Dynamic fuzzy reliability and safety assessment of passive safety systems in small modular reactors

by

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The above committee determined that the thesis is acceptable in form and content and that a satisfactory knowledge of the field covered by the thesis was demonstrated by the candidate during an oral examination. A signed copy of the Certificate of Approval is available from the School of Graduate and Postdoctoral Studies.

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Abstract

Small Modular Reactors (SMRs) have garnered significant interest in recent years, and they may play an essential role in the future of energy supply and power generation. One major advantage associated with SMRs is their improved safety, which is expected to be accomplished by integrating a wide range of novel design elements, such as Passive Safety Systems (PSS) and components. Passive safety systems rely on natural processes rather than active intervention, hence possessing some unique features compared to traditional safety systems. Safety analysis of SMR's PSSs encounters challenges, including Limited Operating Experience (OPEX), limited data availability, and above all, dynamic behaviour of the system. Systematic analysis of the reliability and safety of PSSs is yet to be performed to understand and evaluate the reliability and safety of these systems.

Probabilistic Safety Assessment (PSA) has played an important role in evaluating the reliability and safety of Nuclear Power Plant (NPPs) operations in the past decades. However, several limitations associated with the classical PSA, such as failing to capture the dynamic processes and timing sequences of events, make it difficult to be directly utilized to evaluate the safety of PSSs. These could potentially be addressed to a large extent by incorporating fuzzy logic and Artificial Neural Network (ANN) into the analysis, thus addressing some intrinsic properties associated with PSSs.

This thesis proposes a dynamic fuzzy-PSA, fuzzy-FMEA (Failure Mode and Effects Analysis) and ANN-based fault tree analysis. The Passive Residual Heat Removal System (PRHRS) in the CAREM (Spanish: Central Argentina de Elementos Modulares)-25 small reactors under the Station Blackout (SBO) accident is analyzed to demonstrate the performance of the ANN-based FT analysis and dynamic fuzzy logic analysis. The effectiveness of the PRHRS in removing residual heat is evaluated using both methods. It is shown that engaging fuzzy logic into the PSA and Failure mode & Effects Analysis (FMEA) can handle uncertainty and imprecision in data and knowledge and improve classical risk assessment methods by implementing dynamics fuzzy operators and Pandora gates (Priority-AND and Priority-OR). On the other hand, ANN-based FT can analyze and handle a large number of data irrespective of the number of Basic Events (BEs), logical gates, and system complexity and identify patterns that would be difficult and time-consuming for classical FT analysis. Comparing the results of these two methods with existing research in the open literature shows that these models are valid and more efficient than conventional PSA methods.

In the future work, ANN and fuzzy logic are expected to be linked together to enhance the capabilities of classical PSA when analyzing the reliability and safety of PSSs in SMRs.

Keywords: CAREM-25; Passive Safety System; Artificial Neural Network; Probabilistic Safety Assessment; Fuzzy Logic, FMEA

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Dedication

This thesis is dedicated to all the girls and boys who lost their lives in the recent revolution in Iran following the tragic death of Mahsa Amini. Your courage, determination, and unwavering commitment to justice and freedom have inspired countless people around the world, and your memory will never be forgotten. As we navigate these uncertain times, let us remember the sacrifices you made and your dreams for a better future. Let us honour your memory by continuing to fight for a world where justice, equality, and human dignity are upheld for all.

In addition to Pirouz, the last surviving Asiatic cheetah cub was born in captivity last year. Pirouz's life was tragically cut short by acute kidney failure, which claimed his life just two days before he was set to turn 10 months old. As the last survivor of his litter, Pirouz represented hope and resilience for a critically endangered species. His loss is a heartbreaking reminder of the urgent need to protect and conserve the remaining Asiatic cheetah population. May Pirouz's memory serve as a call to action for all of us to work tirelessly towards preserving the incredible diversity of life on this planet. Let us honour his life by continuing to fight for a world where all species, including our own, can thrive in harmony.

May your spirits live on in the hearts of those who continue to fight for a brighter tomorrow.

Rest in peace.

STATEMENT OF CONTRIBUTIONS

In this thesis, we present a comprehensive study on risk and safety analysis of Small Modular Reactors (SMRs) by evaluating and comparing traditional methods, such as Probabilistic Safety Assessment (PSA) and Failure Modes and Effects Analysis (FMEA), with innovative approaches employing fuzzy logic and Artificial Neural Networks (ANN). We focus on the passive safety system of the CAREM-25 type reactor and address challenges arising from the unique design, new technologies, complex interactions between systems and components, and limited operating experience associated with SMRs.

