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THESIS

INTEGRATION OF MODELS TO ENHANCE THE VERIFICATION PROCESS OF NUCLEAR SYSTEMS

by

Alan Matias Avelar

June 2025

Thesis Advisor:	Oleg A. Yakimenko
Co-Advisor:	Jian Su, Federal University of Rio de Janeiro
Second Reader:	Joseph T. Klamo

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13. ABSTRACT (maximum 200 words)

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INTEGRATION OF MODELS TO ENHANCE THE VERIFICATION PROCESS OF NUCLEAR SYSTEMS

Alan Matias Avelar
Capitão de Corveta, Brazilian Navy
B.S. Che E., Fluminense Federal University, 2010
MS, Rio de Janeiro Federal University, 2013
PhD, University of Sao Paulo, 2023

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Approved by: Oleg A. Yakimenko
Advisor

Jian Su
Co-Advisor

Joseph T. Klamo
Second Reader

Oleg A. Yakimenko
Chair, Department of Systems Engineering

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The lack of integration between computer-aided engineering (CAE) and model-based systems engineering (MBSE) tools hinders the assessment of how design changes affect system requirements. To address this challenge, this thesis proposes a model breakdown structure methodology implemented using MathWorks' System Composer to integrate MBSE and CAE models. The Brazilian Multipurpose Reactor is used as a case study to demonstrate the effectiveness of the proposed methodology. An enhanced, automated verification process is achieved by linking system requirements to a finite element analysis that calculates fuel and cladding temperature distributions in a slow loss of flow accident scenario. First, a Latin hypercube design is employed to evaluate how variations in design factors influence cladding temperature. Second, the Wilks' theorem is applied to calculate the maximum response with a 95% confidence level and 95% probability. The results indicate that the 95/95 upper limit of the peak cladding temperature remains below the onset of nucleate boiling. Furthermore, the integrated model is expected to significantly reduce the effort required for uncertainty quantification.

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LIST OF ACRONYMS AND ABBREVIATIONS

ANOVA	analysis of variance
API	application programming interface
BDBA	beyond design-basis accident
BEPU	best estimate plus uncertainty
CAD	computer-aided design
CAE	computer-aided engineering
CFD	computational fluid dynamics
CNEN	Brazilian Nuclear Energy Commission
COI	critical operational issue
CONOPS	concept of operations
DBA	design-basis accident
DEC	design extension conditions
DEE	digital engineering ecosystem
DLL	dynamic-link library
DoD	Department of Defense
DOE	design of experiments
DT	digital twins
FEA	finite element analysis
FMI	functional mock-up interfaces
HLA	high-level architecture
IAEA	International Atomic Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
INCOSE	International Council on Systems Engineering
IPEN	Nuclear and Energy Research Institute
KPP	key performance parameter
LHD	Latin hypercube design
LOCA	loss of coolant accident

LOFA	loss of flow accident
M&S	modeling and simulation
M2M	model-to-model
M2T	model-to-text
MATLAB	matrix laboratory
MBS	model breakdown structure
MBSE	model-based systems engineering
MOE	measure of effectiveness
MOP	measure of performance
MTR	material testing reactor
NEA	Nuclear Energy Agency
NPP	nuclear power plant
NTHC1	Neutronics and Thermal Hydraulics Code
ONB	onset of nucleate boiling
PCT	peak cladding temperature
PDE	Partial Differential Equation Toolbox™
PFT	peak fuel temperature
PPF	power peaking factor
RIA	reactivity-initiated accident
RMB	Brazilian Multipurpose Reactor
SCRAM	reactor trip
SE	systems engineering
SLOFA	slow loss of flow accident
STK	Systems Tool Kit
SysML	Systems Modeling Language
U.S. NRC	U.S. Nuclear Regulatory Commission
V&V	verification and validation

EXECUTIVE SUMMARY

Digital engineering strategy aims to shift communication from documents to digital models. In this context, model-based systems engineering (MBSE) is intended to improve communication among stakeholders (International Council on Systems Engineering 2023). However, high-fidelity modeling and simulation (M&S) are typically conducted using domain-specific tools, such as computer-aided engineering (CAE), rather than MBSE. Consequently, these tools do not inform MBSE whether the system meets the requirements (Nigischer et al. 2021).

To address this gap, this thesis proposes a model breakdown structure (MBS) methodology to integrate MBSE and CAE models. This integrated approach allows system developers to evaluate the impact of design factors on system requirements by applying design of experiments and uncertainty quantification. In the MBS methodology, both techniques should be applied sequentially. First, the design of experiments helps identify which design factors are relevant for each system measure of effectiveness. Second, uncertainty quantification is performed based on the factors identified as significant. The objective of this research is to develop a unified, enhanced verification approach using MBSE and simulation to evaluate uncertainty in the system measures of effectiveness.

Additionally, this research seeks to support the licensing process of nuclear systems. Given that the licensing process is crucial for the development of new reactors, applying an integrated MBSE–CAE methodology enables the use of the best estimate plus uncertainty (BEPU) approach for verifying regulatory requirements. This may help reduce the cycle time from data gathering to decision-making in the licensing process (Zhang and Schneidesch 2023).

A. BACKGROUND

In the traditional document-based approach to systems engineering (SE), most of the technical information generated about the system is contained in documents, specifications, and reports. On the other hand, in a model-based approach, a system model captures a significant amount of information. Thus, leveraging MBSE should improve communications among system developers and decision-makers (International Council on Systems Engineering 2023).

Notwithstanding, for formal analysis and evaluation activities, such as design space exploration and verification, domain engineers typically create additional models using specific CAE tools. Although CAE tools can satisfy the extended calculation needs regarding simulation and computation, they have limited or no interconnectivity with MBSE modeling editors. This lack of integration hinders the existence of a common system model for all stakeholders. Conversely, MBSE and CAE models are often created and executed separately by different experts, leading to inconsistencies and redundant work (Nigischer et al. 2021).

Lastly, an 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 some safety requirements (International Atomic Energy Agency 2016). Second, because in the BEPU approach, uncertainty analysis is applied to determine safety margins in the verification process of regulatory requirements (Zhang and Schneidesch 2023). Therefore, a structured model-based implementation of uncertainty analysis may enhance the verification of regulatory requirements.

B. PROPOSED SOLUTION

The proposed methodology involves a set of interconnected models constituting a digital engineering ecosystem (DEE) in which requirements are linked to both simulation and test models. This approach aims to enable automatic data exchange between the MBSE modeling editor and CAE methods. Ideally, the uncertainty quantified in the simulation results is applied to enhance the verification process. In this context, the MBS provides evidence that the system meets the specified requirements and helps determine the safety margin.

The DEE is organized within MATLAB and Simulink environments. System Composer, which is an add-on to MATLAB and Simulink, is utilized as an MBSE requirements editor. The Partial Differential Equation (PDE) Toolbox™ is applied to solve a transient finite element analysis (FEA), where the core heat transfer of the Brazilian Multipurpose Reactor (RMB) is analyzed in a slow loss of flow accident (SLOFA). A requirement to verify the possibility of the onset of nucleate boiling (ONB) is implemented by the FEA thermal model.

Verification is conducted using Latin hypercube designs (LHD). This allows us to identify the relationship between design factors and peak cladding temperature (PCT) (Chen et al. 2023). Additionally, Wilks' theorem is applied for uncertainty quantification, analyzing the PCT with 95% probability and 95% confidence (95/95) (Zhang and Schneidesch 2023).

C. KEY FINDINGS

The integrated model created using System Composer provides an effective way to interconnect MBSE with high-fidelity simulations. The results obtained by the FEA were collected, analyzed, and applied to verify a safety-related functional requirement. First, code-to-code comparison is performed against the Neutronics and Thermal Hydraulics Code (NTHC1) results (Ribeiro et al. 2020). The results showed good agreement for PCT. Second, the experimental design showed that the thermal power before the reactor trip (SCRAM) is the most important factor for PCT.

The analysis indicates that the 95/95 uncertainty band of the PCT remains below the ONB requirement. This means that the 95th quantile of the cladding temperature will be less than the ONB, with 95% confidence. Furthermore, the application of LHD and Wilks' theorem can effectively reduce the amount of computational effort compared to full factorial designs and Monte Carlo simulations. However, the order of the Wilks' theorem ought to be selected based on the number of factors that are being analyzed.

D. CONCLUSION AND FUTURE WORK

In conclusion, the developed methodology successfully addressed a commonly observed lack of integration between MBSE and CAE. A set of interconnected models performed requirement verification, design space exploration, and uncertainty analysis using the results obtained in a transient FEA. Harnessing a BEPU approach can leverage MBSE to enhance the verification of regulatory requirements of nuclear systems, thereby supporting the licensing process. Moreover, future challenges should focus on enhancing the effectiveness of the methodology in assessing various CAE methods across distinct domains, such as computational fluid dynamics, computational electromagnetics, computational chemistry, and multi-physics simulations.

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I. INTRODUCTION

Model-based systems engineering (MBSE) has become an essential methodology for managing the development of complex systems. This digital representation of the traditional document-based systems engineering (SE) process increases the ability to manage the development of complex systems by enabling a system model to be viewed from various levels of abstraction (International Council on Systems Engineering 2023; Khandoker et al. 2022). The Systems Modeling Language (SysML) is the main modelling language for MBSE, which is intended to support all phases of a system life cycle, including tasks such as verification and validation (V&V) (Nigischer et al. 2021; X. Zhang et al. 2023; Mengyan et al. 2024).

Computer-aided engineering (CAE) methods are useful tools for design verification. Currently, most of these tools, typically multi-physics simulations, are installed in isolated, discipline-specific data repositories (Mengyan et al. 2024; Romero, Pinquié, and Noël 2022; Khandoker et al. 2022). In fact, according to Gu et al. (2024), existing MBSE methodologies are not integrated with the modeling and simulation (M&S) of complex systems' physical characteristics, limiting its application. Therefore, MBSE leverages SE but faces a lack of coordination of its models with the engineering domain, 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; L. Zhang et al. 2022). Figure 1 illustrates this gap. This undesired situation is caused by the diversity of tools, absence of an integrated MBSE–M&S framework, and the lack of automated feedback to the SysML tool.

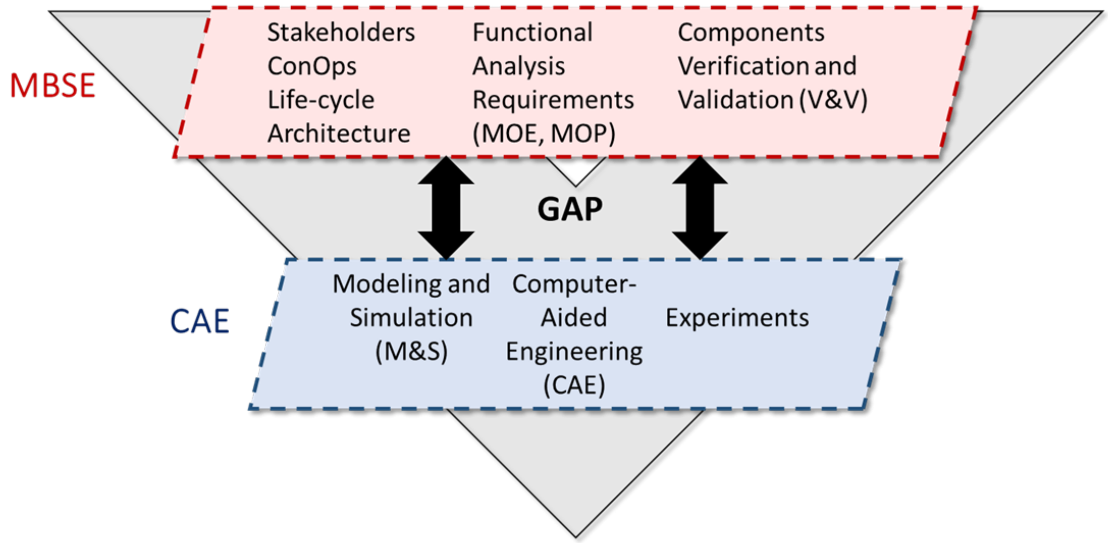


Figure 1. Lack of integration between MBSE and CAE domains.

The main cause of this gap is that complex engineering projects deal with different computer codes (e.g., Ansys, PDMS, and HYSYS), as shown in Figure 2. In the 1990s, the U.S. Department of Defense (DoD) conducted some effort to mitigate this issue, which culminated in high-level architecture (HLA) (Dahmann 1997; Gorecki et al. 2018). HLA is a standard that provides an architectural basis for simulation interoperability (Dahmann 1997; Gorecki et al. 2018; Petty and Morse 2004). To the best of the author's knowledge, HLA was a failure because the owners of established software tools did not want to restructure their software to meet the rules. Nonetheless, the Institute of Electrical and Electronics Engineers (IEEE) still provides recommended practices for HLA in IEEE 1730 (2022). Moreover, cross-domain issues due to the significant number of disciplines involved may lead to Abilene paradox situations with poor group decision-making (Halbesleben, Wheeler, and Buckley 2007). This occurs because there is no clear connection between the proposed design changes and originally established system requirements and stakeholder needs (Beery 2016).

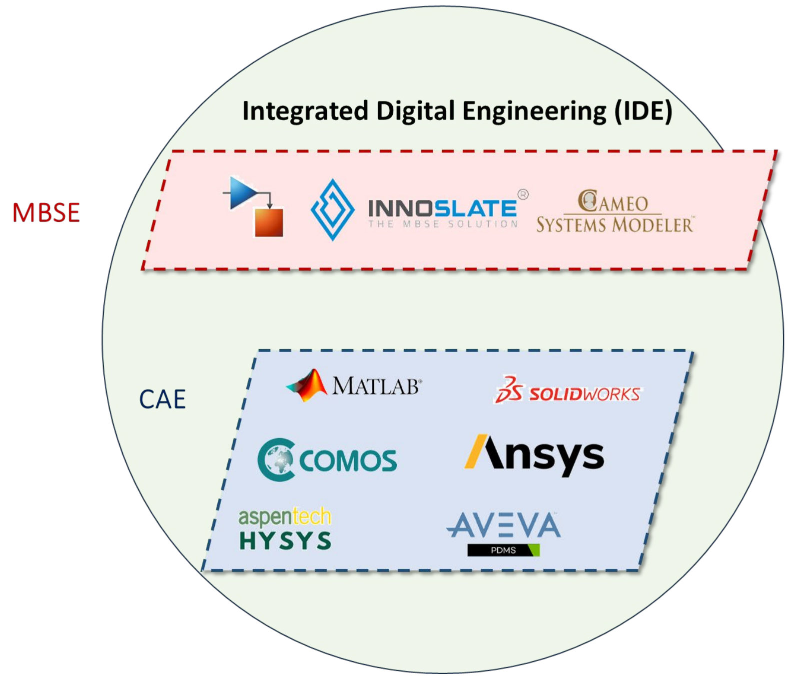


Figure 2. Multi-domain simulations in engineering projects.

A second cause is the absence of an integrated MBSE–M&S framework. As SysML was maturing, an MBSE initiative was organized by the International Council on Systems Engineering (INCOSE) in 2007 (Dickerson and Mavris 2013). This initiative had M&S interoperability as one of its main themes and established research focus on the interaction of models throughout system development. Although the level of maturity in MBSE evolved throughout the years, in a model-driven approach, the emphasis is shifted towards achieving concurrency in design and verification. Noticeably, the use of integrated approaches that aid decision-makers in the analysis of a system performance is an MBSE application (Bickford et al. 2020). Thus, current efforts position MBSE as an enabler of a coordinated, consistent set of models across different domains of engineering (Bickford et al. 2020; International Council on Systems Engineering 2021). In the near future, CAE methods might replace manual engineering calculations, and SE will be predominantly model-based (International Council on Systems Engineering 2021). In this context, the SysML software will provide a framework for on-demand assessment (Bickford et al. 2020). Systems engineers are going to use ontologically connected models, which will be updated in real time (International Council on Systems

Engineering 2021). Hence, MBSE evolution is aligned with the vision for digital twins (Bickford et al. 2020; Mengyan et al. 2024). According to INCOSE (2021), by 2035, a family of integrated MBSE–M&S frameworks may exist.

Lastly, the lack of automated feedback regarding simulation results to the SysML tool hinders the assessment of design changes on system requirements (Nigischer et al. 2021). Indeed, simulations do not inform MBSE tools and, consequently, system developers and decision makers on whether the system meets the requirements. Thus, this step is often a manual activity. In recent years, several authors conducted work to narrow this gap (Gu et al. 2024; Khandoker et al. 2022; Nigischer et al. 2021; L. Zhang et al. 2022). According to Nigischer et al. (2021), two approaches were applied to transfer parameters between SysML and simulation environments: model-to-model (M2M) and model-to-text (M2T) transformations. However, both fail to provide automated feedback regarding the simulation results to the SysML tool. One of the few approaches providing automated results feedback is the use of plugins (Nigischer et al. 2021). Export files (e.g., XML and CSV) provide tighter integration by using specific plugins for SysML editors, which either access the simulation environment or export files with code scripts. Although plugins create linkages, the degree of automation increases significantly when the MBSE editor has direct access to the simulation environment.

Simulation-based tests are employed to verify regulatory requirements during the licensing process of nuclear systems, using either a best estimate plus uncertainty (BEPU) approach or a conservative approach (International Atomic Energy Agency 2016). The conservative approach uses conservative models, conservative boundary conditions, and penalizing rules to ensure that uncertainties in the modeling of the system response are bounded, providing a high level of assurance to the stakeholders. In contrast, the BEPU approach uses both deterministic and probabilistic insights to assess safety margins. It is a time-consuming process that requires engineering judgment. In this context, MBSE can help to overcome difficulties caused by the incompleteness of established BEPU approaches to make it more feasible (X. Zhang et al. 2023).

Therefore, the coordination of system-level and domain-level tools plays a key role in assessing the impact of design changes across platforms from various disciplines on system requirements. Noticeably, the key factor for an automated process is the simulation result feedback to the SysML tool. Furthermore, MBSE can support the utilization of the BEPU approach in the safety analysis of nuclear systems.

A. OBJECTIVE

This thesis focuses on integrating MBSE and CAE methods to assess the effect of design changes on system requirements. Additionally, it aims to support the utilization of the BEPU approach to enhance the verification of regulatory requirements for nuclear systems.

Ultimately, this thesis seeks to answer the following research questions:

How can the integration of models facilitate the analysis of design changes?

How can the integration of models improve the verification process?

How can the integration of models be applied to support decision-making in the licensing process of nuclear systems?

B. BENEFITS FOR STAKEHOLDERS

The potential benefits of this research are the following:

- A novel integrated methodology in which system requirements can be implemented and verified using the results obtained from finite element analysis (FEA).
- An enhanced verification process through a structured BEPU analysis, involving both the design of experiments (DOE) and Wilks' theorem.

Several stakeholders can benefit from this study, as follows:

- MBSE software developers
- Military and civilian organizations that develop nuclear systems
- Universities that conduct research related to nuclear systems

- Regulatory authorities
- Laboratories that develop nuclear safety codes

C. THESIS ORGANIZATION

The remaining chapters of this thesis are organized as follows: Chapter II reviews the literature to outline the motivation for this thesis and position this research in relation to existing studies. Chapter III proposes a novel methodology entitled model breakdown structure (MBS). Chapter IV provides a detailed description of the multi-physics model of the Brazilian Multipurpose Reactor (RMB), which is used as a case study. Chapter V provides the results of the simulations and analyzes the effectiveness of the methodology. Chapter VI concludes the thesis and suggests future challenges.

II. LITERATURE REVIEW

The literature review is organized into three sections. The first section discusses the motivation for integrating model-based systems engineering (MBSE) and systems development environments, such as computer-aided engineering (CAE) methods. The second section emphasizes the importance of CAE methods in the verification process, as well as the current limitations of commercial MBSE tools. Lastly, the third section reviews the progress of the best estimate plus uncertainty (BEPU) approach in the licensing process of nuclear systems and examines the application of MBSE in the nuclear energy sector.

The discussions on systems engineering (SE) processes are outside the scope of this literature review, as this research inherently follows a similar approach. Therefore, revisiting the classical goals of the SE process is unnecessary. Additionally, this review does not focus on descriptive architectural products of MBSE methodologies that use the Systems Modeling Language (SysML). Instead, this review examines studies that have extended MBSE methodologies, primarily to enhance the verification process of complex systems, such as nuclear power plants (NPPs).

A. THE SYSTEM MODEL AS AN INTEGRATED FRAMEWORK

SE is the nexus between stakeholder needs and domain engineers, facilitating integration and collaboration to develop and maintain systems that meet requirements. Although this holistic approach has gained more value throughout the years, its potential benefits concerning decision-making are still an important area of research. In 2018, the U.S. Department of Defense (DoD) established a digital engineering strategy whose main goal is to change the means of communication from documents to digital models (Department of Defense 2018). One of its focus areas is the SE transformation initiative, which aims to modernize how systems engineers use model-based approaches to specify, develop, and verify systems. Current efforts include improving capabilities in different areas such as integration of modeling environments, including those applied to 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, 189). Dickerson and Mavris (2013) studied the history of MBSE and traced the historical contributions of software to support SE over the last 50 years. They concluded that model-based approaches to SE have evolved to a level of maturity that is now commercially supported. Typical benefits of MBSE include an increased ability to manage system complexity and improved communications among the stakeholders.

The MBSE approach aims to make models more intuitive to improve SE effectiveness throughout the entire life cycle. For instance, SysML is "a general-purpose graphical modeling language for specifying, analyzing, designing, and verifying systems" (Dickerson and Mavris 2013, 2). SysML is used to capture the system model while supporting various abstraction techniques and providing the ability to view the system from different perspectives and levels of abstraction, such as a black-box view and white-box view (Raphael and Smith 2013). MBSE practitioners use SysML to construct models of a system's architecture, functions, and requirements. Additionally, model-based reasoning is useful for diagnosis of complex systems where there are a significant number of reasons for malfunctioning (Raphael and Smith 2013). Therefore, successful MBSE implementation not only requires the translation of stakeholder needs into requirements but also the utilization of system behavior modeling to support design, analysis, and verification activities.

Modeling languages for systems are widely used in MBSE to design complex systems that integrate various disciplines, such as mechanical, electrical, and control engineering. However, they are often not fully integrated into a unified system development environment. Currently, the emergence of SysML offers the ability of practicable behavioral models to support system analysis, design, and development (Wolny et al. 2020). Nevertheless, while SysML is gaining broad acceptance across the industry, a more holistic framework describes how the system model relates to other kinds of modeling and simulation (M&S) (Friedenthal, Moore, and Steiner 2015). Thus, for the purpose of this study, a model is a relationship between variables that represent causes and variables that represent effects, and a simulation is a representation of the system behavior as a function of time and space (Raphael and Smith 2013; Friedenthal, Moore, and Steiner 2015).

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 (Friedenthal, Moore, and Steiner 2015). Notwithstanding, in a broader development context, the system model is a set of interconnected models that exist as an integrated framework, as shown in Figure 3. In this approach, changes to the system requirements or design are propagated across all related models. Notably, frameworks that integrate models to assist decision-makers in evaluating system performance represent an application of MBSE (Bickford et al. 2020; Mengyan et al. 2024). Therefore, the rise of MBSE introduces a structured approach through interconnected models to attain this objective.

