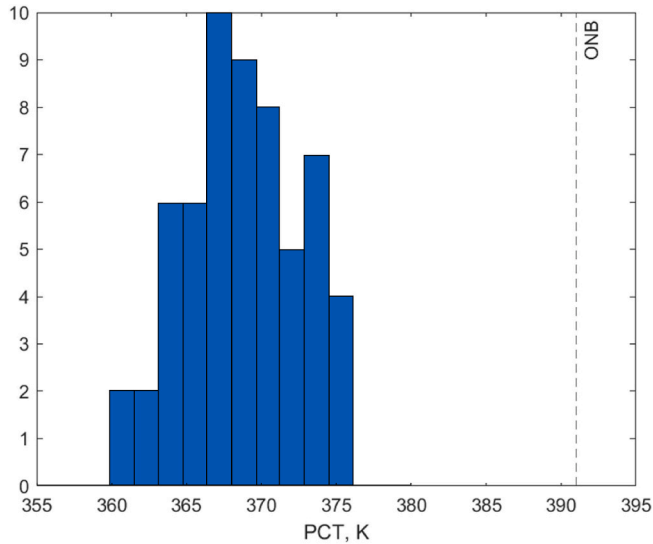
Table 6
ANOVA results for key factors and two-way interactions.

Source	Sum Sq.	d. f.	Mean Sq.	F	Prob > F
Thermal power	6651.33	1	6651.33	7,608,452.18	<0.0001
Fuel density	0.02	1	0.02	21.66	<0.0001
Fuel specific heat	0.01	1	0.01	8.78	0.0038
Cladding density	0.02	1	0.02	23.39	<0.0001
Cladding specific heat	0.01	1	0.01	6.07	0.0154
Cladding thermal conductivity	0.01	1	0.01	15.90	0.0001
Cladding density and cladding specific heat	0.01	1	0.01	16.19	0.0001
Cladding density and cladding thermal conductivity	0.01	1	0.01	7.19	0.0085

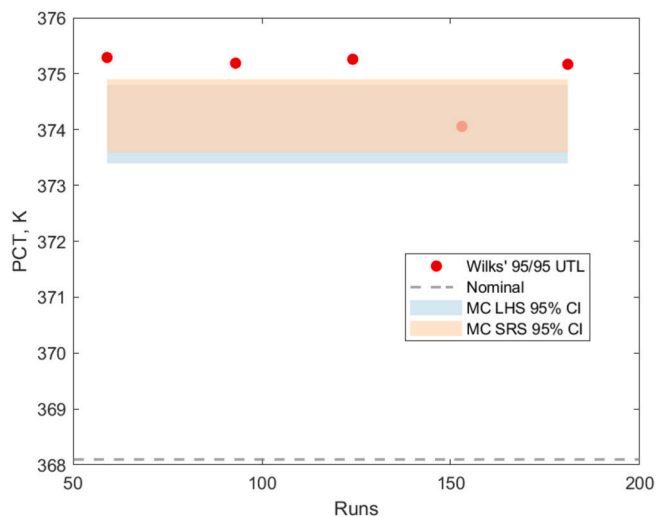
Table 7

Comparison of the number of runs and PCT obtained using different orders of the Wilks' theorem.

Order of the Wilks' theorem	Number of Runs	95/95 PCT upper limit, K
1	59	375.3
2	93	375.2
3	124	375.3
4	153	374.1
5	181	375.2

**Fig. 8.** Histogram with the results for the 1st-order (59 runs) of Wilks' theorem.

To minimize the number of simulations and reduce computational time, Wilks' theorem has a significant advantage over MC simulations for uncertainty quantification. Fig. 9 shows the comparison of 95 % CI of the 95-percentile PCT obtained by the MC method with 500 runs and by the Wilks' theorem. The CIs of the 95th percentile PCT for LHS and SRS represent the uncertainty around both 95th-percentile estimates. Notably, the 95/95 PCT TLs by Wilks' theorem were more conservative compared against the upper limit of the 95 % CI from the MC simulations, considering both sampling methods, SRS and LHS. Additionally,

**Fig. 9.** Comparison of the 95 % confidence interval (CI) of the 95-th percentile PCT by Monte Carlo (MC) simulations with 500 runs and the PCT95/95 upper tolerance limit by Wilks' theorem.

the higher the sample size, the narrower the 95 % CI of the PCT95 for both SRS and LHS. Therefore, the MC method, which demands more computational effort, could mitigate the conservatism of Wilks' theorem and provide a more accurate result. Moreover, the difference in the MC simulation results was not significant considering different sampling methods. These results are in agreement with other studies (Chen et al., 2023; Kang, 2021; Song et al., 2023).