We propose a fuzzy PSA technique that considers fuzzy numbers for failure rates and combines fuzzy set theory with probability theory to represent and propagate uncertainties in the failure rates of components and systems. Through a case study of the CAREM-25 type reactor's Passive Residual Heat Removal System (PRHRS), we demonstrate that the fuzzy PSA provides a more accurate understanding of the system's overall failure risk by capturing uncertainties more effectively than traditional PSA. Furthermore, we develop an innovative risk analysis approach using Fuzzy Fault Tree Analysis (FFTA) and Fuzzy Event Tree Analysis (FETA) to address the uncertainty in input data and improve the accuracy of safety assessments. The proposed approach is applied to the Isolation Condenser System (ICS) failure and coupled with a fuzzy-logic-based FMEA to identify the weaknesses and potential failure modes of the PRHRS system.

In addition to the fuzzy probabilistic safety assessment approach, we propose mapping fault trees into a deep learning framework to overcome the limitations of traditional Fault Tree (FT) analysis, leveraging the capabilities of ANNs for fault prediction and consequence analysis. The results indicate a high similarity between the traditional FT and ANN-based models.

In summary, our thesis contributes to the risk and safety analysis of SMRs by proposing innovative methods that improve the accuracy of traditional techniques and address the challenges posed by uncertainties and imprecisions. Future research should enhance these approaches by incorporating expert judgment, handling imprecise data, and addressing uncertainties in the overall risk assessment process. This research paves the way for further advancements in safety-critical system risk assessment by combining fuzzy set theory, probability theory, and deep learning frameworks.

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List of Abbreviations

ADS Automatic Depressurization System 19, 70

ANN Artificial Neural Network iv

BEs Basic Events iv, 37, 62, 78

CAFTA Computer Aided Fault Tree Analysis System 104

CCF Counter-Current Flow 69

CCFs Common Cause Failures 103

CDF Core Damage Frequency 9

CDF Core Damage Frequency 37

D Detectability 22

DID Defense-In-Depth 8

ECCS Emergency Core Cooling System 37

EPZ Emergency Planning Zone 11

FFTA Fuzzy Fault Tree Analysis 37

FIS Fuzzy Inference System 37

FMEA Failure mode & Effects Analysis iv

FT Falut Tree 62, 64, 105

FTA Fault Tree Analysis 78, 104

HFE Human Factor Engineering 10

HXs Heat Exchangers 18

IAEA International Atomic Energy Agency 6

IC Isolation Condenser 68

ICS Isolation Condenser System 3

iPWR Integral Pressurized Water Reactor 9

LNPP Large Nuclear Power plants 10

LOCA Loss Of Coolant Accident 9, 68

MSE Mean Square Error 60

NC Natural Circulation 37, 97

NPP Nuclear Power plants 11

O Occurrence 22

OPEX Operating Experience 10

PRHRS Passive Residual Heat Removal System 68

PSA Probabilistic Safety Assessment iv

PSS Passive Safety Systems iv

REPAS Reliability Evaluation of Passive Systems 13

RMPS Reliability Methods for Passive Safety Functions 13

RMSE Root Mean Square Error 61

RPV Reactor Pressure Vessel 68, 69, 84, 97

S Severity 22

SBLOCA Small Break Loss of Coolant Accident 68

SBO Station Blackout 19, 80, 83, 84, 104

SMRs Small Modular Reactors 1

SOE Safe Operating Envelope 11

SSCs Structures, Systems, and Components 21

TE Top Event 37

TFN Triangular Fuzzy Number xi, 75, 78

Chapter 1

Introduction

1.1 Background

Small Modular Reactors (SMRs) have garnered significant interest in recent years, and they may play an essential role in the future of energy supply and power generation. With new safety system designs in these SMRs, power can be presented in remote areas and implemented on the sea, underground, and under the sea, which makes SMRs an important part of the future of global power generation. Canada has one of the most promising SMR markets rapidly expanding, predicted to encompass a potential value of $5.35 billion between 2025 and 2040 [2].