To be effective, efforts to integrate MBSE and engineering models through frameworks must address the challenging connections between different software. For instance, Beery (2016) presented a framework that investigated the relationship between system architecture and analysis using external simulations. The research combined SysML and simulation models to assess system requirements. Nevertheless, no feedback regarding the results was provided to the SysML tool. Although the proposed framework conducted detailed analysis of system performance using external models, the last step was the presentation of the simulation results instead of their feedback to the SysML tool. Previous work conducted by Kande (2011) also proposed a framework for integrating the models developed using SysML to create an executable platform for detailed design. Virtual engineering models were represented using SysML blocks. Information was converted from SysML to C++ to be executed, and dynamic-link library (DLL) files were plugged into engineering software to run the simulation cases. This approach kept consistency across the process, as models in both environments remained synchronized. Although comprehensive frameworks have narrowed the gap between SysML and simulations to reduce the extent of rework required to evaluate the system using different parameters, they require cross-platform adaptations to be fully integrated.

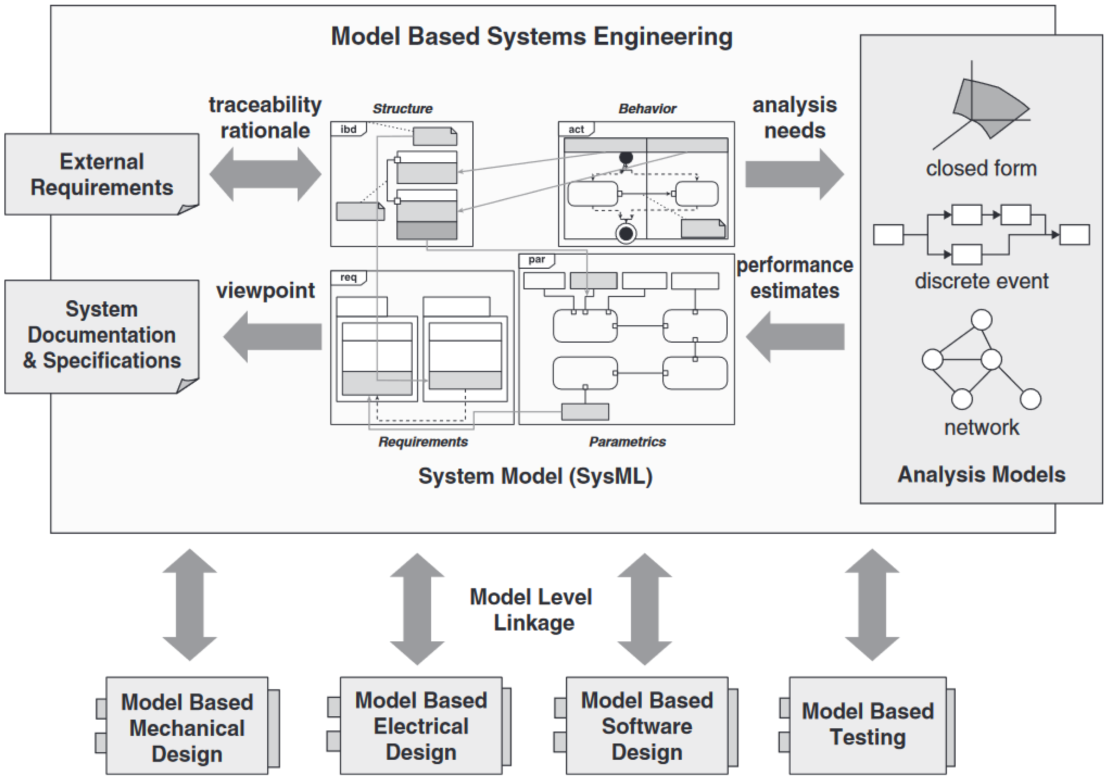
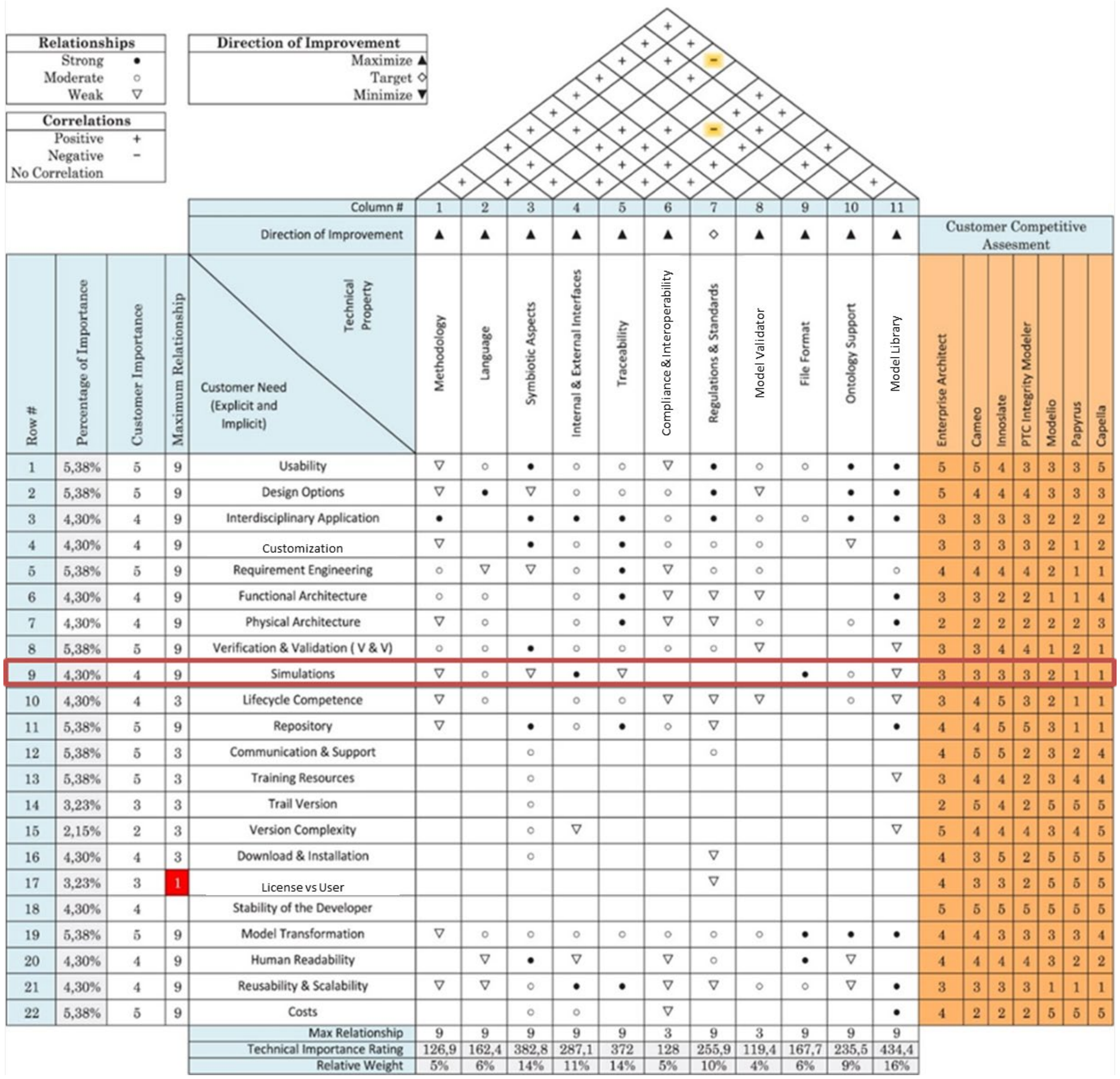


Figure 3. The system model described as a framework. Source: Friedenthal, Moore, and Steiner (2015).

Several authors also highlighted that a comprehensive approach involving MBSE and multi-domain simulation is limited by current SysML capabilities. For instance, Nigischer et al. (2021) investigated the state of the art and future perspectives for multi-domain simulation using SysML. The research explored the available model extensions and plugins to transfer parameters to different simulation environments. They concluded that tool-specific plugins may either generate scripts as export files or directly access simulation environments. Considering a more holistic approach, Khandoker et al. (2022) investigated the selection of an MBSE tool based on discipline specific requirements. They created guidelines to find the ideal tool for specific industrial applications by highlighting the key criteria each type of industry might consider. Furthermore, they proposed a filtration method to select an ideal MBSE tool for interdisciplinary application. Nonetheless, the authors found that there is no SysML tool that satisfies all user needs from various engineering disciplines. For example, Figure 4 shows the weakness of MBSE tools regarding simulation needs (i.e., connection of architecture models with simulations to calculate system performance), as most tools share a reasonable grade (3 out of 5). In fact, integration standards (e.g., functional mock-up interfaces (FMI) and high-level architecture (HLA)) were considered successful for model exchange and co-simulation in specific domains (Gorecki et al. 2018). Therefore, the performance of commercial SysML tools in terms of simulations is insufficient, particularly for complex systems.

Recent studies adopted a clean slate approach and established a novel, integrated methodology. Nonetheless, the functionalities of the new tools limit their effectiveness. For instance, Gu et al. (2024) proposed a system engineering methodology focused on M&S to overcome the limitations of SysML regarding its integration into system development environments. This new methodology relies on an integrated modeling language, which is based on SysML, Modelica, and discrete event system specification (L. Zhang et al. 2022). The main goal is to achieve "seamless integration of requirement analysis, function analysis, the design synthesis of system logic and physical aspects, and system verification and validation through a unified modeling language" (Gu et al. 2024, 202). As shown in Figure 5, there is a closed loop process connecting requirements with verification and validation (V&V), which allows early verification of requirements, mitigating the number of future corrections. Although this methodology has bridged the gap between MBSE and M&S, it lacks capabilities that are exclusive to CAE tools, such as the discretization of space and time to solve partial differential equations using the finite difference method.



Row #	Percentage of Importance	Customer Importance	Maximum Relationship	Customer Need (Explicit and Implicit) / Technical Property	Methodology	Language	Symbiotic Aspects	Internal & External Interfaces	Traceability	Compliance & Interoperability	Regulations & Standards	Model Validator	File Format	Ontology Support	Model Library	Enterprise Architect	Cameo	Innoslate	PTC Integrity Modeler	Modelio	Papyrus	Capella
				Column #	1	2	3	4	5	6	7	8	9	10	11	Customer Competitive Assesment						
				Direction of Improvement	▲	▲	▲	▲	▲	▲	◇	▲	▲	▲	▲							
1	5,38%	5	9	Usability	▽	○	●	○	○	▽	●	○	○	●	●	5	5	4	3	3	3	5
2	5,38%	5	9	Design Options	▽	●	▽	○	○	○	●	▽		●	●	5	4	4	4	3	3	3
3	4,30%	4	9	Interdisciplinary Application	●		●	●	●	○	●	○	○	●	●	3	3	3	3	2	2	2
4	4,30%	4	9	Customization	▽		●	○	●	○	○	○		▽		3	3	3	3	2	1	2
5	5,38%	5	9	Requirement Engineering	○	▽	▽	○	●	▽	○	○			○	4	4	4	4	2	1	1
6	4,30%	4	9	Functional Architecture	○	○		○	●	▽	▽	▽			●	3	3	2	2	1	1	4
7	4,30%	4	9	Physical Architecture	▽	○		○	●	▽	▽	○		○	●	2	2	2	2	2	2	3
8	5,38%	5	9	Verification & Validation (V & V)	○	○	●	○	○	○	○	▽			▽	3	3	4	4	1	2	1
9	4,30%	4	9	Simulations	▽	○	▽	●	▽				●	○	▽	3	3	3	3	2	1	1
10	4,30%	4	3	Lifecycle Competence	▽	○		○	○	▽	▽	▽		○	▽	3	4	5	3	2	1	1
11	5,38%	5	9	Repository	▽		●	○	●	○	▽				●	4	4	5	5	3	1	1
12	5,38%	5	3	Communication & Support			○				○					4	5	5	2	3	2	4
13	5,38%	5	3	Training Resources			○								▽	3	4	4	2	3	4	4
14	3,23%	3	3	Trail Version			○									2	5	4	2	5	5	5
15	2,15%	2	3	Version Complexity			○	▽							▽	5	4	4	4	3	4	5
16	4,30%	4	3	Download & Installation			○				▽					4	3	5	2	5	5	5
17	3,23%	3	1	License vs User							▽					4	3	3	2	5	5	5
18	4,30%	4		Stability of the Developer												5	5	5	5	5	5	5
19	5,38%	5	9	Model Transformation	▽	○	○	○	○	○	○	○	●	●	●	4	4	3	3	3	3	4
20	4,30%	4	9	Human Readability		▽	●	▽		▽	○		●	▽		4	4	4	4	3	2	2
21	4,30%	4	9	Reusability & Scalability	▽	▽	○	●	●	▽	▽	○	○	▽	●	3	3	3	3	1	1	1
22	5,38%	5	9	Costs			○	○		▽					●	4	2	2	2	5	5	5
				Max Relationship	9	9	9	9	9	3	9	3	9	9	9							
				Technical Importance Rating	126,9	162,4	382,8	287,1	372	128	255,9	119,4	167,7	235,5	434,4							
				Relative Weight	5%	6%	14%	11%	14%	5%	10%	4%	6%	9%	16%							

Figure 4. Assessment of MBSE tools and costumer needs, highlighting the simulations need. Adapted from Khandoker et al. (2022).

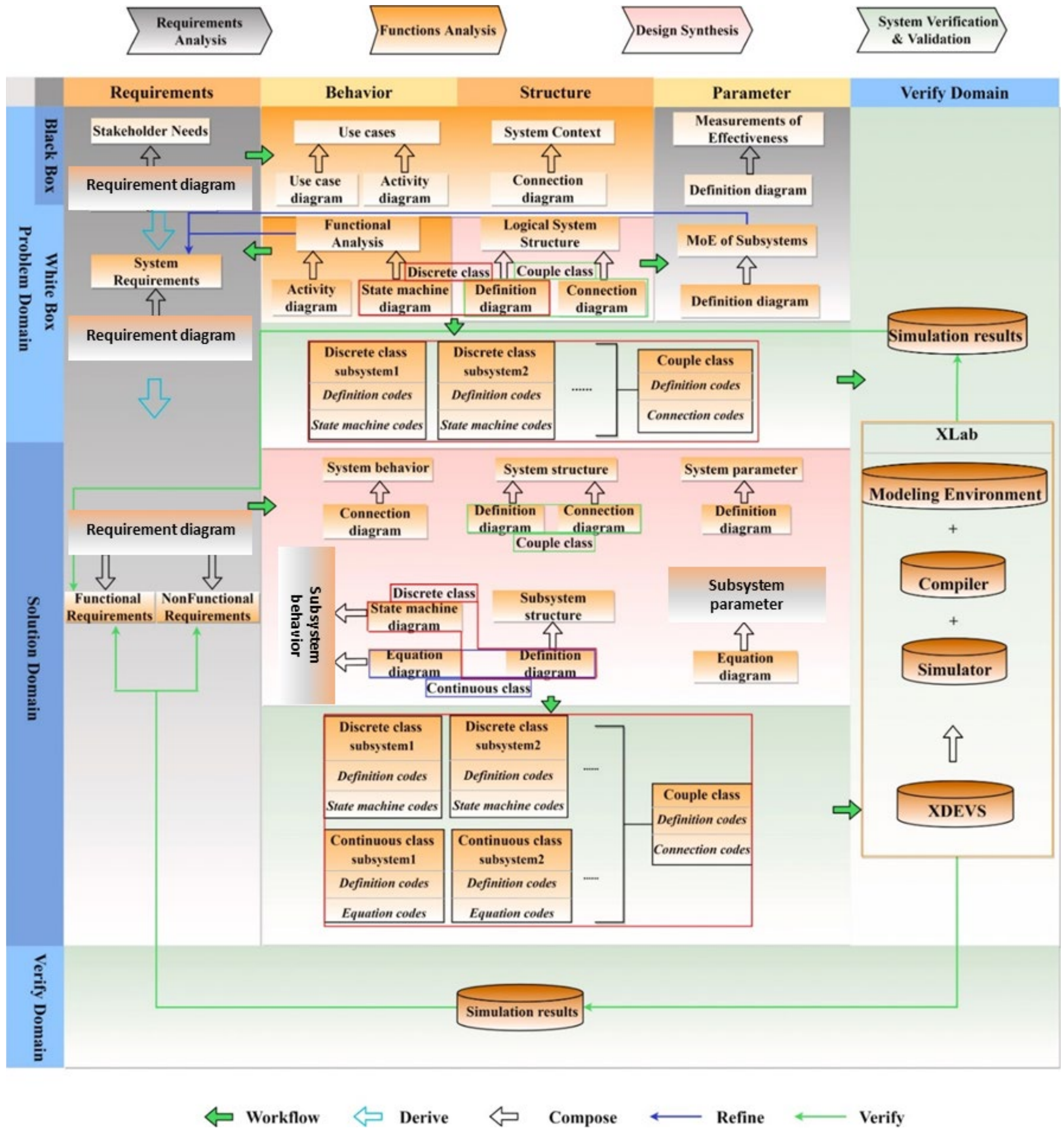


Figure 5. System design and verification framework based on X-SEM. Source: Gu et al. (2024).

Digital engineering is defined as "an integrated digital approach that uses authoritative sources of system data and models as a continuum across disciplines to support life cycle activities from concept through disposal" (Department of Defense 2018, 3). Digital engineering may address challenges associated with complexity and uncertainty by providing an agile and interactive development environment. Regarding complex systems, a significant barrier for digital engineering is the lack of integration between MBSE and simulation environments. Different approaches attempted to bridge this gap. However, they either demand cross-platform adaptations or face significant limitations in terms of problem-solving capabilities, which constrains the ability to analyze how changes across design platforms impact system requirements (Nigischer et al. 2021; Gu et al. 2024). Furthermore, system developers lack an integrated framework that supports decision-making and provides feedback on simulation results to determine whether the system meets the requirements (Beery 2016; Rangel 2021).

B. VERIFICATION PROCESS USING INTEGRATED COMPUTER-AIDED ENGINEERING METHODS

SE is an interdisciplinary approach that considers both the business and the technical stakeholder needs. For technical assessments, model-based reasoning can support decision-making if models respect important relationships based on physical and chemical principles (Raphael and Smith 2013). Computational models are commonly applied in engineering tasks (e.g., simulation, diagnosis, synthesis, and behavior analysis of complex systems) (X. Zhang et al. 2023; Rangel 2021). Their length scales may range from nanometers to several thousand kilometers. For instance, Figure 6 shows that the modeling of a chemical process spans from quantum mechanics and molecular simulation to plant optimization and enterprise analysis. In practice, many engineering disciplines, business analysts, and project managers contribute to the design of an enterprise (Giachetti 2016). In this context, different computer-aided design (CAD) tools and CAE methods (e.g., finite element analysis (FEA) and computational fluid dynamics (CFD)) should be integrated to ensure that concomitant projects will converge into the desired vision of the enterprise.

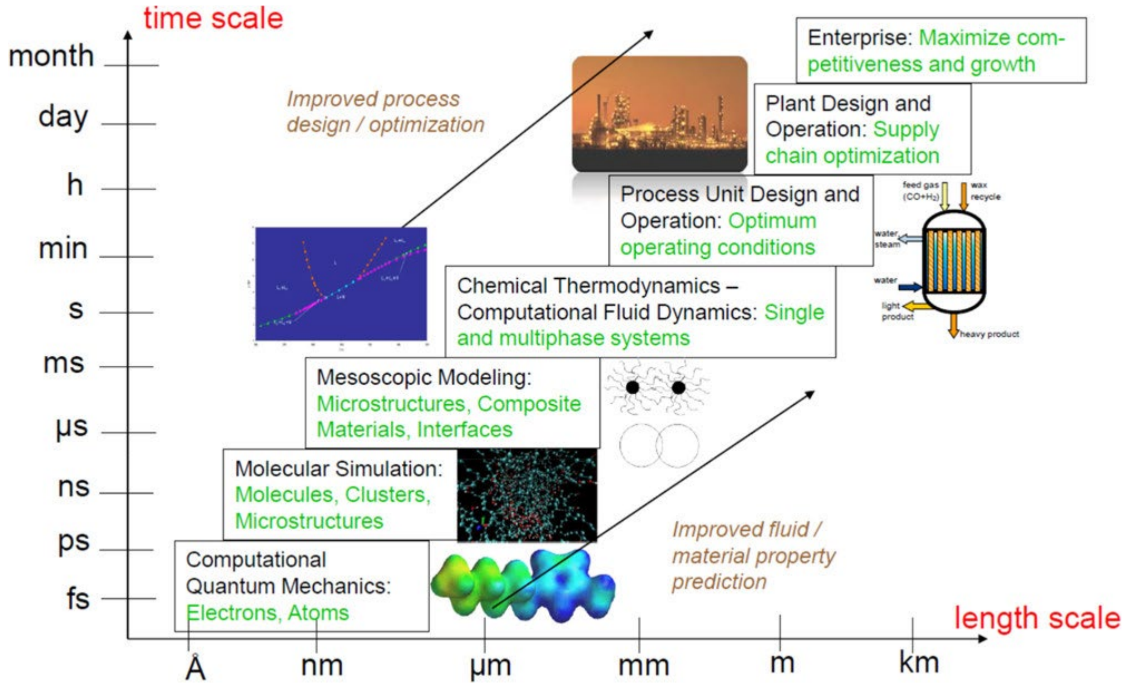


Figure 6. Process simulation spectrum of length and time scales. Source: de Hemptinne et al. (2022).

MBSE approaches look forward to supporting SE throughout the entire system life cycle. Regarding the verification process, the main challenge is to couple descriptive and physics-based models to use simulation-based tests (Gu et al. 2024). This study considers that in a verification process, "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, 49). 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, 49). Consequently, model-based reasoning derived from simulations facilitates the verification process, whereas tests and experiments serve to provide validation. MBSE ought to support both processes. Therefore, in this thesis, simulation results are considered as evidence for verification purposes and experimental data that uses operational environment conditions are evidence for validation purposes.

Modern MBSE approaches face significant barriers as they look forward to providing a holistic system model that facilitates the use of external solvers (e.g., CAE methods) for complex simulations. For instance, Rangel (2021) boosted the use of Cameo Systems Modeler to execute models of combat systems that run in a Simulink environment. The author found that the integration posed a considerable challenge, as it necessitated extensive modifications to both models to generate an executable MBSE model. Similarly, Dam (2020) presented the lessons learned in the creation of a digital engineering ecosystem (DEE), where the integration of Innoslate with other tools such as MATLAB/Simulink and Ansys Systems Tool Kit (STK) was applied to perform system verification through co-simulation using application programming interfaces (APIs). For instance, Figure 7 (a) shows an Innoslate action diagram that interconnects both STK and MATLAB co-simulations. APIs were designed to get to the critical parameters in STK model output and insert them into MATLAB. Figure 7 (b) presents the script that is executed as the MATLAB block from the action diagram is activated, which has two Innoslate APIs (matlab.post and matlab.get). The streamlined use of MATLAB to interface with STK models allowed the analysis of complex multi-physics models. Nevertheless, many software tools do not have APIs for integration as they are still essentially desktop tools, which makes it difficult to integrate them with cloud computing tools. To date, the integration of MBSE and complex simulations (i.e., CAE tools) requires additional APIs or is constrained by tools that are not compatible with cloud computing.