In this study, all simulations, including DOE and uncertainty quantification analyses, were conducted in MATLAB R2024b using a parallel computing pool comprising 14 cores on an Intel Core i5-13600K processor (5.1 GHz), equipped with 32 GB of RAM and an NVIDIA GTX 980 GPU. Other experimental designs can be applied, but confounding is likely to occur, as the effect of one factor cannot be separated from the effect of another factor or from a blocking effect. Conversely, the number of runs can be reduced by using the 1st order of Wilks' theorem, which gives a conservative estimate. Hence, the MBS methodology is flexible and practical for full-scale reactor licensing processes. First, BEPU frameworks have been widely used in this context. Second, parallel computing can make FFD and Monte Carlo simulations feasible. Lastly, MBSE tools are commercially available.

3.6. The MBS methodology

The utilization of MBSE has various advantages to nuclear safety analysis. By integrating requirements verification and uncertainty analysis, a structured, streamlined process is applied for BEPU analysis to support decision-making. In the MBS methodology, system requirements are organized and linked with both simulation models and test cases, as shown in Fig. 10(a). By applying the probabilistic distribution for relevant factors on a BEPU analysis, the MBS allows developers to calculate the licensing margin and quantify the effect of factors' uncertainties on the system measures, as shown in Fig. 10(b). The BEPU analysis creates a statistical layer that fills the gap between MBSE and CAE and determines how many times and which input decks should be used for each analysis. Moreover, it performs statistical analysis of the uncertainty band, enabling the assessment of licensing margins. Thus, the V&V layer is composed of test cases that control the execution of multi-physics models and the statistical analysis of simulation results. The overall layered concept of the MBS is also shown in Table 8. It establishes a standard statistical methodology for V&V and analysis of probabilistic measures of effectiveness, suitability, and performance.

The main advantage of this methodology is its ability to analyze the impact of design changes on system requirements. For instance, in the event of a design modification or an update to an evaluation model, the effect on the licensing margin can be promptly assessed, as the evaluation model is linked to the SysML tool. The MBS is supposed to keep the connection between the proposed design changes and originally established system requirements and stakeholders' needs, across the disciplines.

The tasks of identification of key factors and uncertainty quantification are sequentially modeled to provide relevant data for decision-making. The purpose of the identification of key design factors is to explore the design space and understand how design changes impact system requirements. While this process also informs the selection of factors for uncertainty quantification, it does not imply that other factors should be excluded. The purpose of uncertainty quantification is to integrate typical BEPU analysis into MBSE. Thus, both results—key factors and licensing margin—are valuable inputs for decision-making. This approach can be applied across various requirements and simulations to support comprehensive trade-off analyses.

After the same approach is extended to other system requirements and models, a traceability matrix between them is suggested to allow the system engineer to map information flow across the MBS. As a digital thread, this methodology is not restricted to a single tool. In fact, system developers have a significant number of tools at their disposal. In this