(a)

(b)

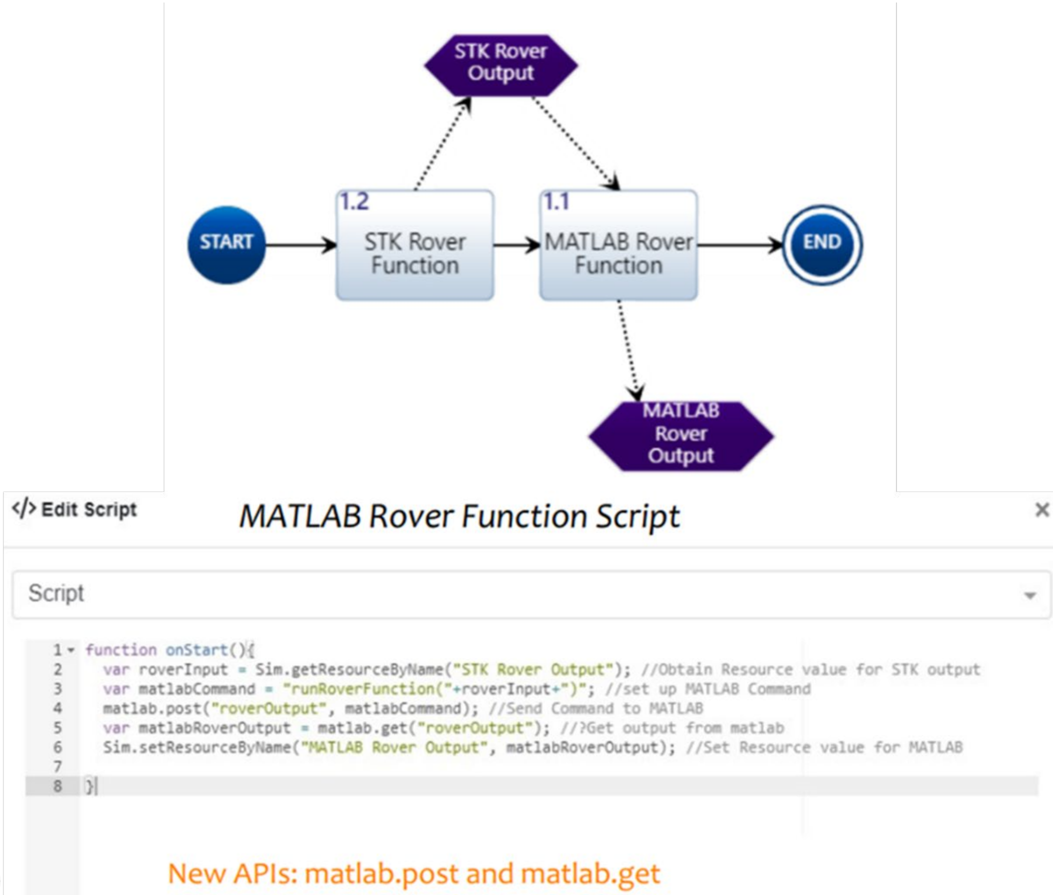


Figure 7. STK and MATLAB co-simulations inside Innoslate action diagram (a) showing APIs (b) used to transfer data from MATLAB. Source: Dam (2020).

Even though APIs create linkages, the degree of automation increases significantly when the MBSE editor has direct access to the simulation environment, thereby eliminating the need for additional procedures. Recently, MathWorks (2024) released the System Composer, which connects the architecture to design models in MATLAB and Simulink. Thus, engineers can populate the architecture with multi-physics models. System Composer is built as the architecture layer of Simulink, enabling models to be directly referenced from the architecture components. Figure 8 (a) illustrates this concept where both architecture and domain models belong to the same tool. The architecture model is then simulated as a Simulink model to generate results for analysis, as shown in Figure 8 (b). Moreover, requirements are linked to architecture components, ports, interfaces, or variables. Using the linking mechanism, it is possible to identify how requirements are met in the architecture model. Therefore, a native connection arises when the MBSE tool emerges directly from powerful engineering tools such as MATLAB.

(a)

(b)

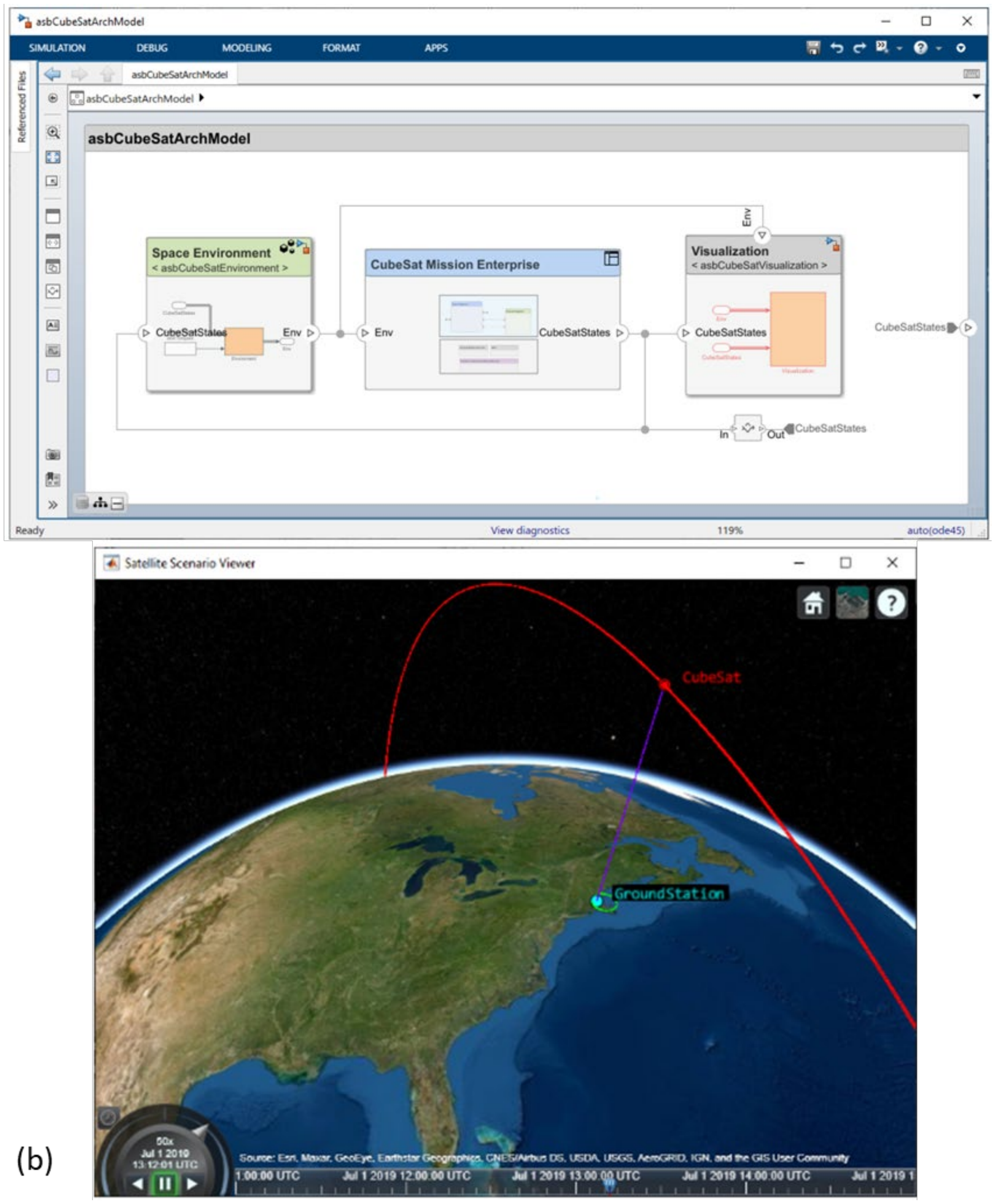


Figure 8. Example of System Composer architecture model (a) naturally integrating with the Simulink design model (b). Source: MathWorks (2024).

The selection of an MBSE tool should consider its native capabilities when trying to replace the use of multiple software applications. Regarding M&S capabilities, the possibility of having powerful CAE methods (e.g., FEA) directly connected to the MBSE tool mitigates the gap between various levels of abstraction. Table 1 presents a comparison of modern MBSE tools available in the market and highlights the fact that only MATLAB provides both capabilities. This native connection establishes a singular condition that enhances the application of simulation-based tests for requirements verification. Henceforth, CAE methods can be integrated into a comprehensive MBSE environment.

Table 1. Tools' capabilities to perform MBSE and CAE methods.

Tool	**MBSE**	**CAE**	**Single platform**
Magic Systems of Systems Architect (No Magic, n.d.)	Yes	No	No
Innoslate (SPEC Innovations, n.d.)	Yes	No	No
ModelCenter (Ansys, n.d.-a)	No	Yes	No
STK (Ansys, n.d.-b)	No	Yes	Yes
MATLAB (MathWorks 2024)	Yes	Yes	Yes

As the systems engineer must have a broad understanding of different disciplines, MBSE must be able to communicate across different models. Basically, there are two distinct approaches. In the traditional approach, illustrated in Figure 9 (a), MBSE aims to support SE throughout the entire system life cycle. On the other hand, in the desired approach shown in Figure 9 (b), it can also seamlessly integrate requirements and engineering disciplines.

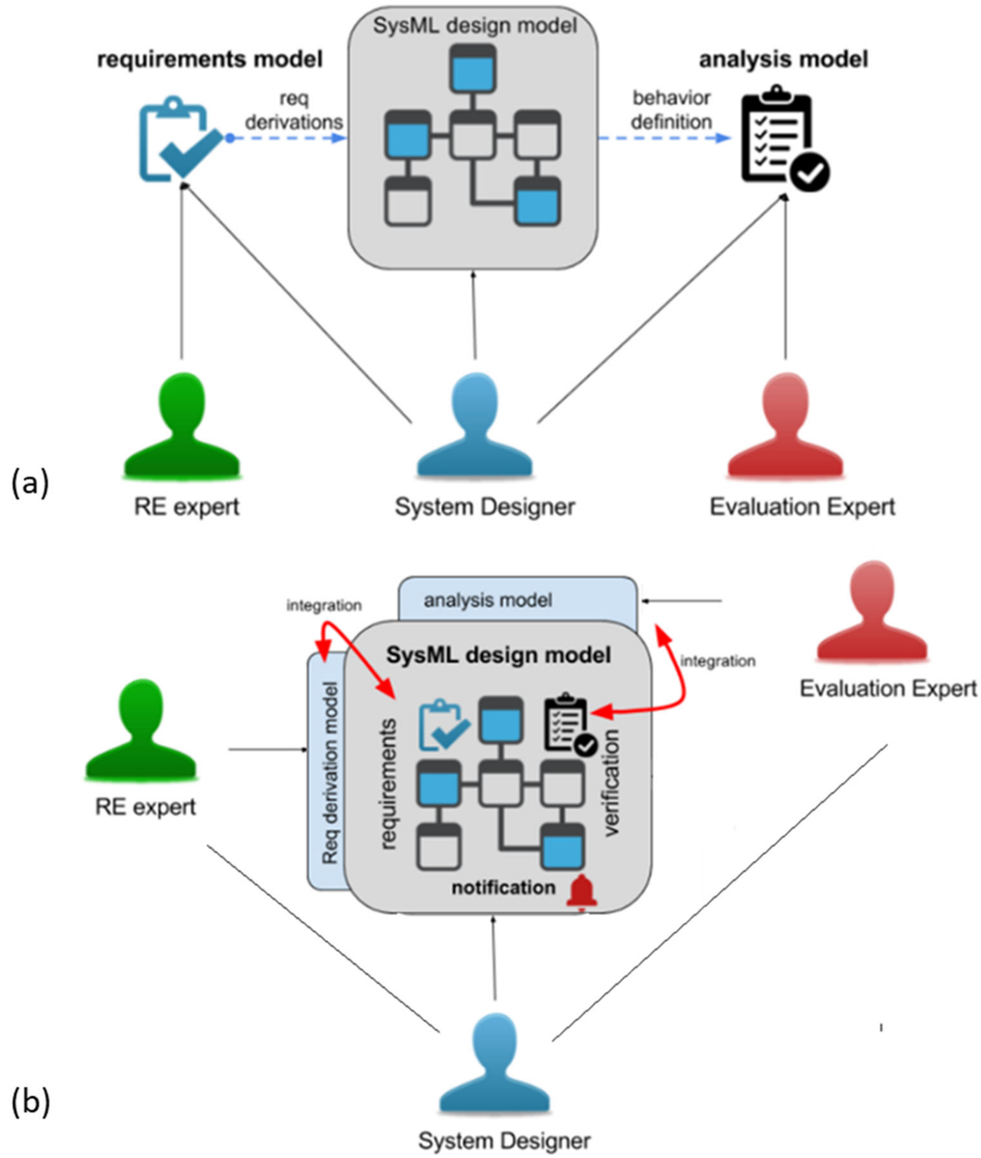


Figure 9. Two ways to conduct MBSE: traditional approach (a) and integrated approach (b). Adapted from Tsadimas (2018).

C. VERIFICATION OF REGULATORY REQUIREMENTS FOR NUCLEAR SYSTEMS

CAE are powerful tools that can simulate nuclear systems to support the verification of regulatory requirements. They contribute to a deeper understanding of the system behavior and complement system codes by analyzing relevant phenomena on a detailed scale (Rivera et al. 2024). Additionally, these tools can be applied in the licensing process of nuclear systems to assess safety margins and support the verification of regulatory requirements. This process is a significant barrier to the development of new reactors (Mignacca, Locatelli, and Sainati 2020). Figure 10 presents the average time (in years) for licensing an NPP in different countries. It shows that it takes, on average, 11 years to license an NPP in the United Sates (Nuclear Energy Agency 2021). Additionally, Figure 11 shows that in the last twenty years no significant growth has been observed in terms of power generation from NPPs worldwide (International Atomic Energy Agency 2023). Conversely, several licenses were renewed for operating lifespan extensions. Therefore, regulatory requirements may hinder reactor construction.

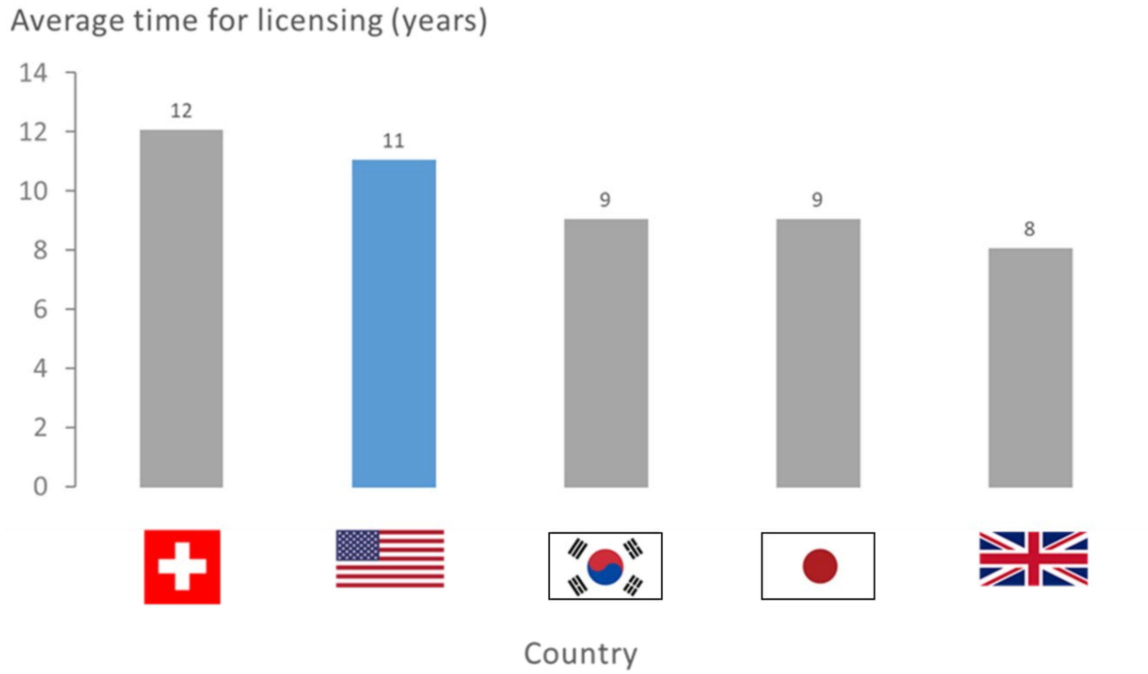


Figure 10. Average time for licensing an NPP before construction and commissioning by country. Adapted from Nuclear Energy Agency (2021).

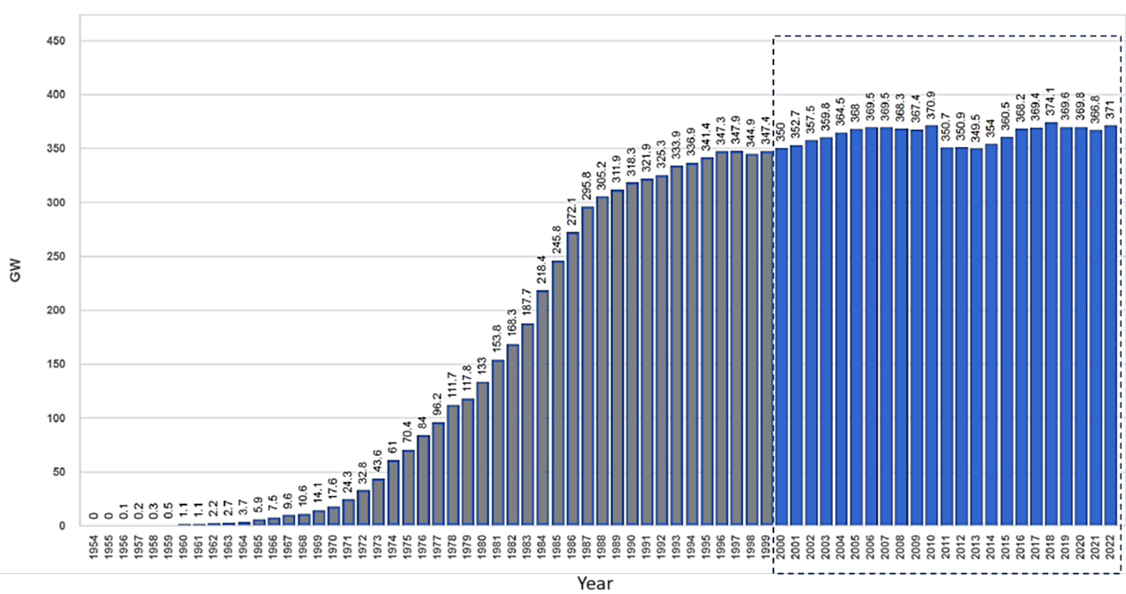


Figure 11. Nuclear power in the world throughout the years. Adapted from International Atomic Energy Agency (2023).

Throughout the licensing process, regulatory requirements are verified using safety analysis reports, which allows the assessment of the NPP behavior and the consequences of accidents. According to the United States Nuclear Regulatory Commission (U.S. NRC) (2021b; 2021a), a design-basis accident (DBA) is “a postulated accident that a nuclear facility must be designed and built to withstand without loss to the systems, structures, and components necessary to ensure public health and safety.” On the other hand, a beyond design-basis accident (BDBA) means an accident sequence considered to be too unlikely to be part of the design scope of the nuclear facility. After the Fukushima accident in 2011, the design extension conditions (DEC) concept became an important aspect of the regulatory framework of NPPs (Král and Krhounková 2024). The concept of DEC replaced the classical safety approach for NPPs, as shown in Figure 12. Therefore, lessons learned from the Fukushima accident expanded the design envelope of NPPs.

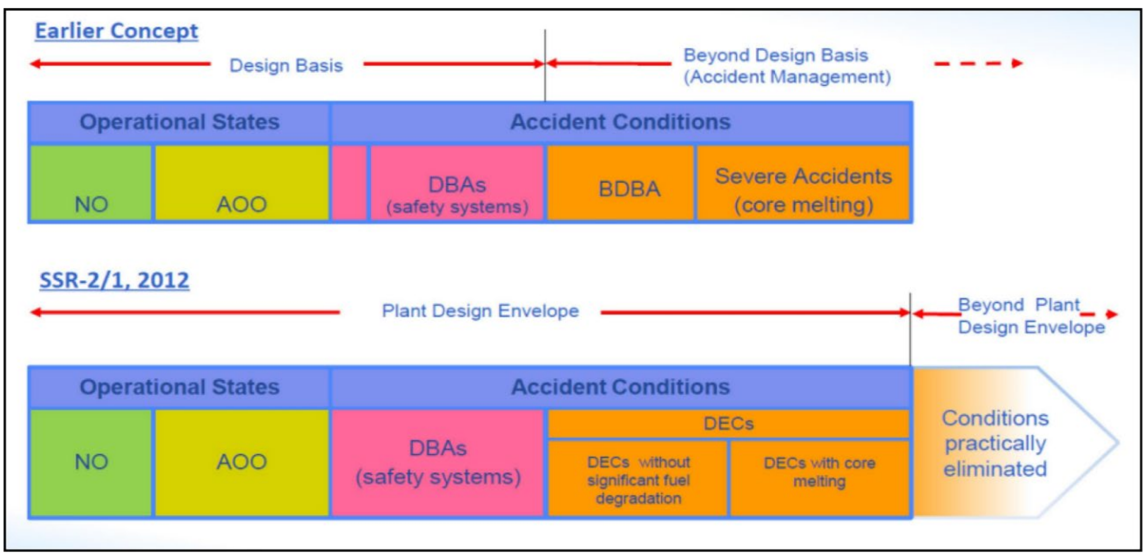


Figure 12. Nuclear safety concepts and the evolution of IAEA standards.
Source: Král and Krhounková (2024).

The main functions of nuclear systems are related to safety. Examples of safety functions include cooling the fuel, controlling reactivity, and containing radioactive release, as shown in Figure 13. Safety-related systems, structures, and components must remain functional during and following DBA. The analysis of DBA can be either based on conservative or best estimate (realistic) models (International Atomic Energy Agency 2016). According D'Auria (2019), the BEPU is an approach of particular interest to the licensing process of NPPs, as it combines both deterministic and probabilistic safety analysis. The BEPU history remounts the U.S. NRC pioneering efforts for V&V of thermal-hydraulic codes (Appendix K to 10 C.F.R. § 50.46). Figure 14 illustrates how BEPU is related to modeling, simulation, verification, and validation. In this approach, both experimental results and multi-physics models are considered in the simulation to provide the best estimate along with an uncertainty band, enhancing the licensing process.

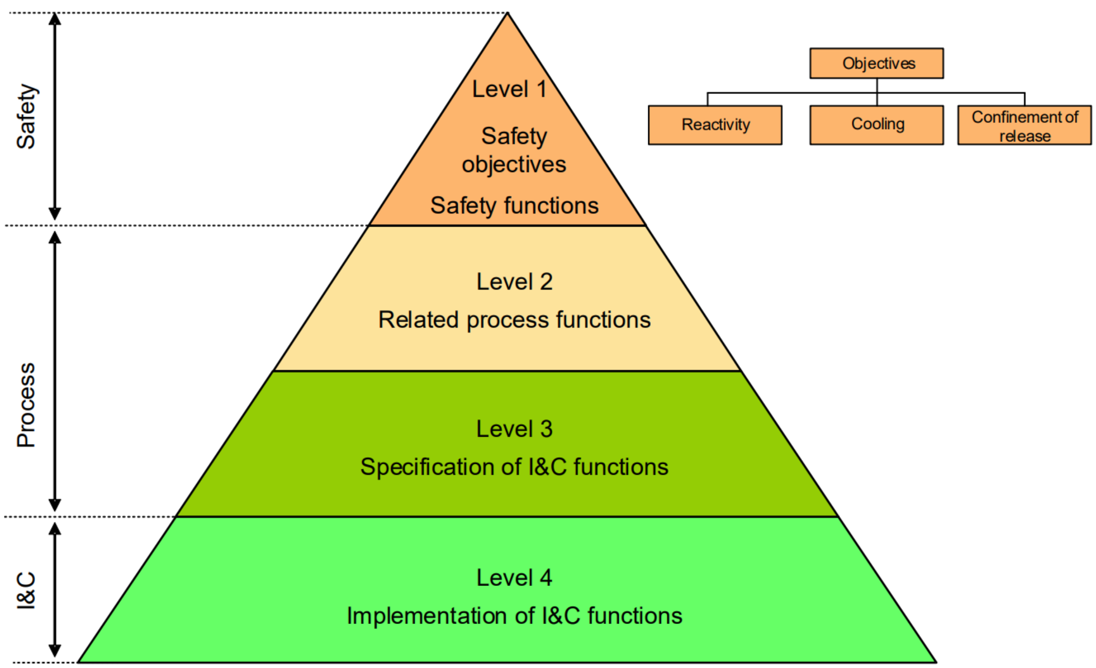


Figure 13. Levels of functions for nuclear systems. Source: International Atomic Energy Agency (2022).

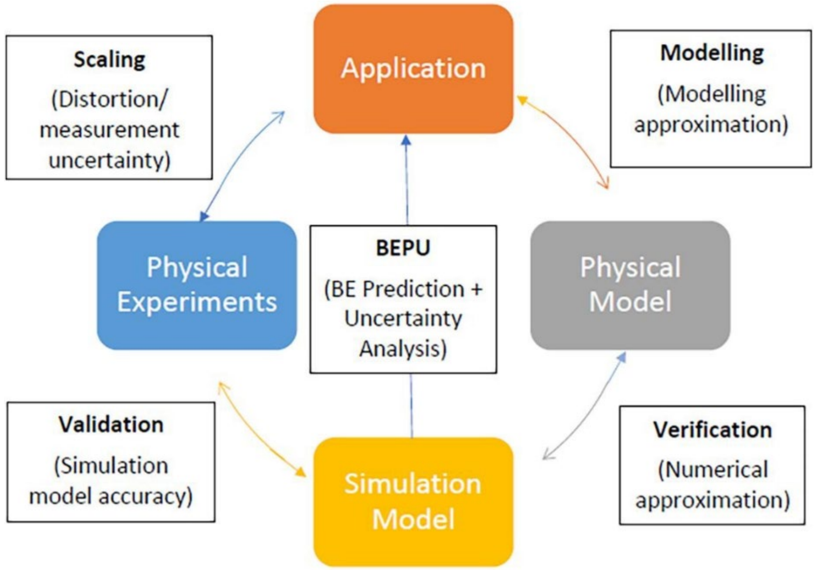


Figure 14. The verification and validation process in relation to the BEPU methodology. Source: Zhang (2019).

The analysis of DEC can use either the BEPU approach or another methodological procedure that addresses a significant level of uncertainty, as fuel degradation and core melting might occur. For instance, Matias Avelar et al. (2023) applied BEPU analysis to study a critical safety phenomenon of water-cooled nuclear reactors. They concluded that oxidation kinetics is a key factor, particularly when the analysis aims to be conservative. Therefore, in the context of nuclear safety analysis, either BEPU or conservative approaches can be applied to verify regulatory requirements across various categories of accident conditions.

The BEPU approach is particularly relevant in the context of licensing margin calculations. The licensing margin is defined as "the difference between the design limit and the upper bound design or safety analysis result (e.g., maximum peak cladding temperature) for the related physical parameter during the analyzed transient" (Jinzhao Zhang and Schneidesch 2023, 2). It differs from the apparent margin, as shown in Figure 15. The probability that the system will meet its requirements can be increased by revisiting the design to add more margin, thereby widening the gap between the two curves. Freixa et al. (2021) compared the results obtained by BEPU methodologies against experimental data from tests. The authors observed that 95% of analyzed output parameters were inside of the BEPU spectrum, which strengthens confidence in its application in the licensing process. Therefore, the development of the BEPU approach for margin quantification based on multi-physics simulations and uncertainty analysis supports the reactor core design.

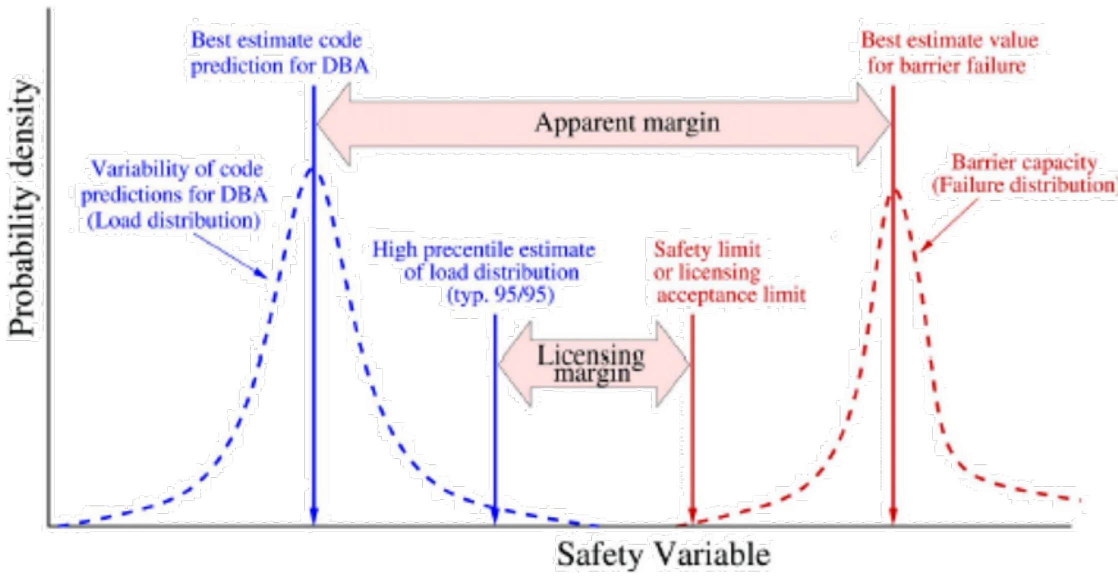


Figure 15. Apparent margin vs. licensing margin. Adapted from Zhang and Schneidesch (2023).

Even though a few studies have applied SE methodologies using an NPP as a case study, no work has linked MBSE to the simulations involved in the design and safety analysis of these systems. For instance, Navas et al. (2018) used MBSE to define the architecture of a nuclear island. They found that this methodology provides benefits for the designer by increasing the level of comprehensiveness. Similarly, Gaignebet et al. (2021) proposed a methodology to help improve communication between stakeholders during commissioning phases of nuclear facilities. Although only the commissioning phase was analyzed, their results corroborate the fact that MBSE can improve decision-making and communication between stakeholders. In a broader context, Ibrahim et al. (2023) conducted a literature review of MBSE applications in the nuclear industry and found qualitative benefits, such as unambiguous system description, consistent mental models of a system, and clear component definitions. Previously, Ibrahim et al. (2022)

had used MBSE to allocate safety-related requirements among subsystems and components to assess whether one or more options adequately address system mission and objectives. They concluded that this approach provides risk-informed insights into the design process. Conversely, Linnosmaa et al. (2019) mentioned that the use of MBSE languages requires significant expertise to extract information from design documents. Notwithstanding, they also agreed that SysML supports classical safety analysis methods. Hence, research related to MBSE in the nuclear energy sector is applied to support early-stage and risk-informed design development using SysML models.

This thesis aims to expand the reach of MBSE by integrating SysML products with CAE methods. Furthermore, it supports the utilization of the BEPU approach in the licensing process of nuclear systems. Recent studies corroborate that the MBSE concept can provide a streamlined method for BEPU analysis (X. Zhang et al. 2023; Mengyan et al. 2024). Table 2 compares the methodology proposed by this study against published works that address MBSE and nuclear systems. Therefore, this work proposes a novel methodology that applies the BEPU approach in a natively integrated MBSE–CAE environment to enhance the verification process of regulatory requirements. This integrated methodology aims to shorten the cycle time from data gathering to decisions in the licensing process of NPPs.

Table 2. Studies that applied MBSE, CAE, and BEPU approaches to the design of nuclear systems.

Reference	**MBSE**	**CAE**	**BEPU**
Freixa et al. (2021)	Yes	No	No
Ibrahim et al. (2023)	Yes	No	No
Gaignebet et al. (2021)	Yes	No	No
Linnosmaa et al. (2019)	Yes	No	No
Ibrahim et al. (2022)	Yes	No	No
De Florio et al. (2024)	Yes	No	No
Zhang et al. (2023)	No	Yes	Yes
This study	Yes	Yes	Yes

The focus of this thesis is to use the digital engineering approach to support decision-making in the licensing process of nuclear systems. One of the main goals of digital engineering is to use digital artifacts as a technical means of communication between stakeholders. Therefore, this holistic set of digital representation of nuclear systems may facilitate collaboration across disciplines and communication with regulatory authorities.

III. METHODOLOGY

This chapter is divided into two sections, each addressing a different aspect of the research process. The first section describes the conceptualization of a novel methodology, entitled model breakdown structure (MBS), which integrates model-based systems engineering (MBSE) and computer-aided engineering (CAE). The other section focuses on methods to enhance the verification process, such as the design of experiments (DOE) and uncertainty quantification.

A. THE MODEL BREAKDOWN STRUCTURE

MBSE is used by systems engineers to support requirements management throughout the system life cycle. The primary objectives of MBSE are to analyze system performance, support the verification and validation (V&V) processes, and improve communication among the stakeholders. Additionally, the integration of MBSE with other computational models, such as CAE methods, leverages the systems engineering ability to orchestrate various multi-physics models to perform in-depth analysis of system behavior and enhance its support for decision-making.

This thesis proposes a novel methodology entitled model breakdown structure (MBS), 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. Figure 16 illustrates the MBS concept, which comprises not only typical systems engineering deliverables but also domain-specific models such as CAE methods, experimental databases, and simulations to provide feedback for test cases (V&V models).

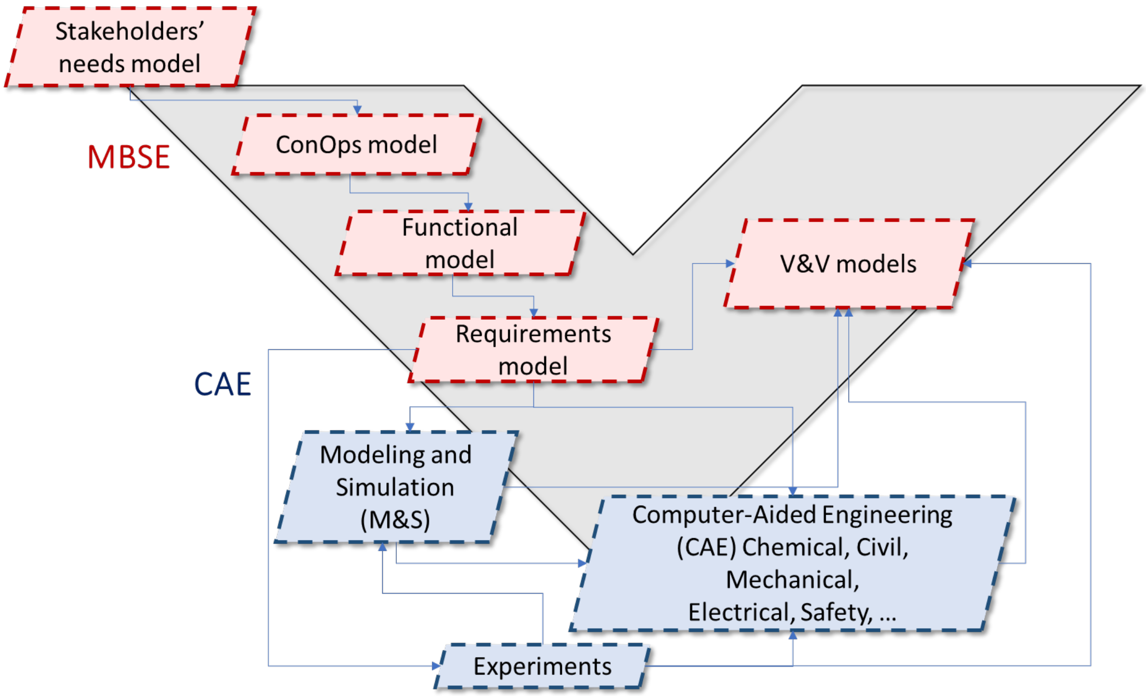


Figure 16. The MBS methodology concept.

The main goal of MBS is to enhance the verification process through the integration of MBSE and CAE. As illustrated in Figure 17, the MBS consists of six initial steps: (1) selecting the MBSE tool; (2) developing a system model; (3) defining a set of requirements; (4) developing and validating a simulation model; (5) verifying requirements using simulation-based tests; and (6) creating an experimental design to provide an initial assessment of which factors have a significant effect on system requirements. For high-risk factors, three additional steps are proposed: (7) building MBS, (8) propagating uncertainties to quantify the uncertainty on the system measures of performance (MOPs) and measures of effectiveness (MOEs), and (9) using their uncertainty bands, which are denominated as BEPU MOP/MOE, to enhance the verification process, by providing automated feedback to the MBSE tool.

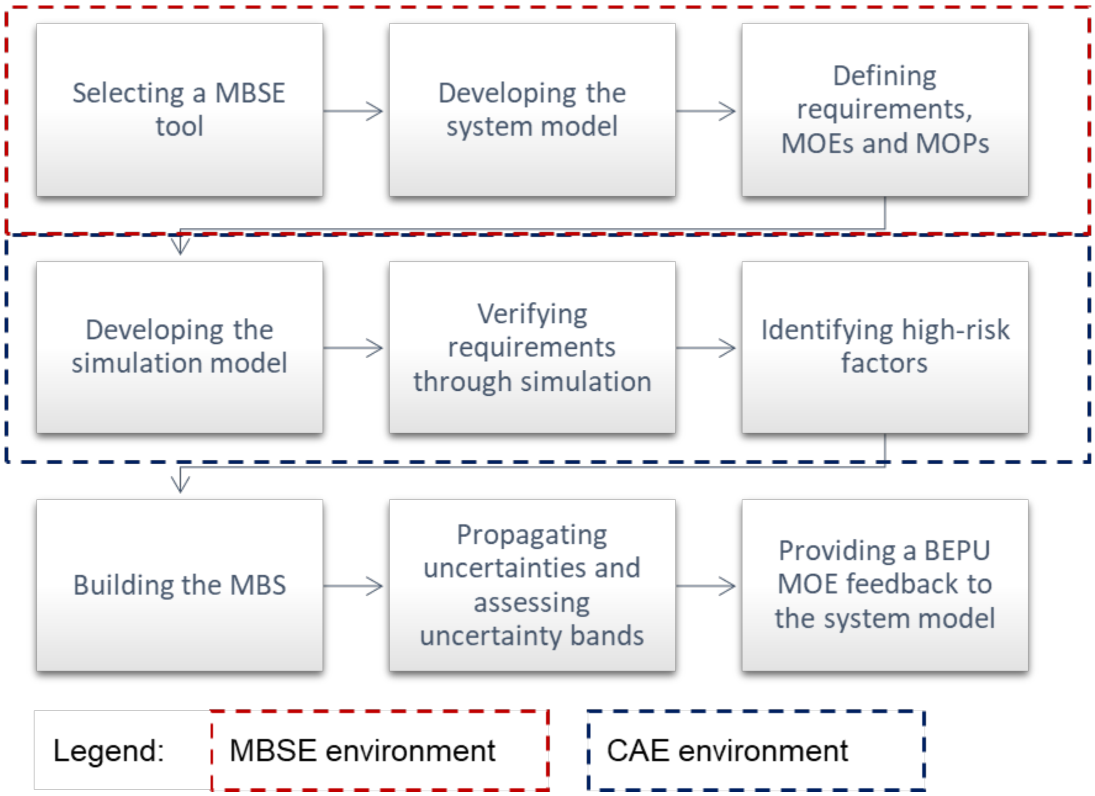


Figure 17. Integrating MBSE tools and CAE methods into the MBS.

The effectiveness of MBS relies on not only integrating MBSE into a system development environment but also its ability to explore the design space and enhance the verification process through the application of both the DOE and BEPU approaches. The former is applied to assess which factors significantly impact the MOPs and MOEs. The latter is applied to conduct uncertainty analysis up to the MOE level and improve the verification process.

The MBS methodology is divided into three parts. The first part of the MBS is conducted in a typical MBSE environment. The system requirements are distributed across computational models from various disciplines. The requirements implementation ensures that requirements can be both verified through simulations and validated through experimental tests, as shown in Figure 18. It is worth mentioning that simulations are applied to verify requirements. On the other hand, when experimental data is available, requirements can be validated. Conversely, the second part of MBS is conducted in a system development environment (e.g., CAE methods) to verify or validate a specific requirement. Additionally, by applying the DOE, it is possible to systematically assess the relationship between factors and their effects on MOPs and MOEs and to determine the factors with the largest effect on system behavior (high-risk factors). The third part integrates both models to enhance the verification process, as shown in Figure 19. The automated BEPU MOE feedback to the MBSE tool is the main benefit of the MBS methodology. Henceforth, the verification process is conducted using the best estimate of the MOE along with its uncertainty band.

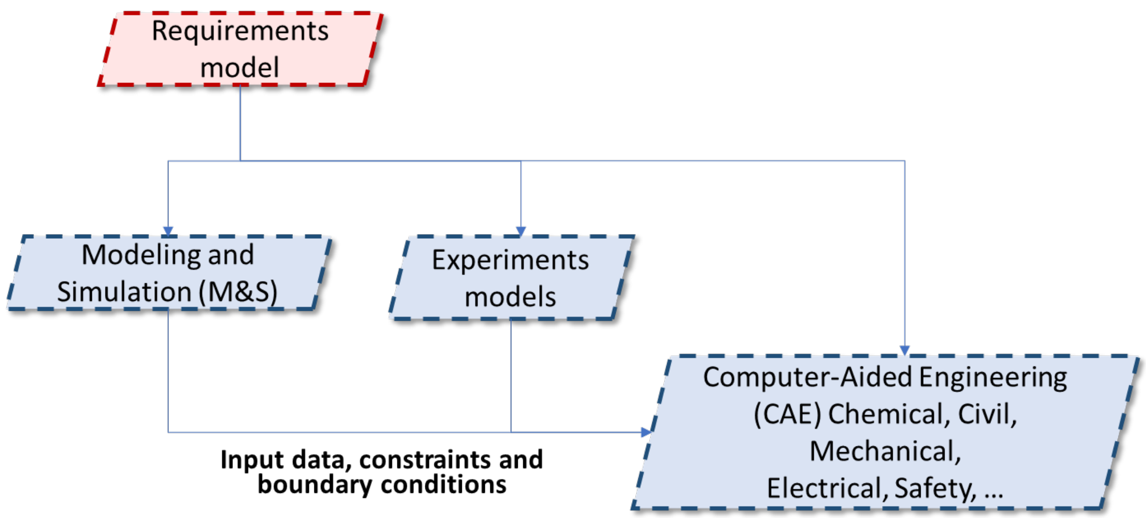


Figure 18. The requirements rainfall from MBSE into system development environments.

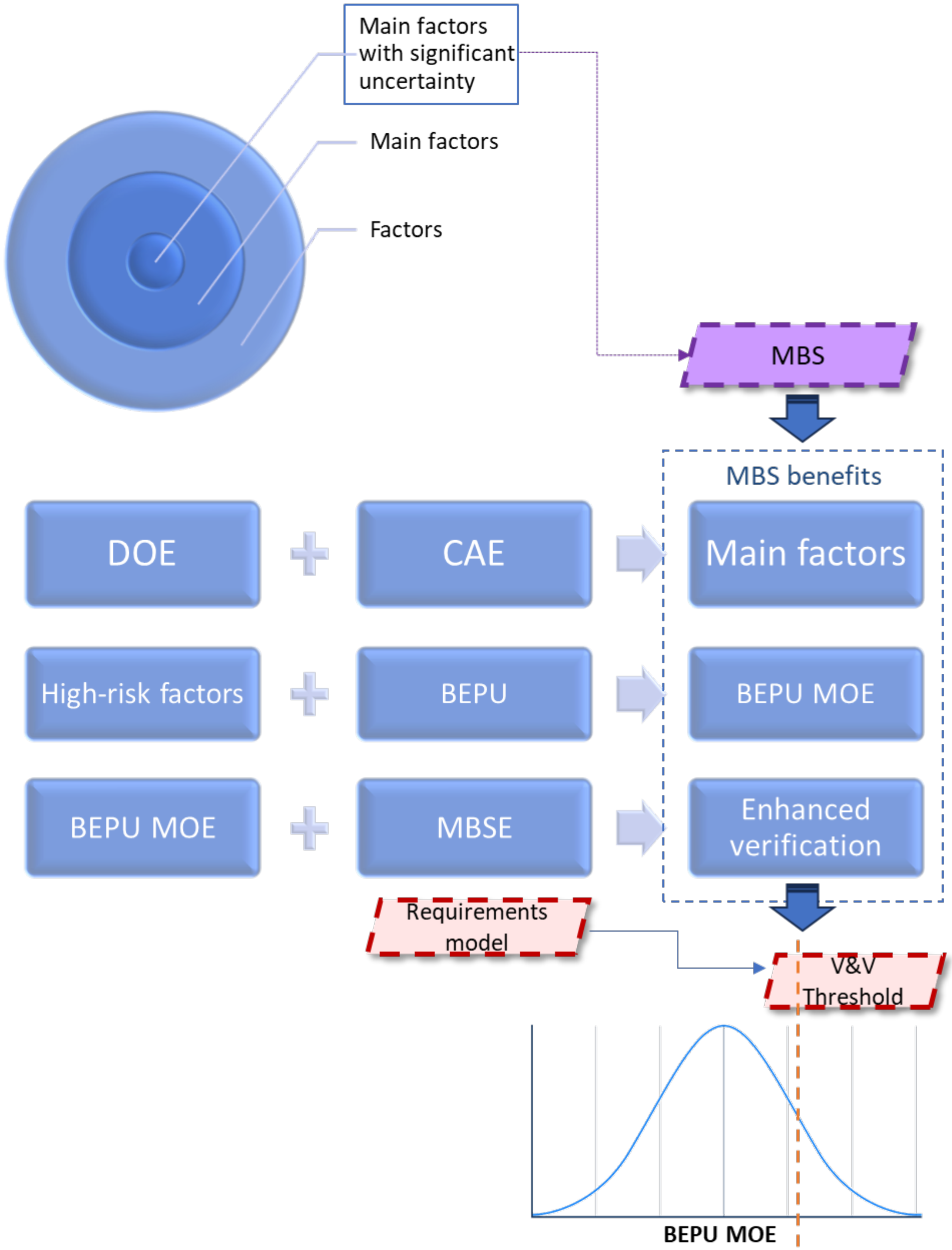


Figure 19. MBS methodology applied to enhance the verification process.