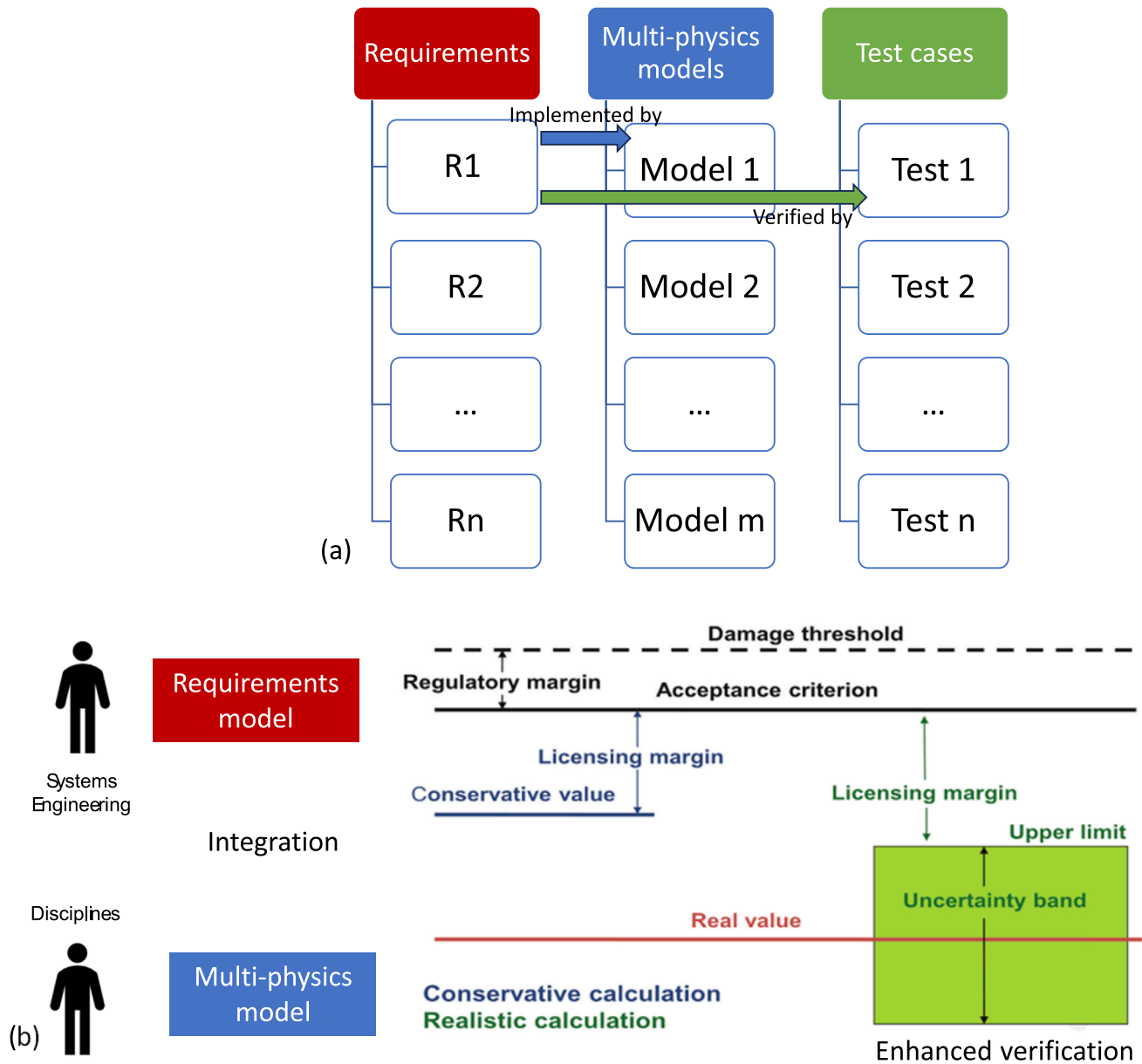


Fig. 10. The MBS (a) and its application to enhance the verification process with both conservative and BEPU analysis (b). Adapted from Freixa et al. (2021).

Table 8
Roles of each MBS layer.

MBS layer	Role
Functional model	Describes a hierarchy of system functions
Requirements model	Captures system requirements clearly
Multi-physics models	Simulate system behaviors
V&V models	Performs statistical analysis to verify and validate requirements

work, the RMB system model was created using two different MBSE tools (MSOSA and System Composer) that could integrate with the same FEA model developed in MATLAB. To avoid limitation in the number of calculations (i.e., one input deck at a time) when using co-simulation, the V&V model should be applied to encompass the BEPU analysis and provide the tolerance limit feedback to the SysML tool. This integrated approach in the licensing process of nuclear installations can help inform regulatory authorities whether safety requirements were met.

First, because the lessons learned from the Fukushima Daiichi accident in 2011 reinforced safety requirements (International Atomic Energy Agency, 2016). Second, uncertainty analysis is applied to determine safety margins in the verification process of regulatory requirements. Therefore, a structured model-based implementation of uncertainty analysis may enhance the verification of regulatory requirements.

MBS is a digital engineering ecosystem that reinterprets the traditional work breakdown structure (WBS) from project management, replacing work packages with engineering models. Although initially conceived to support the licensing process of nuclear systems, its broader purpose is to enhance communication among stakeholders throughout the entire life cycle—from early design phases to decommissioning—by integrating BEPU-oriented digital workflows into the ecosystem. Built on existing SysML digital threads, MBS provides a methodology focused on requirements V&V, linking digital models and databases to demonstrate compliance with specified requirements. In this context, it leverages the BEPU approach to support decision-making through uncertainty analysis throughout the entire lifecycle and across various disciplines.