Additionally, as shown in Figure 20, a traceability matrix between requirements and output variables is proposed as a support tool. This comprehensive approach links requirements to computational models, enabling MBSE to oversee engineering models across multiple disciplines.

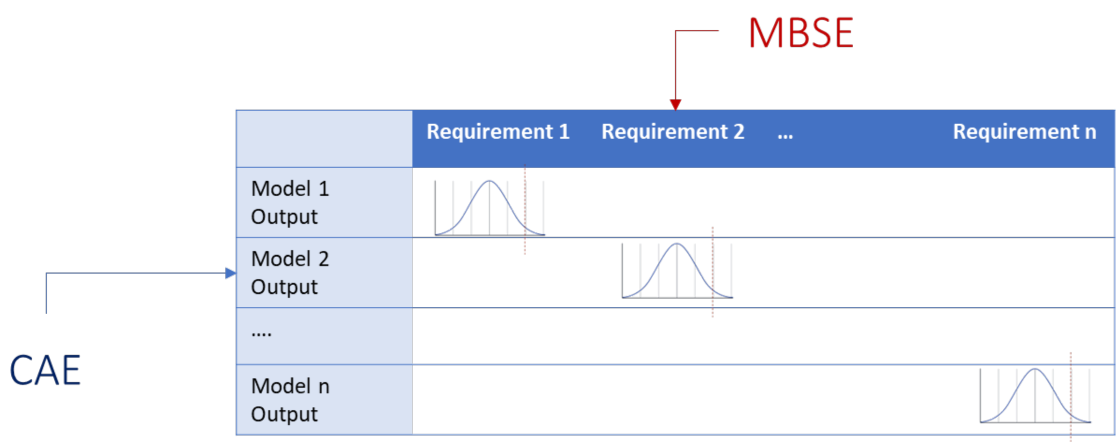


Figure 20. Traceability matrix between requirements and models' outputs.

This comprehensive methodology aims to support systems engineers in gaining a deeper understanding of distinct configurations of the system's behavior under various conditions. It emphasizes which factors the design team should focus on to improve design margins. Moreover, given a particular MOE and the key factors' probability distribution functions, it shows the range of responses the stakeholders should expect from the system's behavior. Once DOE and uncertainty quantification methods are systematically integrated into the MBS methodology, the BEPU analysis can be conducted through a streamlined approach to enhance the verification of safety requirements. Therefore, the novelty of this work resides in providing a holistic understanding of the system's behavior to shorten cycle time from data gathering to decision-making.

The first step in the MBS methodology is the selection of the MBSE tool. To effectively integrate MBSE into a CAE tool, this thesis proposes the use of MathWorks' System Composer. This tool is an MBSE extension to the MATLAB and Simulink environments, enabling the creation, implementation, and verification of system requirements within the same simulation continuum. Notably, this selection allows not only seamless integration but also the utilization of a broad variety of computational tools developed by MathWorks and widely used by engineers, including partial differential equation solvers, FEA, and DOE. This thesis does not endorse one specific tool or modeling language, because MBSE practitioners might select other tools that meet their specific needs. However, the author selected MATLAB for this study because of its broad applicability to diverse engineering applications.

B. METHODS FOR DESIGN OF EXPERIMENTS AND UNCERTAINTY QUANTIFICATION

To enhance the verification process, the MBS methodology employs both DOE and uncertainty quantification methods. The goal is to effectively explore the design space and assess the effect of high-risk factors (e.g., environmental conditions, material properties, and human factors). Even with powerful computers, the analysis using CAE methods can be extremely time-consuming due to their high complexity. Consequently, the selection of both DOE and uncertainty quantification methods is based on their ability to reduce the number of test cases while delivering significant outcomes.

First, Latin hypercube design (LHD) is a statistical method used to generate a near-random sample of parameter values from a multidimensional distribution. LHD has already proven to be a valuable method for DOE, especially when exploring high-dimensional computational models (Hernandez, Lucas, and Carlyle 2012; Ye 1998; Chen et al. 2023). Although LHD reduces the number of experiments compared to a full factorial design, it ensures comprehensive coverage of the entire design space of the factors. Therefore, LHD enables efficient parameter sampling.

Second, the MBS methodology supports Wilks' theorem for uncertainty quantification. This method is widely used in BEPU analysis as it enables an effective uncertainty quantification using a limited number of simulation cases, reducing the required computational effort (D'Auria 2019; Jinzhao Zhang and Schneidesch 2023; Lee et al. 2014; Matias Avelar et al. 2023). A frequent practice is to use a 95% confidence level and 95% probability (Shockling 2015; Jyrkama and Pandey 2017). According to the first order Wilks' theorem, the 95/95 unilateral tolerance limit is the highest value within

59 sample data, provided that the boundaries for all factors are truncated within their 95% confidence interval. Even when considering the second order, the number of cases increases to 93, which is still significantly fewer than the number of simulations for the Monte Carlo method (Lee et al. 2014). In this thesis, both first and second orders of Wilks' theorem were applied.

This ensemble of techniques enables the creation of an uncertainty quantification model for each MOP and MOE. This innovative approach supports the V&V of requirements by collecting the results from a set of systematic analysis and delivering detailed feedback for the requirements management, as illustrated in Figure 21. Ideally, in the MBS, all models are interconnected so that, if necessary, uncertainties can be seamlessly propagated from one model to another.

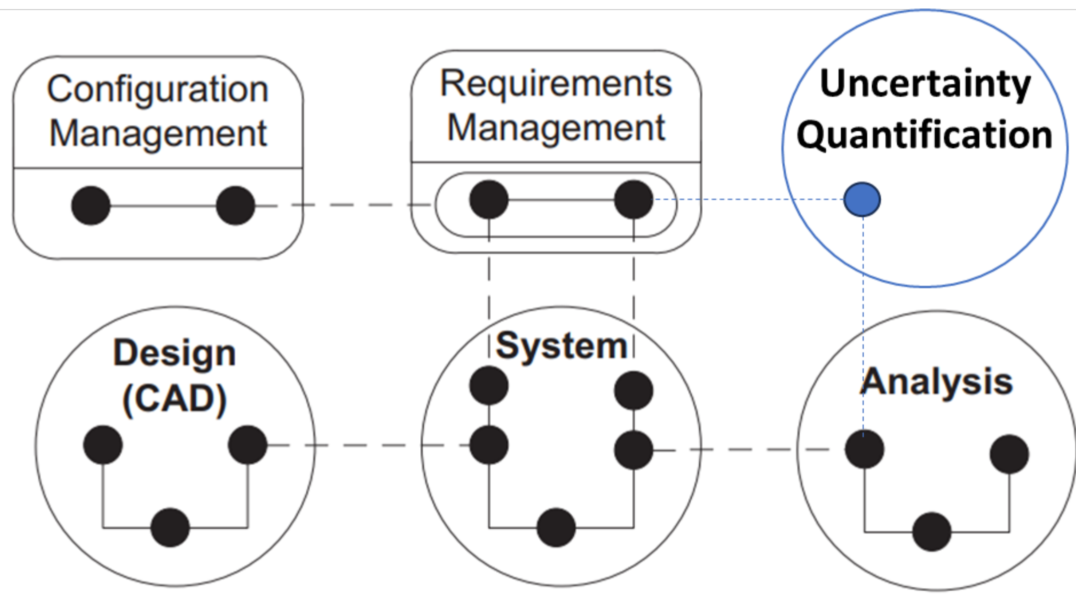


Figure 21. Relationships between processes and models. Adapted from Friedenthal, Moore, and Steiner (2015).

IV. MODELING AND SIMULATION

This chapter describes modeling and simulation (M&S) using both model-based systems engineering (MBSE) and finite element analysis (FEA). To illustrate the effectiveness of the proposed methodology, a case study is presented using the Brazilian Multipurpose Reactor (RMB) as the system of interest. First, the RMB core is described to provide technical background. Second, an MBSE approach is used to define a safety-related requirement based on the functional analysis of the RMB. The following section describes the FEA approach for modeling the RMB core behavior in a slow loss of flow accident (SLOFA). Lastly, the model breakdown structure (MBS) is applied to integrate the models.

A. SYSTEM DESCRIPTION

The Brazilian Nuclear Energy Commission (CNEN) through the Nuclear and Energy Research Institute (IPEN) is leading the project of the RMB, whose main goal is to mitigate the Brazilian dependence on foreign sources of Mo-99 used in nuclear medicine (Durazzo et al. 2024). In addition to radioisotope production, two other requirements were established: provide neutron beams to test fuels and materials and provide the necessary infrastructure to "allow the interim storage, for at least 100 years, of all spent nuclear fuel used in the reactor" (Perrota and Soares 2014, 398).

This new pool-type material testing reactor (MTR) will generate 30 MWth (Ribeiro et al. 2020). Table 3 presents the technical specifications of the RMB core. The RMB core contains 23 fuel elements; each fuel element has 21 plates, with a meat made of enriched (19.75%) Uranium Silicide-Aluminum dispersion (U_3Si_2-Al) clad with Aluminum (Perrota and Soares 2014; Soares et al. 2014). The RMB core is placed inside a chimney surrounded by a heavy water tank, which enables the positioning of materials for irradiation (Soares et al. 2014). Figure 22 presents a schematic view of the reactor core and the reflector tank.

Table 3. RMB core design data. Source: Ribeiro et al. (2020).

Parameter	**Data**
Reactor type	MTR
Fuel meat	U3Si2-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
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

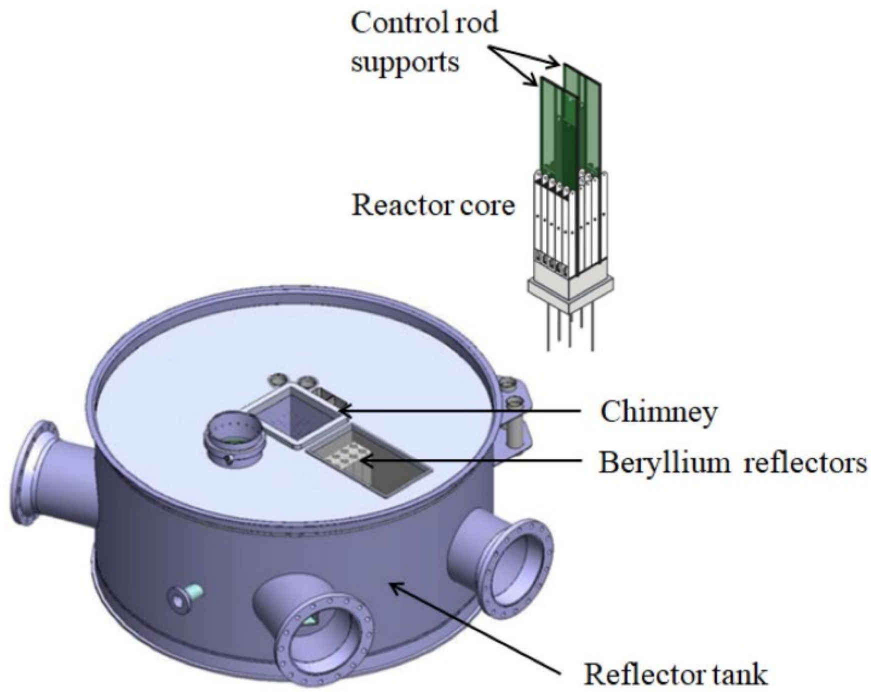


Figure 22. Schematic view of the RMB heavy water reflector tank and reactor core. Source: Ribeiro et al. (2020).

IPEN successfully produced fuel plates using high-uranium-loaded U10Mo-Al and U3Si2-Al dispersions, which represents an important milestone to the project. The applied technique shown in Figure 23 was identical to that used for low-uranium-loaded fuel plates. Fuel assembly (or fuel element) is "a structured group of fuel rods (or plates) containing pellets of fissionable material, which provide fuel for nuclear reactors" (U.S. Nuclear Regulatory Commission 2023). For this particular reactor, instead of fuel rods, the fuel assembly is composed of fuel plates, and instead of pellets, the fissionable material is denominated fuel meats, which are produced employing powder metallurgy methods (Durazzo et al. 2024).

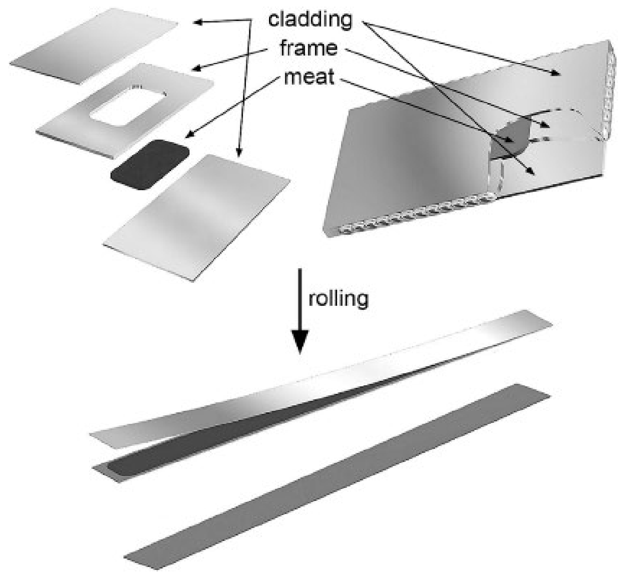


Figure 23. Technique used to manufacture fuel plates. Adapted from Durazzo et al. (2024).

Like other nuclear reactors, during their licensing process, a substantial number of studies must be conducted using M&S to ensure compliance with safety requirements under different accident scenarios. For instance, design-basis accidents (DBA) include loss of flow accidents (LOFA), loss of coolant accidents (LOCA), and the reactivity-initiated accidents (RIA) (Soares et al. 2014; Ribeiro et al. 2020; Akhal, Sidi-Ali, and Benmamar 2023; Housiadas 2000).

B. FUNCTIONAL ANALYSIS

The RMB is a research reactor whose principal aims are to irradiate fuel elements and structural materials of nuclear power plants (NPPs) under a high neutron flux and to produce radioisotopes. Research reactors are also called non-power reactors, and they are largely used for research, training, and development of other sorts of nuclear technology. These reactors contribute to different fields such as nuclear medicine and scientific research in different disciplines, including physics, chemistry, and biology. Despite being a research facility, like any other nuclear reactor, its safety functions need to be categorized following their safety significance. According to the International Atomic

Energy Agency (2022), the identification of all safety-related functions should be done as early as possible in the design of nuclear facilities.

In the MBS, the scope of the functional analysis is to identify and define all system functions and their safety categorization. For instance, this case study considered the first level of safety functions (e.g., reactivity control, cooling, and confinement of radioactive products) as a decomposition of the RMB main use case, as illustrated in Figure 24. Other process-related functions and control-related functions may not be identified at an early phase of the design process. However, it is possible to repeat both identification and categorization processes of safety-related functions throughout the design phases. Conversely, it is advisable to structure functional requirements specification in stages, so that systems engineers can deliver important inputs to the domain engineers.

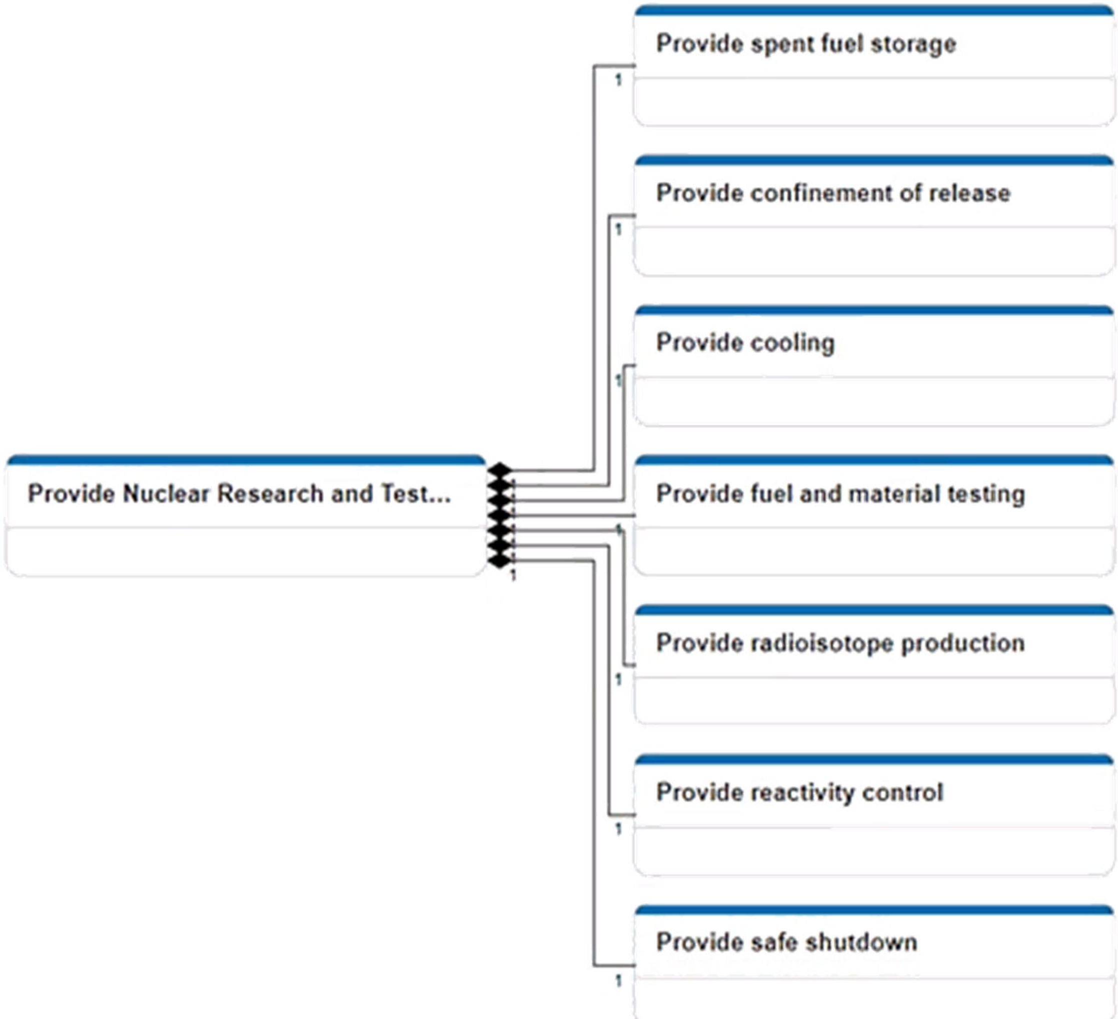


Figure 24. High-level safety functions of the RMB.

C. REQUIREMENT SPECIFICATION

Safety-related functional requirements are assessed by regulatory authorities in safety analysis reports throughout the licensing process of nuclear systems. The accidents list for the RMB considers typical postulated initiating events of research reactors, which have the potential to challenge the safety limits of the reactor. The design-basis accidents (DBA) of the RMB include, among others, 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, 2). It is worth mentioning that design extension scenarios (DEC) (e.g., station blackout for 10 days) are also part of the safety analysis report. Therefore, in the MBS context, models that enable the assessment of safety-related functional requirements are associated with the safety functions.

The RMB concept of operations (CONOPS) states that safety-related systems, structures, and components shall remain functional during and following DBA scenarios. Their functionality ensures that it is possible to shut down the reactor and maintain it in a safe shutdown condition. To exemplify the application of the MBS methodology, the SLOFA scenario was considered due to the availability of simulation results, which are presented in the next chapter, for code-to-code comparison (Ribeiro et al. 2020). Based on this scenario, Table 4 presents a critical operational issue (COI) related to the safe shutdown function, which is properly evaluated by a specific measure of effectiveness (MOE). Additionally, a key performance parameter (KPP), or measure of performance (MOP), is derived to provide the necessary assessment into meeting the MOE. Ultimately, the MOP needs data from a specific technical parameter and a decision criterion (safety-related functional requirement).

Table 4. Example of a technical measure profile.

Technical parameter	**Description**
Safety function	Provide safe shutdown
Critical operational issue (COI)	Can the RMB provide safe shutdown considering a SLOFA scenario?
Measure of effectiveness (MOE)	The ability to remove heat from the reactor core during and after the SLOFA.
Measure of performance (MOP) or 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	Cladding temperature
Criterion	Peak cladding temperature (PCT) < 391.15 K

The design process follows the same structure and sequence. For instance, cooling is one of the most important functions in terms of nuclear safety, especially in the scenario of a loss of flow accident. Although the critical operational issue is stated in an interrogative form to doubt if the RMB can provide safe shutdown during and, following this type of accident, provide cooling is one of the aspects of the safe shutdown process. As the decay heat must be removed, a direct engineering measure of cooling (i.e., the basis for describing the cooling performance) is the heat transferred from the fuel system to the primary circuit. Nonetheless, a usual MOP is the temperature at the interface between the fuel-cladding outer surface and the coolant. The temperature at this interface is critical due to the possibility of relevant thermal-hydraulic phenomena, such as onset of nucleate boiling (ONB), departure from nucleate boiling (DNB), and metal-water reaction in more severe scenarios (Matias Avelar et al. 2023). Therefore, it is fundamental to verify the peak cladding temperature (PCT) throughout the accident scenario to evaluate the effectiveness of cooling as a safety function.

Up to this point, there has not been a noticeable difference compared to other systems engineering processes. It started with the CONOPS and functional analysis, which derived a COI, a MOE, a MOP, and a specific requirement (acceptance criterion). However, the main advantage of the MBS compared to other systems engineering methodologies is that MBSE is integrated into the system development environment. Thus, in the MBS, requirements are linked to variables, implemented by multi-physics models, and tested by verification and validation (V&V) models. Hence, cooling effectiveness can be evaluated using a FEA that determines the PCT progression during the accident.

D. SYSTEM ANALYSIS

To study the core behavior during a SLOFA scenario, FEA was employed using the Partial Differential Equation (PDE) Toolbox™ in MATLAB. The fuel and cladding were considered as the main components in this scenario. Three phases were investigated: steady state, SLOFA transient, and cold shutdown. Figure 25 (a) shows the cross section of the RMB fuel assembly. The dashed-line box represents the boundaries of the physical domain for the hottest subchannel. The heat transport equation is applied at both fuel (F1) and cladding (F2) domains, shown in Figure 25 (b), considering two directions, axial (z) and longitudinal (x), along the length and width of the fuel plate, respectively. Figure 25 (c) shows the FEA mesh in both domains.

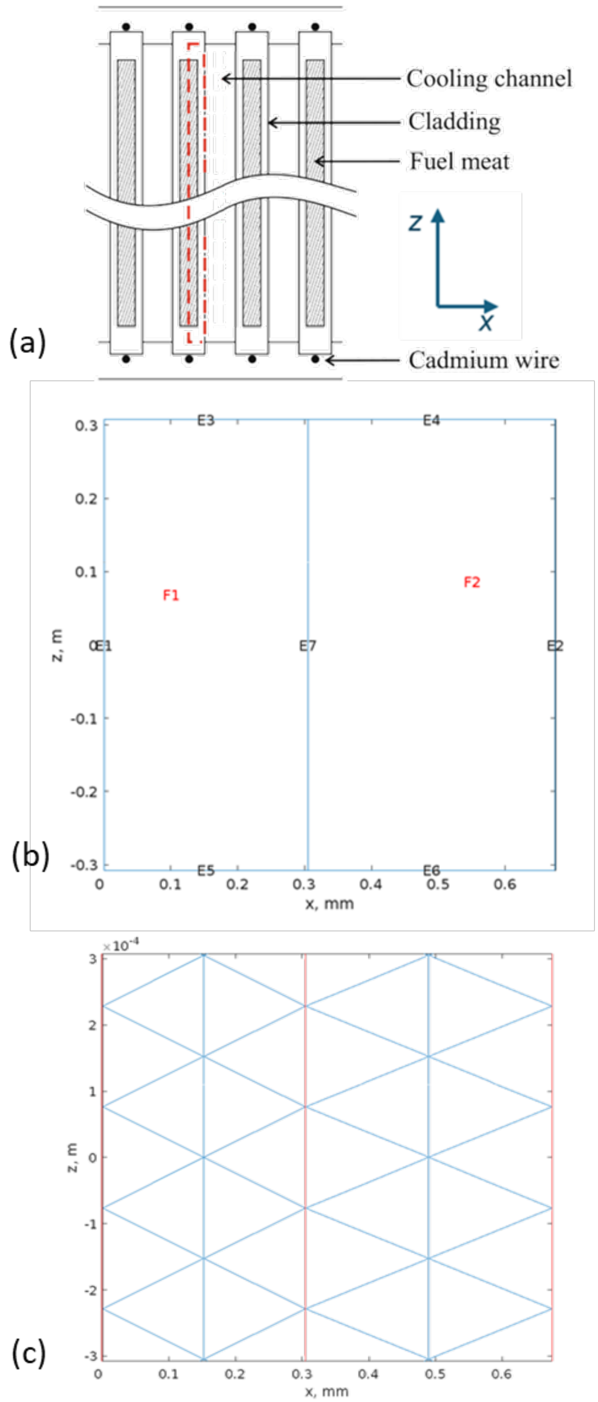


Figure 25. A schematic view of the cross section of the RMB fuel assembly (a), fuel plate domain and interfaces (b), and FEA mesh (c). Adapted from Ribeiro et al. (2020).

The temperature distribution in both domains is obtained by solving the heat Equation (1):

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

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.

This equation is solved for each finite element using the PDE Toolbox™ in MATLAB. A mesh sensitivity test was performed using code-to-code comparison 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:

$$\frac{\partial T_f}{\partial x} = 0,\ at\ x = 0, \tag{2}$$

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

$$k_c \frac{\partial T_c}{\partial x} = k_f \frac{\partial T_f}{\partial x},\ at\ x = x_f, \tag{4}$$

$$\frac{\partial T_f}{\partial z} = 0\ and\ \frac{\partial T_c}{\partial z} = 0,\ at\ z = \pm L/2. \tag{5}$$

In Equations (2)–(5), subscripts f and c refer to fuel and cladding, respectively. Boundaries are addressed in the x coordinate as x_f and x_{co} for the fuel-cladding and cladding-coolant interfaces, respectively. Additionally, h is the convective heat transfer coefficient of the coolant, which was calculated using the Dittus-Boelter correlation for turbulent flow given by Equation (6):

$$h = 0.023Re^{0.8}Pr^{0.4}k_w/D_h\ , \tag{6}$$

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 volumetric heat generation rate in the fuel domain Q is given by Equation (7):

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

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 generated in the fuel after shutdown was calculated using the Wigner-Way formula seen in Equation (8):

$$P(t) = 0.0622\, P_0(t^{-0.2} - (t_0 + t)^{-0.2}), \tag{8}$$

where P_0 is the thermal power before the reactor shutdown, t is the time elapsed since the reactor shutdown, and t_0 is the operating time before the shutdown.

The coolant flow rate $m(t)$ decreases exponentially, with a time constant of 25 s, according to Equation (9):

$$m(t) = 849.92\, e^{\left(-\frac{1}{25}\right)}. \tag{9}$$

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

E. INTEGRATION OF MODELS

The development of the digital engineering environment (DEE) comprises three distinct models. The system model, built using System Composer, presents the RMB use cases, high-level safety functions, requirements, and Simulink models for each scenario (e.g., SLOFA). Additionally, Simulink models are connected to variables in the MATLAB workspace that are either created or imported into MATLAB from different types of models (e.g., FEA or experimental database). Ultimately, the V&V models run tests to verify or validate the requirements.

The main advantage of the MBS using MATLAB is the integration between the FEA results and the verification process. First, the safety-related functional requirement associated with the PCT was modeled as a constraint using a data dictionary. Second, a Simulink model was created to execute the simulation. Lastly, a test case was executed to compare the simulation result against the requirement. The entire process using interconnect models is illustrated in Figure 26 (a). The requirement is related to the constraint criterion, implemented in a simulation, and verified by the test case, as shown in Figure 26 (b).

The requirements were linked to other models using the requirements editor. For instance, Figure 27 shows both implementation and verification status of the requirements editor in Simulink, which links the PCT requirement to the SLOFA model that captures the data from the SLOFA simulation and extracts the maximum result throughout the entire simulation time. Equally, the PCT requirement was also linked to a specific test case, which allows tracking the verification progress and that the implementation of the requirement behaves as expected. The possibility of connecting requirements to complex simulations, including statical analysis, contributes significantly to the systems engineering process.

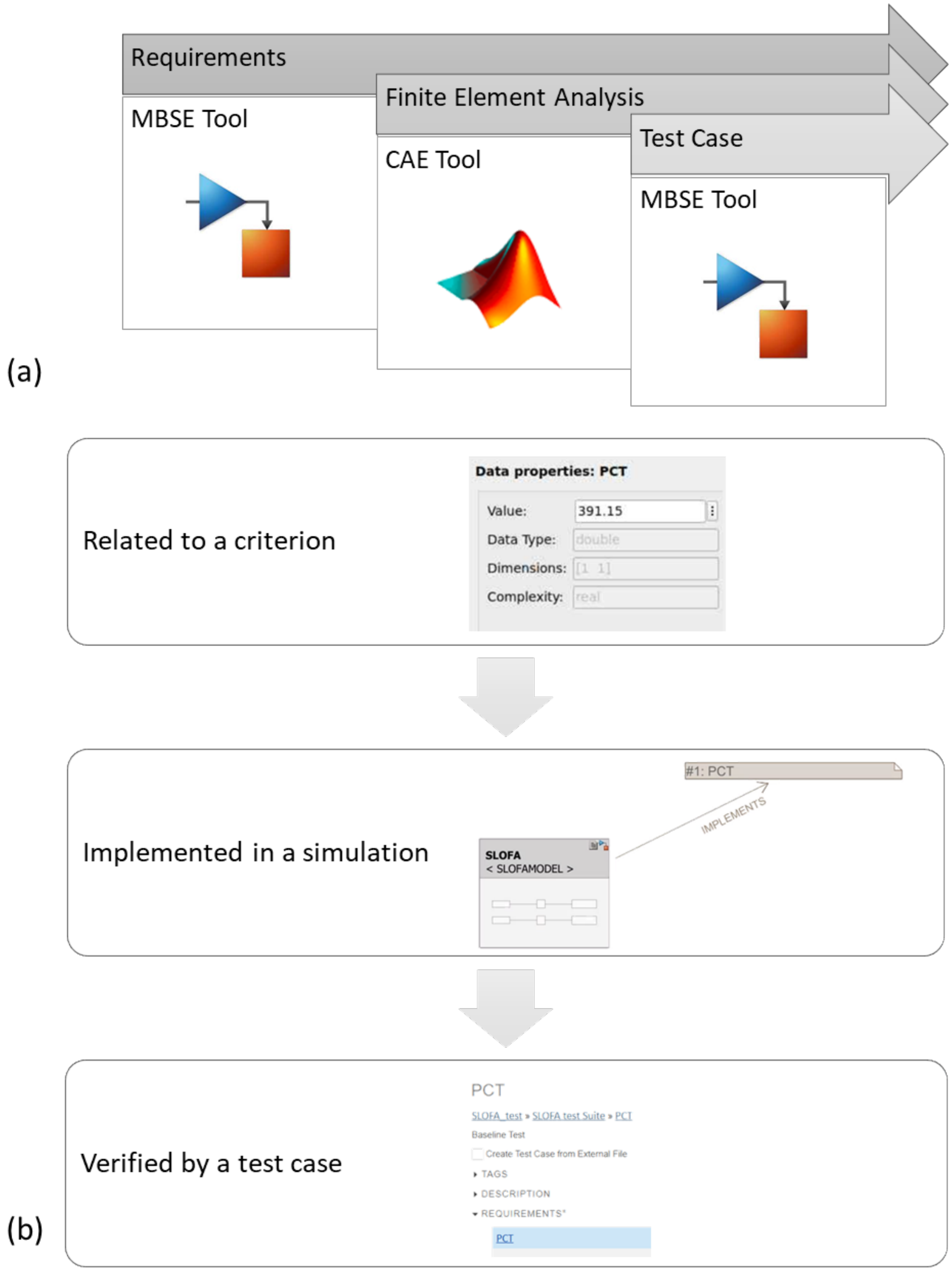


Figure 26. Integrated models (a) for the PCT requirement verification (b) in a SLOFA scenario.

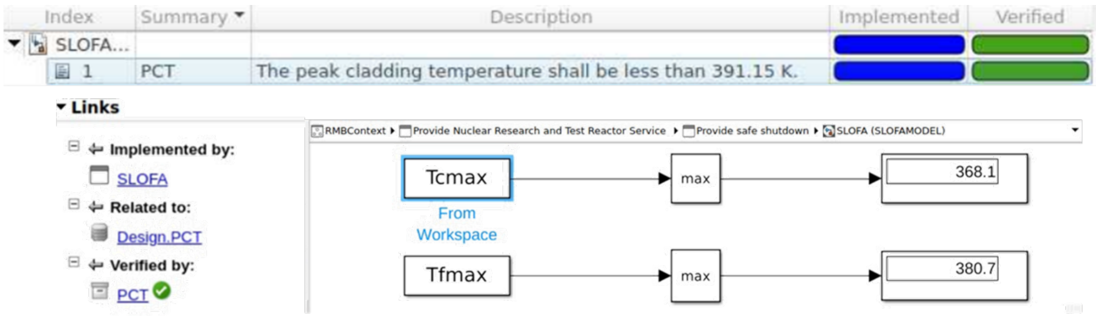


Figure 27. Links to the PCT requirement.

V. RESULTS AND DISCUSSION

This chapter provides a detailed assessment of the model breakdown structure (MBS) outcomes, using the Brazilian Multipurpose Reactor (RMB) as a case study. First, it describes the finite element analysis (FEA) results for the slow loss of flow accident (SLOFA) scenario. Additionally, the RMB core is systematically evaluated using the design of experiments (DOE) and uncertainty quantification, offering insights for system analysis, design, and development. The data collected from the FEA is applied to verify the peak cladding temperature (PCT) requirement. Lastly, insights on various aspects are provided, including the tool selection, the accuracy of the uncertainty quantification process, and how to implement the MBS.

A. FINITE ELEMENT ANALYSIS

The results from the FEA were collected and analyzed. The simulation was set to start (at t = 0 s) with all nodes from cladding and core at 300 K. The reactor's thermal power was set at its nominal value (30 MW). The simulation results showed that the steady state was rapidly achieved, and the system was kept with constant attributes up t = 50 s, when the loss of flow started to occur. Figure 28 shows the steady state temperature distribution. Noticeably, the PCT is less than the ONB threshold (391.15 K).

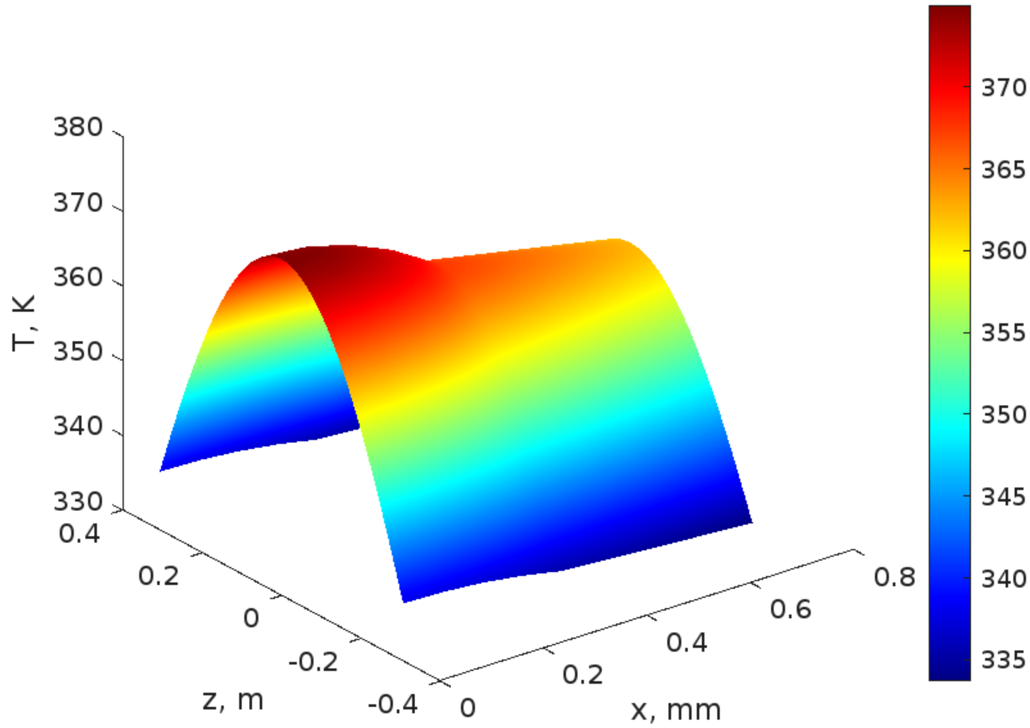


Figure 28. Steady state temperature distribution.

The SLOFA scenario sequence occurs as follows: the reactor is operating at its nominal power when the loss of flow occurs, next the reactor SCRAM (or reactor trip) occurs at approximately 4 s after the start of the loss of flow, and finally the decay heat is removed with the remaining flow rate. The solution of the partial differential equation and boundary conditions enables the assessment of the temperature distribution throughout the entire fuel and cladding domains. During the SLOFA transient, both domains' temperatures are shifted up 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 ONB (Akhal, Sidi-Ali, and Benmamar 2023). Likewise, it is possible to establish additional models for evaluating various aspects of the system, including its behavior throughout other postulated accidents.

Code-to-code comparison was applied to assist model verification, as experimental data was not available. The same accident scenario was studied by Ribeiro et al. (2020) using the Neutronics and Thermal Hydraulics Code (NTHC1). The authors found that the volumetric heat generation rate in the fuel can be modeled using a chopped cosine shape function in the axial direction of the fuel plate, which provided good results compared to the SERPENT code simulation. Therefore, the same simplification was considered in this study. Conversely, the overall decay heat of the core was estimated using the Wigner-Way formula (8) 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 was a constant average coolant temperature (i.e., axially averaged value) applied as a boundary condition for the cladding domain. Figure 29 shows RMB power and coolant flow rate during the SLOFA scenario. The coolant mass flow result is applied to determine the heat transfer coefficient using the Dittus-Boelter correlation for turbulent flow (6). On the other hand, the power results determine the heat that must be transferred to the primary circuit.

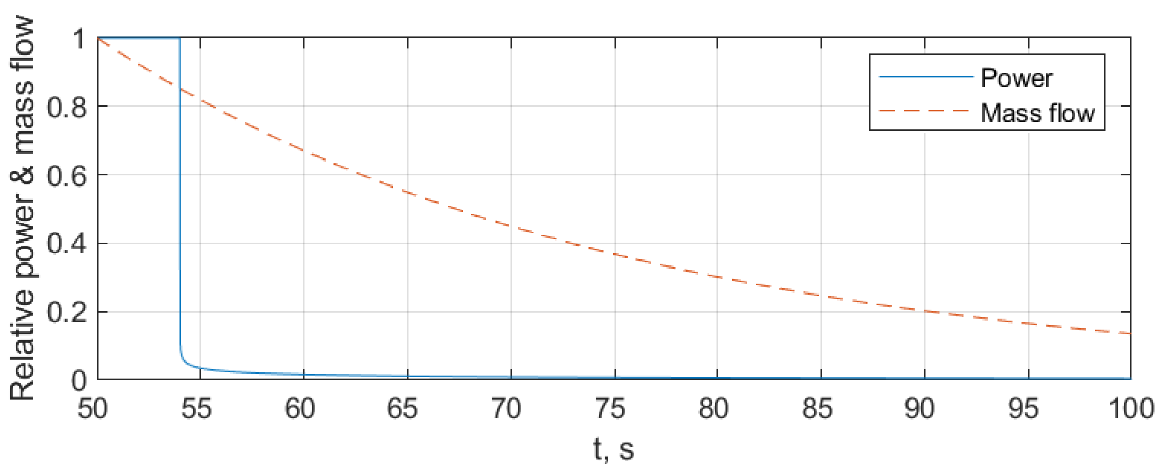


Figure 29. Relative power and mass flow profiles.

The maximum temperature observed for the cladding in the hot subchannel obtained from NTHC1 considering nominal conditions was 369.5 K (Ribeiro et al. 2020). The temperature distribution obtained using MATLAB (at t = 54 s) when the PCT is at its maximum value (368.1 K) is shown in Figure 30. For a conservative calculation, it was assumed that the reactor was operating at its maximum overpower level (15%) when the accident occurred. The RMB model on NTHC1 was revisited and the same calculations were performed using MATLAB. As shown in Table 5, the results showed excellent agreement with the values published by Ribeiro et al. (2020). The MATLAB code for the SLOFA scenario is presented in Appendix A.

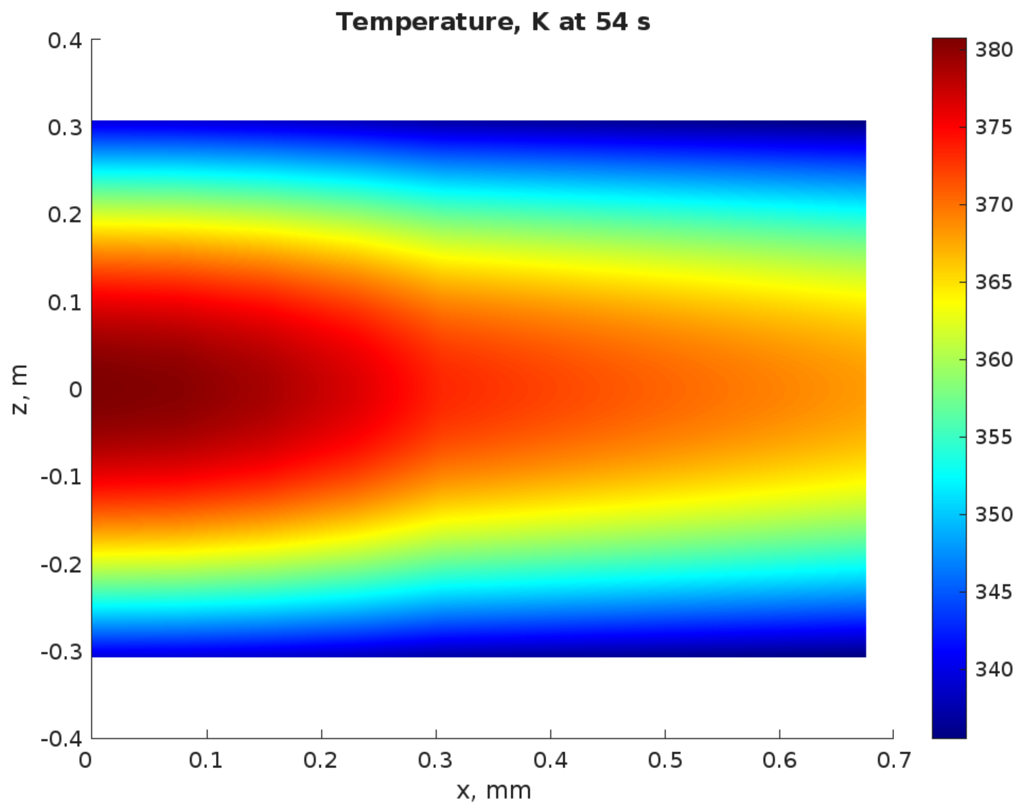


Figure 30. Temperature distribution when the PCT reaches its maximum value (t = 54 s).

Table 5. Code-to-code comparison against NTHC1 for slow loss of flow accident 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

B. REQUIREMENT VERIFICATION USING SIMULATION-BASED TESTS

The integration of model-based systems engineering (MBSE) and simulation-based tests was applied to enhance the verification process. The PCT requirement was verified with results from the FEA using two distinct approaches: best estimate plus uncertainty (BEPU) and conservative (D'Auria 2019). The BEPU approach was based on the nominal calculation (i.e., PCT calculated using variables at their nominal values) along with an uncertainty band that takes the design factors' probability distribution functions into account. On the other hand, the conservative approach used 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 results verified that there is no possibility of nucleate boiling. The cladding hot spot, which refers to the physical location where the maximum temperature value occurs, was investigated throughout the transient. The cladding temperatures computed for this transient remained below the ONB threshold (391.15 K). Therefore, during the transient after the failure of both pump motors, the coolant did not reach the saturation temperature. Figure 31 shows that there is a significant margin (23 K) between the cladding temperature and the ONB criterion. Both fuel and cladding temperatures increase due to the loss of flow. Nevertheless, after the reactor shutdown, power significantly decreases, and the core temperature drops rapidly.