Established regulatory methodologies for realistic large break loss of coolant accident (LOCA) evaluation model can be directly embedded. Thus, development activities are still applicable, such as Phenomena Identification and Ranking Table (PIRT) and model validation, performed mainly via experimental results from integral effects test facilities to assess code's ability to predict system responses. In fact, an MBS should be flexible to encompass regulatory frameworks, experimental databases, and digital engineering environments. It can be directly applied in future licensing processes to manage regulatory requirements, to link the digital environments, and to provide instantaneous access to the data that is needed for decision making. It is worth mentioning that, ideally, the MBS should be able to adapt to different regulatory frameworks, analysis approaches (e.g., conservative or BEPU), and tools (e.g. FEA, CFD or system codes). More features of BEPU may be included in the future, such as procedures for model development, scaling, model V&V, and coupling of codes from different disciplines. Ideally, the acceptance criteria from regulatory requirements would be mapped alongside other system requirements. In fact, future research could capture regulatory frameworks using MBSE tools and assess different designs by changing models. MBS may serve as an integrated digital representation of the licensing models.

4. Conclusion

This work proposed a novel methodology, named the Model Breakdown Structure (MBS), which integrates state-of-the-art MBSE co-simulation with CAE methods (e.g., FEA) and demonstrates how BEPU-oriented workflows can be integrated into SysML-based digital threads. This holistic methodology for digital engineering ecosystems enables the assessment of compliance with safety requirements, spanning from an enterprise system perspective to detailed behavior analysis. In this context, regulatory requirements can be directly connected to simulation models that generate the data needed to demonstrate compliance with acceptance criteria. This digital engineering ecosystem is designed to integrate the BEPU approach within existing SysML-based digital thread architectures to support the licensing process of new reactors. The main benefit to stakeholders is the ability to collect and analyze data using a straightforward process in a model-based structure rather than document-based processes.

The MBS aims to improve communication among stakeholders and to support decision-making across all phases of the system life cycle. Therefore, the MBS ideally should be able to encompass the entire spectrum of models and data sources needed to support decision-making, from early design phases up to decommissioning. In this paper, the Brazilian Multipurpose Reactor (RMB) was used as a case study, and MATLAB's System Composer and Magic System of Systems (MSOSA) were applied as MBSE tools. Core heat transfer was analyzed with a simplified FEA model to evaluate temperature behavior during the transient scenario. A code-to-code comparison confirmed consistency between the MATLAB results and those from the Neutronics and Thermal Hydraulics Code (Ribeiro et al., 2020). The utilization of simplified modeling is particularly useful for design space exploration to reduce computational cost and assess licensing margins at early design phases.

A straightforward process was suggested for design space exploration and uncertainty quantification, as the interconnected modeling approach enabled seamless data flow across different models. Key design factors were identified using FFD and ANOVA. To minimize the number of simulations, and thus reduce computational time, other DOEs such as PB and CCD can be applied. In a broader context, the entire digital thread facilitates DOE as well as other types of analyses, such as sensitivity studies and trade-off evaluations. Wilks' theorem and Monte Carlo simulations were applied for uncertainty quantification. Findings showed that the 95/95 uncertainty band for PCT remained below the onset of nucleate boiling. Moreover, it was recommended to use Wilks' theorem to mitigate computational cost for uncertainty quantification,

especially for complex CAE models. However, with advancements in computing technology expected to enhance processing speed, the Monte Carlo method may ultimately become the preferred standard for such analyses in the long term.

This digital engineering ecosystem establishes a direct link between design changes across disciplines and the originally defined system requirements. Additionally, it enables BEPU-oriented feedback within SysML tools. Future work will extend this approach using coupled neutronic and thermal hydraulics codes, fuel performance codes, and other types of FEA, such as CFD and structural analysis to enhance the verification process of regulatory requirements in the licensing of new reactors.

CRedit authorship contribution statement

Alan Matias Avelar: Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization. **Jian Su:** Validation, Supervision, Methodology, Investigation, Formal analysis. **Claudia Giovedi:** Writing – review & editing. **Fabio de Camargo:** Writing – review & editing. **Joseph T. Klamo:** Writing – review & editing. **Oleg Yakimenko:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Microsoft Copilot to check punctuation in the text. After using this tool/service, the author(s) reviewed and edited the content as needed and took full responsibility for the content of the published article.

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.

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Data availability

Data will be made available on request.

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