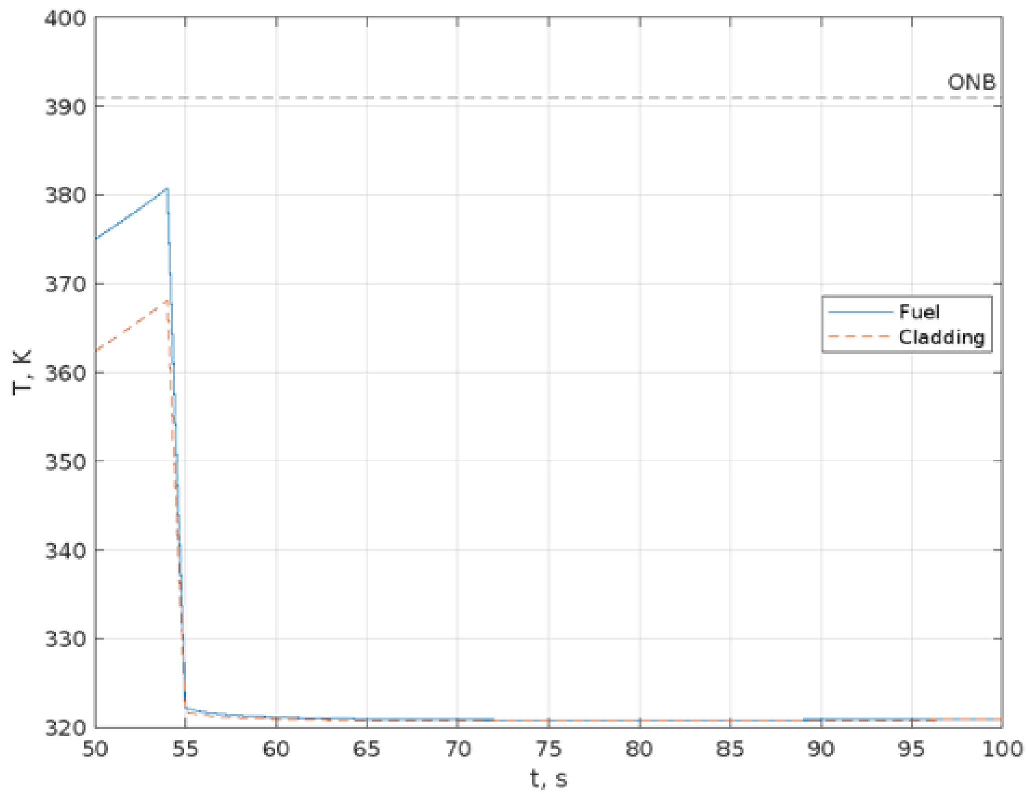


Figure 31. Time histories of fuel and cladding temperatures during the SLOFA scenario against the ONB threshold.

The DOE enabled design space exploration and identification of relevant design factors. First, it allowed the assessment of the effect of fuel and cladding material properties on the PCT. Three material properties were considered: thermal conductivity, specific heat, and density for both fuel and cladding. Accounting for the reactor power, an additional factor was created. Due to the significant computational time required for the simulation in both NTHC1 and MATLAB models, two Latin hypercube designs (LHDs) were built using MATLAB, both with a total of seven factors. Considering the first and second orders of Wilks' theorem for 95% probability and 95% confidence level (95/95), 59 and 93 computational cases were generated, respectively. It is worth mentioning that running a full factorial design with two levels per factor would create $2^7 = 128$ computational cases. Table 6 shows the factors' range, which are based on typical nuclear material properties. Figure 32 presents the simulation results for PCT considering the experimental design with 93 cases and shows that all simulations met the PCT requirement and did not reach the ONB threshold. The code for the LHD design is presented in Appendix B.

Table 6. Factors and their respective ranges for experimental designs.

Factor	**Units**	**Minimum**	**Maximum**
Fuel density	kg m^{-3}	4700	10970
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

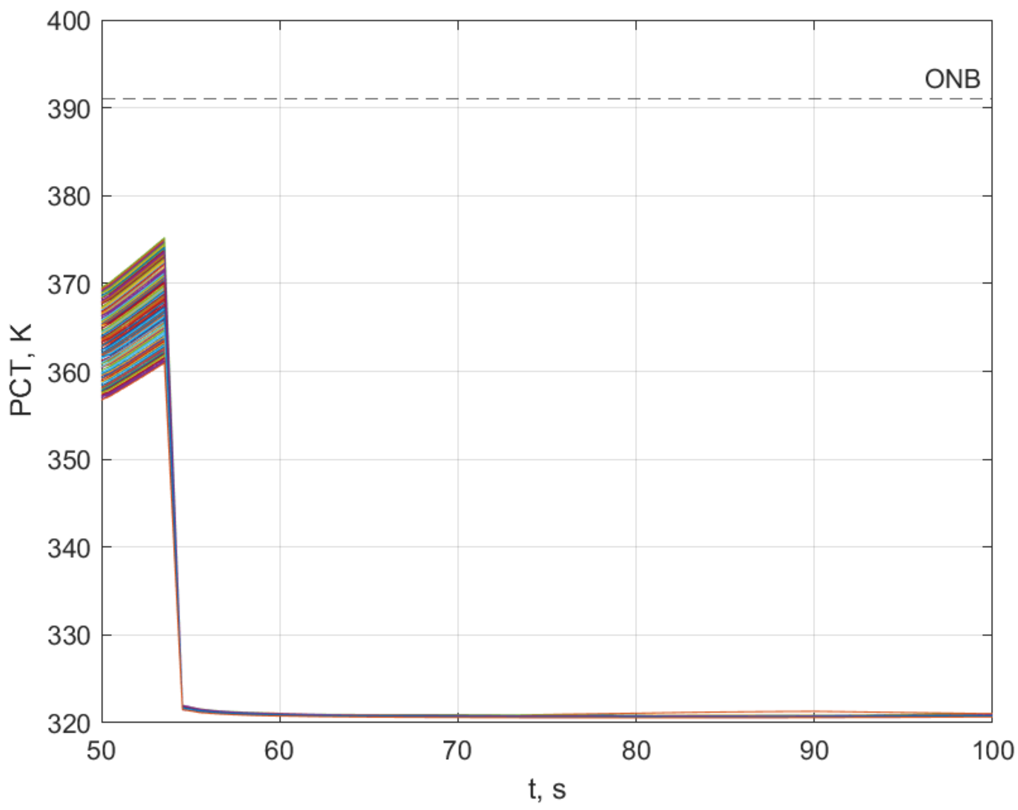
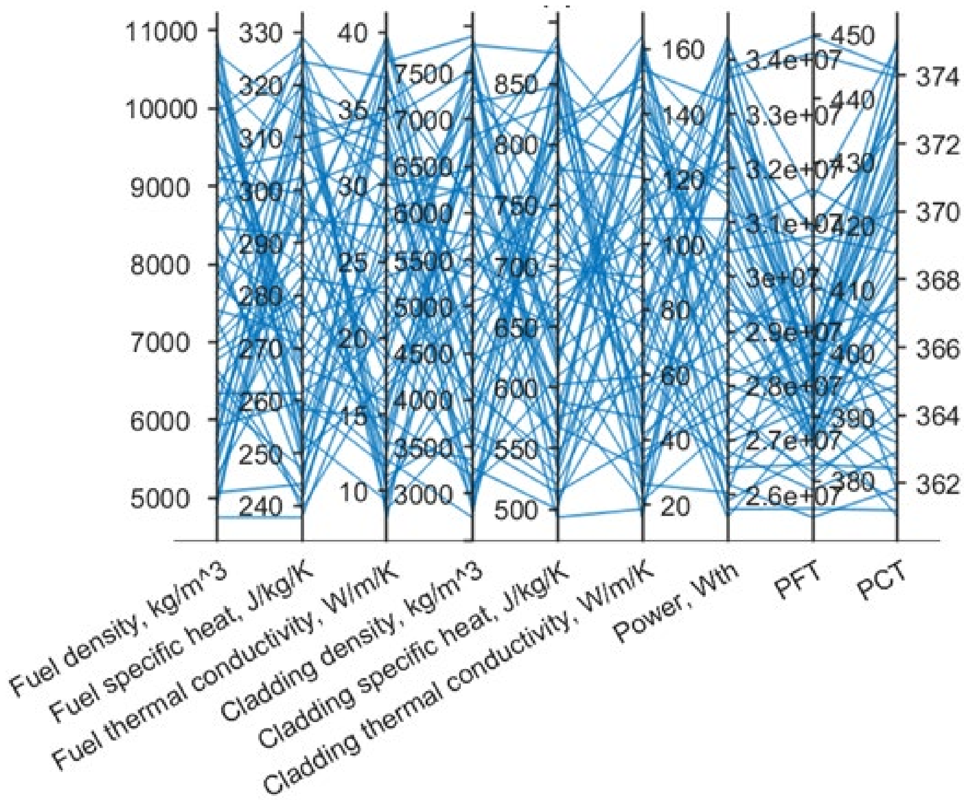


Figure 32. PCT progression for the second order Wilks' theorem LHD.

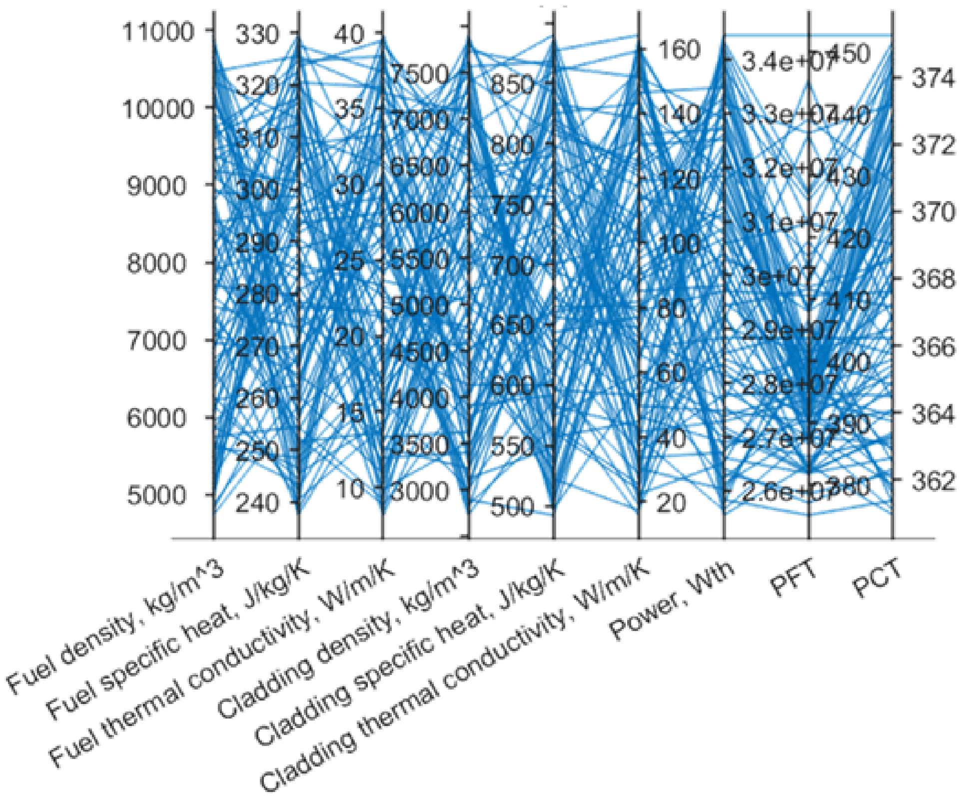
The analysis of variance (ANOVA) indicated the key factors for PCT. Figures 33 and 34 show the exploration of the design space through parallel coordinates plots and the ANOVA results considering the experimental designs with 59 and 93 cases, respectively. Each line in these plots represents an experiment, and each axis in the plot corresponds to a factor. Considering a p-value threshold of 0.01, the ANOVA results identified three statistically significant factors: fuel specific heat, cladding specific heat, and power. Notably, employing a full factorial design would have been a more effective approach for evaluating interactions between factors. However, the main benefit of LHDs is to reduce computational effort when dealing with high-dimensional experiments or complex systems. The code for the ANOVA using MATLAB is presented in Appendix C.

The Wilks' theorem enabled uncertainty quantification of PCT based on the probability distribution functions of key factors. According to the first order of Wilks' theorem, the highest value within the 59-sample data represents the 95/95 unilateral tolerance limit for PCT. Considering the second order, the second highest value within the 93-sample data represents the same limit. Moreover, the variability of the results is reduced as the order of Wilks' theorem increases. Therefore, the higher the order of statistics, the greater the accuracy. However, increasing the order of the Wilks' theorem does not necessarily allow a more conservative estimate of the PCT, as shown in Table 7. These findings were also observed in previous studies (Kang 2021; Lee et al. 2014). Notwithstanding, both 95/95 upper limit for PCT are significantly close to the conservative calculation (375.7 K).



	SumOfSquares	DF	MeanSquares	F	pValue
Fuel density	25.212	1	25.212	3.0392	0.087185
Fuel specific heat	221.04	1	221.04	26.645	3.8988e-06
Fuel thermal conductivity	7.6635	1	7.6635	0.9238	0.34093
Cladding density	17.902	1	17.902	2.158	0.14785
Cladding specific heat	51.566	1	51.566	6.216	0.015881
Cladding thermal conductivity	5.0469	1	5.0469	0.60839	0.43893
Power	593.41	1	593.41	71.533	2.4242e-11
Error	431.37	52	8.2956		
Total	1025.5	58			

Figure 33. Parallel plot and ANOVA results from the 59-cases LHD.



	SumOfSquares	DF	MeanSquares	F	pValue
Fuel density	45.135	1	45.135	5.8744	0.017459
Fuel specific heat	356.58	1	356.58	46.409	1.2398e-09
Fuel thermal conductivity	12.71	1	12.71	1.6542	0.20185
Cladding density	23.631	1	23.631	3.0756	0.083039
Cladding specific heat	74.612	1	74.612	9.7108	0.0024902
Cladding thermal conductivity	10.994	1	10.994	1.4309	0.23491
Power	950.89	1	950.89	123.76	2.4779e-18
Error	660.77	86	7.6834		
Total	1612.8	92			

Figure 34. Parallel plot and ANOVA results from the 93-cases LHD.

Table 7. Comparison of the 95/95 PCT upper limit using LHD and Wilks' theorem.

Order of the Wilks' theorem	Number of runs	95/95 PCT upper limit, K
1	59	375.2
2	93	375.0

Although three factors were considered statistically significant, power was the only significant factor for PCT prediction. First, the p-value of less than 10^{-17} indicated that power is statistically significant in predicting PCT. Additionally, the linear regression indicated that power explains 99.999% of the PCT variation. Therefore, power was considered as a high-risk factor for uncertainty quantification.

The sequence LHD, ANOVA, and Wilks' theorem enabled accurate uncertainty quantification with reduced computational effort by propagating only the high-risk factors. Compared to Monte Carlo methods, the Wilks' theorem was selected as it requires fewer computational cases. The reactor operational profile was described by a normal distribution with 30 MW mean and 2.29 MW standard deviation (i.e., the 95% confidence interval lies within 25.5 and 34.5 MW). To assess the 95/95 uncertainty band, the power probability distribution function was limited (i.e., truncated) to the $\pm$ 1.96 σ (standard deviation) range. The number of runs followed the order statistics, as shown in Table 7. Figure 35 shows the PCT results for the first order of Wilks' theorem. Conversely, Figure 36 shows the PCT results for the second order of Wilks' theorem. Both orders resulted in 375.3 K as the 95/95 PCT upper limit. This result is the same as predicted by the conservative analysis (cf. Table 5). Noticeably, as a single factor was considered relevant, there is less motivation to consider higher order statistics. Notwithstanding, analogously to the DOE context, for a higher number of factors, the use of higher order statistics (e.g., second or third order statistics) is recommended. Even though it involves an increase of the sample size, it also increases the accuracy of the tolerance limit found (Martorell et al. 2017; Trivedi and Novog 2023). Therefore, the completion of the LHD is highly recommended prior to the uncertainty propagation to reduce the number of factors, and consequently, reduce the necessity of higher order statistics to increase accuracy.

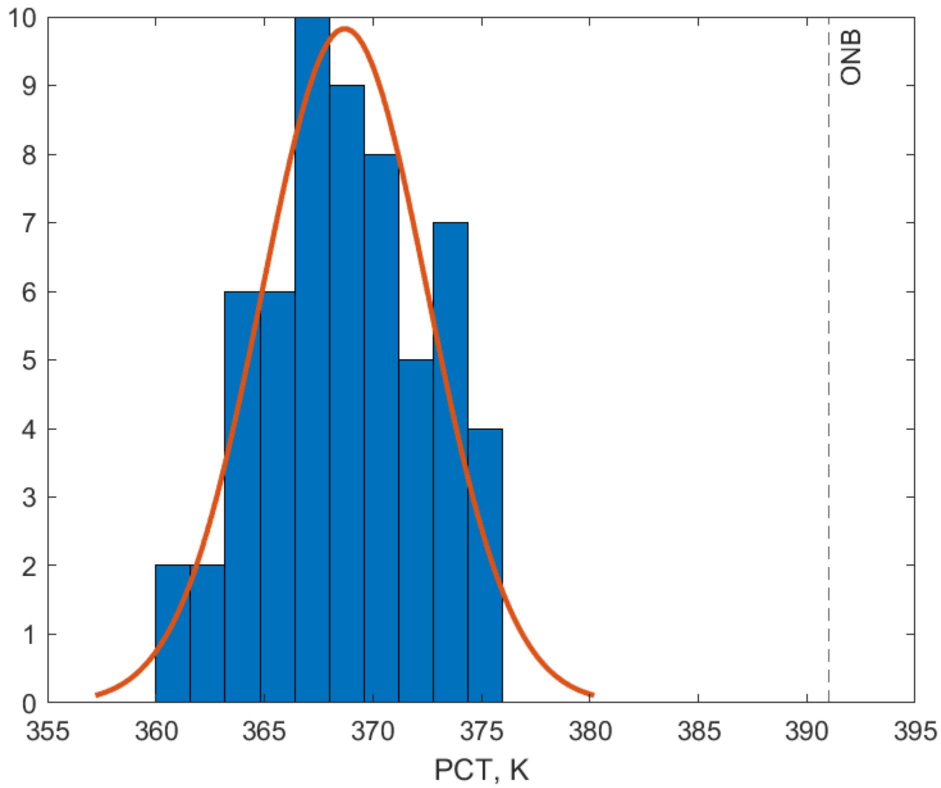


Figure 35. PCT histogram after the propagation of power probability distribution considering the first order statistics.

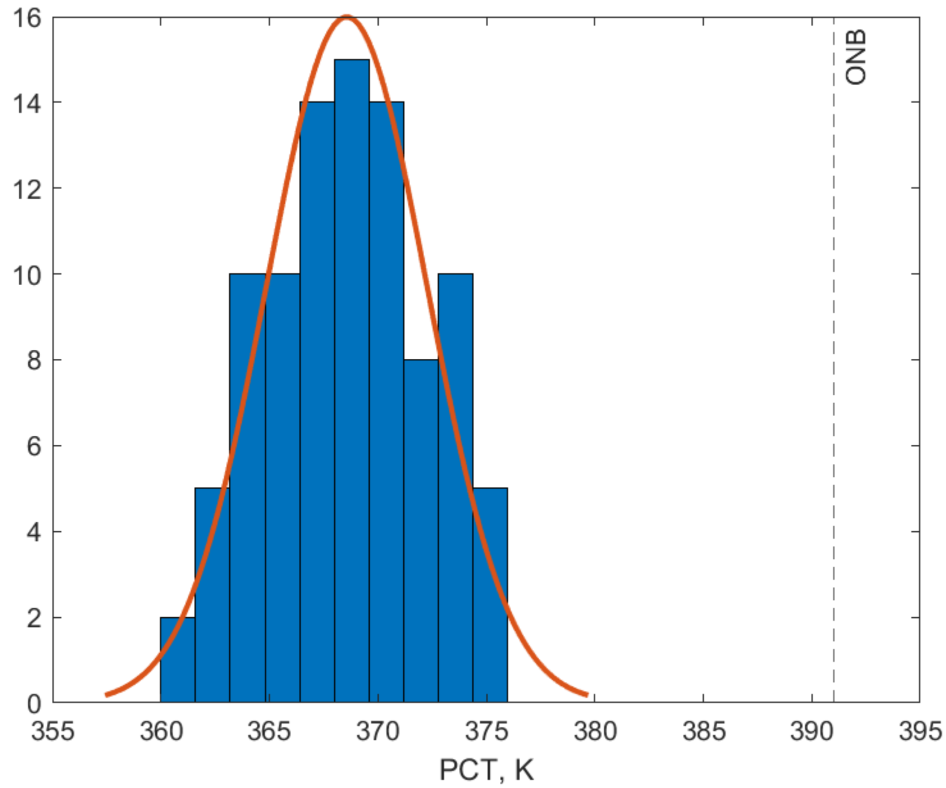


Figure 36. PCT histogram after the propagation of power probability distribution considering the second order statistics.

C. BENEFITS, INSIGHTS, AND TRADE-OFF BETWEEN COMPUTATIONAL TIME AND ACCURACY

Integrating MBSE and CAE enabled studying the physical behavior of a complex system via mathematical modeling and data analysis, leveraging computer-aided systematic decision-making. This integration provided the nexus within systems engineering and domain sciences, while offering a scientific basis for holistic system development. For instance, using a simulation-based test, it is possible to analyze the impact of design changes on the system effectiveness.

The implementation of MBS using RMB as the system of interest was conducted using MATLAB and Simulink. In fact, system developers have a significant number of tools at their disposal. However, in this study, system analysis needed the capabilities of solving partial differential equations and a finite differences method. Currently, there are not many options available regarding these specific engineering domain analysis capabilities, while connecting with MBSE tools. Some recent developments include advanced MBSE software that features the built-in simulation tools based on the X language (Gu et al. 2024). As usual, MBSE enables various early design activities (e.g., functional analysis and architecture). However, it can be challenging to perform verification of multidisciplinary requirements. Consequently, it is difficult to ensure consistency between system-level and detailed design, which usually results in a limited verification ability of MBSE tools. For instance, although the system V&V using the X language does not rely on external simulation tools, due to the current limitations, it only supports modeling of ordinary differential equations (Gu et al. 2024). On the other hand, MATLAB offers the Partial Differential Equations (PDE) Toolbox™, which allows solving transient engineering problems in two or three physical dimensions. This ensures that complex mathematical models can be solved and requirements that depend on this type of simulation can be promptly verified, effectively avoiding design errors. This approach enhances the likelihood of success with multidisciplinary teams by enabling trade-off analysis through MBSE.

Once the integration of MBSE and CAE is achieved, it opens the opportunity to apply a DOE to explore the design space systematically. A DOE provides a structured approach to determine the relationship between various input factors and the resulting outputs, which is essential for identifying optimal designs, performing trade-off analysis, and understanding system behavior under varying conditions. Traditional DOE methods, such as a full factorial design, can provide a comprehensive exploration of the design space. However, they can become time-consuming and computationally expensive, especially when more factors are introduced. To mitigate this, the use of an LHD is considered as a more efficient approach. LHD allows for a more representative sampling of the design space with fewer computational cases, leading to significant reductions in computational time without compromising the quality of the results (Chen et al. 2023; Hernandez, Lucas, and Carlyle 2012). By sampling the entire space more evenly, LHD makes it possible to explore the design space more efficiently while enabling effective ANOVA results and achieving high accuracy in the uncertainty analysis.

To further streamline the BEPU quantification process, Wilks' theorem is applied for the prediction of the 95% probability and 95% confidence (95/95) uncertainty band. This statistical approach offers a way to quantify uncertainty to enhance the verification process by offering reliable estimates of potential system performance under uncertain conditions. The number of computational cases required for uncertainty quantification using Wilks' theorem is dependent on the order of the theorem (Lee et al. 2014; Shockling 2015; Wilks 1941). For the first and second orders, sets of 59 and 93 cases, respectively, were generated. This reduction in the number of cases compared to a Monte Carlo simulation is a key benefit, as it allows for efficient yet accurate estimation of uncertainties. However, it is important to carefully select the order of Wilks' theorem based on the number of factors being analyzed to ensure that important factors are properly identified and that the results are accurate for uncertainty analysis. This careful balancing of computational effort and statistical reliability is crucial in achieving both efficiency and trustworthiness in the licensing process.

Most regulatory-approved BEPU approaches for nuclear systems for verifying safety criteria rely on propagating input uncertainties through models implemented in computational codes using Wilks' theorem to determine how many calculations are needed to meet standard tolerance levels (typically 95/95). These approaches often focus on upper or lower tolerance limits based on first order statistics, which can be calculated with a small sample size, usually requiring 59 runs (X. Zhang et al. 2023; Shockling 2015; Jyrkama and Pandey 2017). This method is advantageous because it yields conservative results with fewer simulations, reducing the high computational costs associated with running complex models for nuclear power plants. However, with 59 samples, the ability to achieve an accurate 95/95 estimate will depend on the complexity of the model (i.e., the number of factors). Therefore, a high-dimensional space (i.e., a significant number of factors) generally requires more samples to get robust estimates. In practice, achieving a precise 95/95 estimate might be challenging with high-dimensional spaces. Thus, for high-dimensional models, it is recommended to increase the order of the Wilks' theorem to generate more samples and ensure a more accurate and reliable estimation. Conversely, this thesis suggested that the utilization of a DOE associated with

ANOVA can help reduce the number of factors, and consequently, increase the accuracy of uncertainty analysis.

The MBS concept is illustrated in Figure 37(a) using a similar idea as a work breakdown structure. The main difference is that it presents which models are interconnected. By applying the probabilistic distribution for relevant factors on a BEPU analysis, the MBS allows system developers to calculate the licensing margin and quantify the effect of factors' uncertainties on the system measures, as illustrated in Figure 37(b). The BEPU analysis creates a statistical layer that fills the gap between MBSE and CAE and determines how many runs and which input decks should be used for each behavioral CAE method execution. Moreover, it executes statistical analysis to provide the verification model with an uncertainty band that allows the assessment of licensing margins. This intermediate layer controls the execution of multi-physics models and concatenates the simulation results for test cases. The overall layered concept of the MBS layers is shown in Table 8. Ideally, statistical analysis of experimental results can also be applied to validate requirements in the MBS. Therefore, it establishes a systematic methodology for the statistical analysis of probabilistic measures of effectiveness, providing an assessment of design margins on V&V results.

The MBS breaks the paradigm by connecting system development models with MBSE. In this new approach, MBSE can be viewed as a maestro leading various engineering disciplines. Each engineer plays a specific role within their discipline, whether in design, analysis, or testing. In this analogy, MBSE ensures that all parts come together harmoniously, guiding the V&V, and the integration of the entire system. In a digital engineering context, the MBS connects MBSE with CAE, and other computational models, facilitating a seamless, synchronized approach to complex system development. This methodology ensures that the digital representation of the system and in-depth analysis of its components are interconnected to meet all the requirements.

Table 8. Role of each MBS layer.

MBS layer	Role
Functional model	Describe the hierarchy of system functions.
Requirements model	Establish the system requirements.
Statistical models	Conduct statistical analysis to provide uncertainty bands, which enable the assessment of margins.
Multi-physics models	Simulate system behaviors.
V&V models	Use statistical models' output and experimental results to verify and validate requirements.

In this study, the RMB system model was designed using the System Composer module from Simulink as an MBSE tool. Additionally, a multi-physics model was developed in MATLAB using FEA to simulate the core behavior during a SLOFA scenario. Finally, the third part of MBS enhanced this automated analysis capability, into system effectiveness knowledge and performance information by revealing the main factors through a DOE, and by propagating probability distributions of these factors. To the best of the author's knowledge, previous studies have demonstrated that the various stages of MBSE usage can significantly help the system development process, but specifically to this methodology, stakeholders see high value on the automated simulation feedback because it allows the analysis of complex systems, such as nuclear power plants (NPPs) (Beery 2016; Nigischer et al. 2021; X. Zhang et al. 2023). Furthermore, the exploration of design space and the presentation of uncertainty bands allows a deeper understanding of the system behavior and an improved requirement verification process.

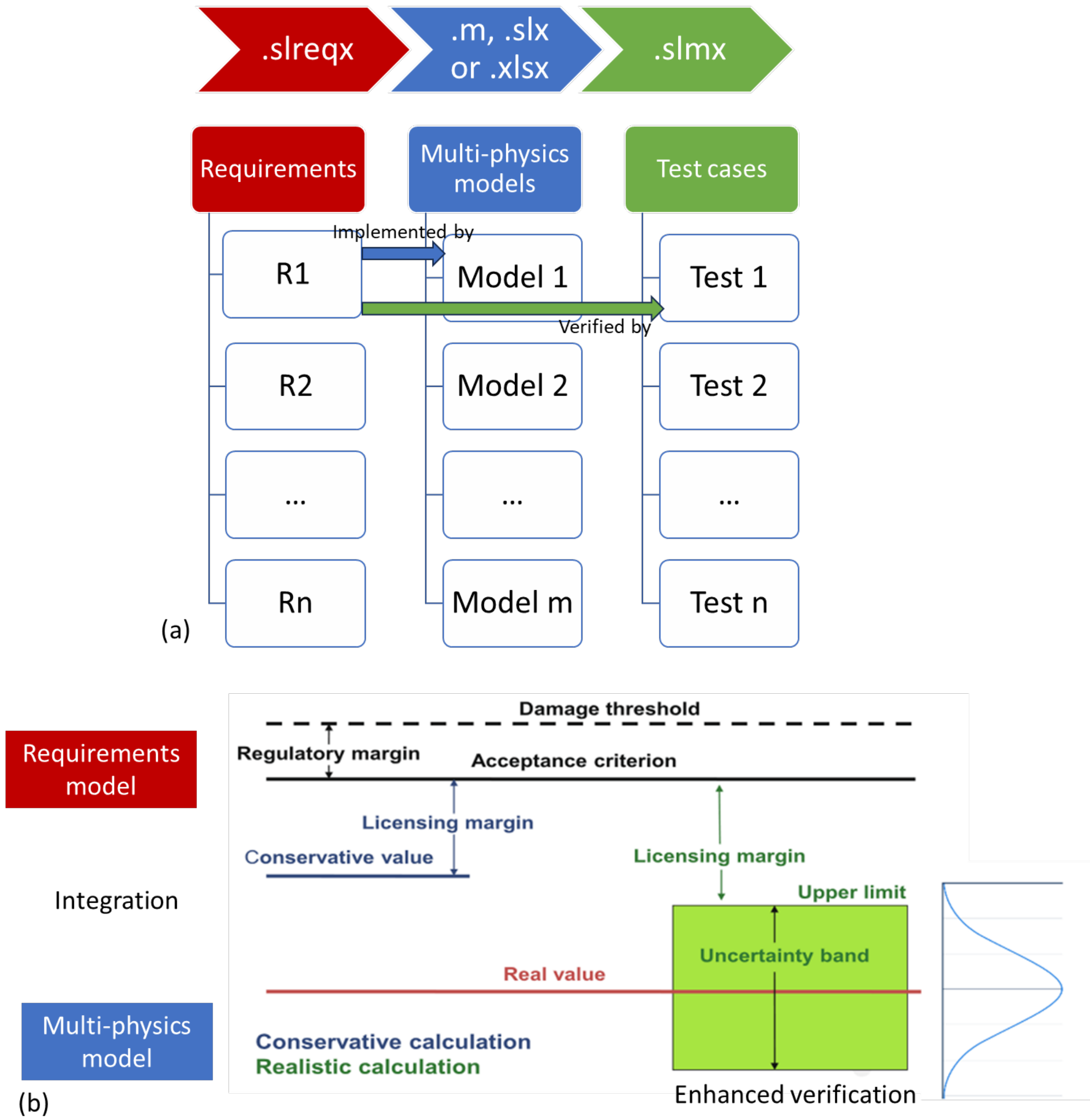


Figure 37. The proposed MBS methodology applied to integrate models (a) and to enhance the verification process with both conservative and uncertainty analysis (b). Adapted from Freixa et al. (2021).

VI. CONCLUSION AND FUTURE WORK

This thesis proposed a straightforward methodology, entitled model breakdown structure (MBS), which integrates model-based systems engineering (MBSE) and computer-aided engineering (CAE) to enhance the verification process of nuclear systems. The Brazilian Multipurpose Reactor (RMB) is used as a case study to demonstrate the effectiveness of the proposed methodology in analyzing complex systems.

This thesis demonstrated how to use MathWorks' System Composer to address the gap between MBSE and CAE. A slow loss of flow accident scenario of the RMB core was studied using finite element analysis (FEA). The safety-related functional requirement associated with the peak cladding temperature (PCT) was modeled as a constraint using a data dictionary and verified by a Simulink model that analyzed the FEA results.

This interconnected structure enabled the integration of the entire spectrum of models, from the enterprise vision up to a detailed FEA. The core heat transfer was solved using the Partial Differential Equation (PDE) Toolbox™. The results enabled a detailed assessment of the temperature behavior throughout the transient. Additionally, code-to-code comparison showed strong agreement between the results obtained using the MATLAB toolbox and the Neutronics and Thermal Hydraulics Code.

The MBS supported an enhanced verification process using statistical methods. Uncertainty quantification of key factors was obtained through the application of Latin hypercube designs and Wilks' theorem. These methods can effectively reduce the amount of computational effort compared to full factorial designs and Monte Carlo simulations. The results indicated that the 95/95 uncertainty band of the PCT is below the onset of nucleate boiling threshold. Furthermore, the completion of the design of experiments (DOE) prior to the uncertainty quantification reduced the number of factors and, consequently, reduced the necessity of higher order statistics to increase accuracy.

The integrated model was able to significantly reduce the effort required for uncertainty quantification. Therefore, the integration of MBSE and CAE facilitated the analysis of design changes and improved the verification process of nuclear systems by providing a streamlined approach for DOE and the best estimate plus uncertainty (BEPU) analysis. This novel methodology can be applied to reduce the cycle time from data gathering to decision-making in the licensing process of nuclear systems.

Based on the findings of this thesis, recommended future work includes leveraging MBSE to support the BEPU approach for the verification of regulatory requirements during the licensing process of nuclear systems, applying the MBS to various types of CAE methods (e.g., computational fluid dynamics, computational electromagnetics, computational chemistry and multi-physics simulations), performing statistical analysis of experimental results to enhance the validation process, and extending the MBS methodology to enhance the verification process of other types of systems.

APPENDIX A. MATLAB MODEL

The following MATLAB code was created and used to conduct the finite element analysis (FEA) of the slow loss of flow accident (SLOFA) scenario of the Brazilian Multipurpose Reactor:

```
%% RMB SLOFA PFT PCT function
% Adapted from https://doi.org/10.1016/j.anucene.2020.107449
% Alan Matias Avelar
function [PFT, PCT, Tfmax, Tcmax] =
PSLOFAQ(ro_f,cp_f,k_f,ro_c,cp_c,k_c,power)
% Fluid properties
ro_w = 987; % kg/m^3
cp_w = 4182; % J/(kg*K)
k_w = 0.65; % W/(m*K)
% Geometry
xfo = 0.61E-3 / 2; % m
xci = xfo; % m
xco = 6.75E-4; % m
C1 = 65E-3; % active core length m
Nplates = 23*21; % 23 fuel assemblies with 21 plates each
L = 0.615; % active height m
Le = 0.775; % extrapolated height m
Lp = 0.655; % plate height m
% Thermal-Hydraulics
m0 = 849.92; % kg/s
ph = C1; % heated perimeter m
az = 70.5E-3*2.45E-3/2; % m2
xw=az/70.5E-3+xco; % m
dh = 2.41E-3; % hydraulic diameter
ni_w = 523.45E-6; % Pa*s
Pr = ni_w * cp_w / k_w; % Prandtl number
Re = dh*m0/23/42/az/ni_w;  % Reynolds
% Calculate Nusselt  using Dittus-Boelter correlation
if Re < 2300
   Nu = 4.36;
else
   Nu = 0.023 * Re^0.8 * Pr^0.4;
end
% Convection coefficient, W/(m^2-K)
h = Nu * k_w / dh;
hmax=39857.33;
% create 2D model and mesh
thermalmodel = createpde("thermal","transient");
f = [3, 4, 0, xfo, xfo, 0, L/2, L/2, -L/2, -L/2]';
c = [3, 4, xci, xco, xco, xci, L/2, L/2, -L/2, -L/2]';
gd = [f, c];
ns = char('fuel','cladding'); ns=ns';
```

```
sf = 'fuel+cladding';
g = decsg(gd,sf,ns);
geometryFromEdges(thermalmodel,g);
% Generate mesh for visualization
generateMesh(thermalmodel,"Hmax",xfo/2);
% Assign thermal properties to domains
thermalProperties(thermalmodel,"Face",1,"ThermalConductivity",k_f,...
                              "MassDensity",ro_f,...
                              "SpecificHeat",cp_f);
thermalProperties(thermalmodel,"Face",2,"ThermalConductivity",k_c,...
                              "MassDensity",ro_c,...
                              "SpecificHeat",cp_c);
% Heat source
thermalVal = ...
@(location,state) myfunWithAdditionalArgs(location,state,power);
internalHeatSource(thermalmodel,thermalVal,"Face",1);
% Boundary conditions
thermalBC(thermalmodel,"Edge",2,...
                      "ConvectionCoefficient",@heatTransferC,...
                      "AmbientTemperature",320);
thermalBC(thermalmodel,"Edge",[1 3 4 5 6],...
                      "ConvectionCoefficient",0,...
                      "AmbientTemperature",320);
thermalIC(thermalmodel,300); % Initial condition
tfinal = 100; % final time
tss=50; % time to show steady state
ttrip=54; % time to trip
tlist = linspace(1,tfinal);
%thermalmodel.SolverOptions.RelativeTolerance=1E-5;
thermalresults = solve(thermalmodel,tlist);
% Plot results at steady state
T = thermalresults.Temperature;
msh = thermalresults.Mesh;
% Plot fuel and cladding T profiles
Y=linspace(-L/2,L/2);
X=zeros(size(Y));
Tf = interpolateTemperature(thermalresults,X,Y,tss);
X=ones(size(Y))*xco;
Tc = interpolateTemperature(thermalresults,X,Y,tss);
% Plot fuel and cladding T profiles
Y=linspace(-L/2,L/2);
X=zeros(size(Y));
Tf = interpolateTemperature(thermalresults,X,Y,ttrip);
X=ones(size(Y))*xco;
Tc = interpolateTemperature(thermalresults,X,Y,ttrip);
% results at final state
% fuel and cladding T profiles
Y=linspace(-L/2,L/2);
X=zeros(size(Y));
Tf = interpolateTemperature(thermalresults,X,Y,tfinal);
X=ones(size(Y))*xco;
```

```
Tc = interpolateTemperature(thermalresults,X,Y,tfinal);
Tfmax=interpolateTemperature(thermalresults,0,0,tlist);
Tcmax=interpolateTemperature(thermalresults,xco,0,tlist);
PFT=max(Tfmax); PCT=max(Tcmax);
fprintf("Peak Cladding Temperature is %g K \n",PCT);
fprintf("Peak Fuel Temperature is %g K \n",PFT);
end
% heat transfer coefficient
function HTC = heatTransferC(location, state)
HTC = zeros(1,numel(location.y));
if(isnan(state.time))
% Returning a NaN when time=NaN tells
% the solver that the boundary is a function of time.
 HTC(1,:) = NaN;
 return
end
tSLOFA=50; % time Loss of all cooling pumps at reactor full power
m0 = 849.92; % kg/s
m = m0*exp(-(state.time-tSLOFA)/25);
if state.time <= tSLOFA % cooling pumps are operating
   m=m0;
end
if m>m0
  m=m0;
end
C1 = 65E-3; % active core length m
ph = C1; % heated perimeter m
az = 70.5E-3*2.45E-3/2; % m2
dh = 2.41E-3; % hydraulic diameter
ni_w = 523.45E-6; % Pa*s
cp_w = 4182; % J/(kg*K)
k_w = 0.65; % W/(m*K)
Pr = ni_w * cp_w / k_w; % Prandtl number
Re = dh*m/23/42/az/ni_w;  % Reynolds
% Calculate Nusselt  using Dittus-Boelter correlation
if Re < 2300
   Nu = 4.36;
else
   Nu = 0.023 * Re^0.8 * Pr^0.4;
end
% Convection coefficient, W/(m^2-K)
HTC(1,:) = Nu * k_w / dh;
end
function Q = myfunWithAdditionalArgs(location,state,power)
Q = zeros(1,numel(location.y));
if(isnan(state.time))
% Returning a NaN when time=NaN tells
% the solver that the heat source is a function of time.
 Q(1,:) = NaN;
 return
end
```

```
ttrip=54; % time to trip
PPF = 3; % power peaking factor
P0=power; % reactor power P is provided by the neutronics model
xfo = 0.61E-3 / 2; % m
C1 = 65E-3; % active core length m
Nplates = 23*21; % 23 fuel assemblies with 21 plates each
L = 0.615; % active height m
Le = 0.775; % extrapolated height m
V=Nplates*(L*2*xfo*C1);% volume of fuel in the core
P=P0*6.22E-2*((state.time-ttrip)^(-0.2)-(ttrip+(state.time-ttrip))^(-
0.2));
if state.time <= ttrip % reactor operating at full power
   P=P0;
end
if P>P0
  P=P0;
end
Q(1,:)=PPF*P/V*cos(pi*location.y/Le); % W/m^3
end
```

APPENDIX B. EXPERIMENTAL DESIGN

The following MATLAB code was created and used for the design of experiments (DOE) using Latin hypercube design (LHD):

```
%% DOE - LHD
% Alan Matias Avelar
clc
clear all
min= [4700 237 8 2700 490 15 30e6*0.85];
max=[10970 330 40 7930 892 165 30e6*1.15];
X = lhsdesign_modified(93,min,max);
y = corr(X); %(sum(y(:).^2) - length(min))/2;
for i=1:height(X)
% Fuel properties
ro_f = X(i,1); % kg/m^3
cp_f = X(i,2); % J/(kg*K)
k_f = X(i,3); % W/(m*K)
% Cladding properties
ro_c = X(i,4); % kg/m^3
cp_c = X(i,5); % J/(kg*K)
k_c = X(i,6); % W/(m*K)
% Power
power = X(i,7); % W
[PFT, PCT, Tfmax, Tcmax] = PSLOFAQ(ro_f,cp_f,k_f,ro_c,cp_c,k_c,power);
D(i,:)=[Tfmax, Tcmax, PFT, PCT];
end
figure(1); % PFT
for i=1:height(X)
plot(linspace(0,100),D(i,1:100)); hold on;
xlabel('t, s');ylabel('PFT, K');
end
savefig('PFT_LHw2.fig'); saveas(gcf,'PFT_LHw2.png');
hold off; close all
figure(2); % PCT
for i=1:height(X)
plot(linspace(0,100),D(i,101:200)); hold on;
xlabel('t, s');ylabel('PCT, K');
end
savefig('PCT_LHw2.fig'); saveas(gcf,'PCT_LHw2.png');
hold off; close all
figure (3); X=[X, D(:,201:202)];
labels = {'Fuel density, kg/m^3','Fuel specific heat, J/kg/K','Fuel
thermal conductivity, W/m/K',...
   'Cladding density, kg/m^3','Cladding specific heat, J/kg/K','Cladding
thermal conductivity, W/m/K',...
   'Power, Wth','PFT','PCT'};
p=parallelplot(X); p.Jitter = 0;
p.CoordinateTickLabels = labels;
```

```
savefig('Parallel_LHw2.fig'); saveas(gcf,'Parallel_LHw2.png'); close all
xlswrite('x_LHw2.xlsx',X);
function
[X_scaled,X_normalized]=lhsdesign_modified(n,min_ranges_p,max_ranges_p)
%lhsdesign_modified is a modification of the Matlab Statistics function
lhsdesign.
p=length(min_ranges_p);
[M,N]=size(min_ranges_p);
if M<N
   min_ranges_p=min_ranges_p';
end

[M,N]=size(max_ranges_p);
if M<N
   max_ranges_p=max_ranges_p';
end
slope=max_ranges_p-min_ranges_p;
offset=min_ranges_p;
SLOPE=ones(n,p);
OFFSET=ones(n,p);
for i=1:p
   SLOPE(:,i)=ones(n,1).*slope(i);
   OFFSET(:,i)=ones(n,1).*offset(i);
end
X_normalized = lhsdesign(n,p,'Criterion','correlation');
X_scaled=SLOPE.*X_normalized+OFFSET;
```

APPENDIX C. ANALYSIS OF VARIANCE

The following MATLAB code was created and used for analysis of variance (ANOVA):

```
%% ANOVA
% Alan Matias Avelar
clc
clear all
factors=["Fuel density" "Fuel specific heat" "Fuel thermal
conductivity"...
    "Cladding density" "Cladding specific heat"...
    "Cladding thermal conductivity" "Power"];
[data] = csvread("x_LH.csv");
data = single(data);
y= data (:,9);
data(:,7) = data(:,7)./1e6;
data (:,8:9)=[];
aovLHw1 = anova(data,y,FactorNames=factors,...
   CategoricalFactors = [],ResponseName="PCT")
mdlLHw1 = fitlm([data(:,2) data(:,5), data(:,7)],y)
mdlLHw1.Rsquared.Adjusted
[data] = csvread("x_LHw2.csv");
data = single(data);
y= data (:,9);
data(:,7) = data(:,7)./1e6;
data (:,8:9)=[];
aovLHw2 = anova(data,y,FactorNames=factors,...
   CategoricalFactors = [],ResponseName="PCT")
mdlLHw2 = fitlm([data(:,2) data(:,5), data(:,7)],y)
mdlLHw2.Rsquared.Adjusted
mdlP = fitlm([data(:,7)],y)
mdlP.Rsquared.Ordinary
g1=data(:,1); g2=data(:,2); g3=data(:,3);
g4=data(:,4); g5=data(:,5); g6=data(:,6);
g7=data(:,7);
p = anovan(y,{g1 g2 g3 g4 g5 g6 g7},'model','interaction',...
   'varnames',{'Fuel density' 'Fuel specific heat' 'Fuel thermal
conductivity'...
    'Cladding density' 'Cladding specific heat'...
    'Cladding thermal conductivity' 'Power'})
```

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LIST OF REFERENCES

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