One of the primary advantages of SMRs is their potential safety improvement, which has been accomplished by integrating a wide range of novel design elements. One of the vital safety features of SMRs is their reliance on PSSs, which are designed to provide redundant and reliable cooling for the reactor in the event of an emergency. Passive safety systems have been implemented to increase the safety and robustness of SMRs, eliminate design vulnerabilities, and reduce the consequences of accidents. In contrast to current active systems, passive systems are the driving force behind nuclear reactor advancements. The passive feature could rely on natural circulation without actuators such as pumps and valves or gravity-driven systems that do not require external power or human intervention to function. Utilizing passive systems is expected to result in increased safety levels for NPPs, besides the cost reduction in power production (by means of simplified design, reduced maintenance, lower staffing requirements and shorter construction times). Therefore, new NPPs utilize PSSs in technological improvements or modernizations. Some examples of passive safety systems that can be used in SMRs include:

- Natural circulation cooling: In this system, the coolant circulates through the reactor naturally, without requiring pumps or other mechanical devices. This can be achieved by using a properly designed coolant system that utilizes the difference in density between hot and cool coolants to drive circulation.
- Gravity-driven cooling: This system uses gravity to drive the coolant through the reactor in the event of a loss of coolant accident. This can be achieved by having a coolant storage tank located above the reactor and connected to the reactor by gravity.

- Passive containment cooling: This system uses natural convection to transfer heat from the containment building to the environment in the event of a loss of coolant accident.
- Passive containment isolation: This system uses gravity or natural forces to close and seal off the containment building in the event of an accident, without the need for operator action or external power (Nuscale, Holtec SMR-160 and Integral Pressurized Water Reactor (iPWR)). These passive safety systems are designed to work automatically and without operator intervention, ensuring the reactor's safety in the event of a loss of power or another emergency.

Although it is expected that PSSs should overperform the active safety systems in emergency situations, systematic safety evaluation of these systems is still needed due to the new and specific features associated with PSSs. The vulnerabilities and weaknesses of the new design associated with the structure, systems and components of SMRs need to be identified. Probabilistic safety assessment has been wildly adopted to evaluate the safety of NPPs in the past decades. It involves examining the probability and potential repercussions of various accident scenarios and using this data to suggest and prioritize safety improvements. Probabilistic safety assessments for SMRs can be more challenging than for traditional NPPs due to several factors, as detailed below:

- Modular design: SMRs are designed as smaller, factory-built units that can be assembled on-site, which can introduce new failure modes and accident scenarios that need to be considered in the PSA.
- New technologies: SMRs often use new and untested technologies, such as advanced fuels and coolants, which can introduce new failure modes and accident scenarios that need to be evaluated in the PSA.
- Limited OPerating EXperience (OPEX): As SMRs are a relatively new technology, there is a limited operating experience to draw from, making it difficult to accurately estimate the likelihood of different accident scenarios.
- Complex interactions: Due to the smaller size of SMRs, the interactions between different systems and components may be more complex and harder to model than in traditional NPPs.
- Dynamic features: Classical PSA cannot represent dynamic features associated with the PSSs in SMRs.

1.2 Motivation

The design and operation of SMRs are still in their early stages, and there is a need for further research and development to understand and evaluate the performance of these reactors. This research investigates potential modifications and improvements in current PSA practice to address the specific features associated with the PSSs in SMRs when performing safety assessments for these systems.

After a comprehensive analysis of existing literature and practical applications, this thesis explores the potential benefits and limitations of using fuzzy logic and ANNs in the safety assessment of the PSSs of SMRs. Some of the specific benefits of incorporating fuzzy logic and ANN into the safety assessment include the following:

1. Improving the accuracy of PSA models: Fuzzy logic and ANN can incorporate uncertainty and subjective judgment into the analysis, improving the robustness and reliability of the models and providing more realistic and representative results.
2. Automating the PSA process: Fuzzy logic and ANN can be used to automate the PSA process, reducing the time and effort required to conduct a comprehensive assessment and increasing the efficiency and consistency of the process.
3. Addressing data unavailability: There may be limited data available about the performance and reliability of a component or system due to innovative design or lack of OPEX, in this case, using generic data leading to uncertainty in the estimated failure rate. Using fuzzy logic and ANN, this problem is solved using data predictions and linguistic variables.
4. Addressing uncertainty: Input inaccuracy can impact the results of a PSA, leading to uncertainty in the estimated probabilities and consequences of different accident scenarios. To address this, dynamic fuzzy-PSA is focused on improving the accuracy and reliability of basic event failure rates.

This thesis aims to develop a dynamic fuzzy PSA to link fuzzy logic concepts with dynamics PSA using a combination of fuzzy numbers and temporal logic gates.

1.3 Scope of the Research

This thesis developed methodologies to incorporate fuzzy logic and ANN in the PSA. Firstly, the FT is mapped into the ANN, and the result shows that using this method can increase the speed of evaluations, regardless of the number of BEs and other inputs and the complex relationship between them. Secondly, a dynamic fuzzy method deals with two significant drawbacks in modelling PSSs in reliability and safety analysis: the assumption of constant failure rates and time treatment in dynamic systems. The former refers to the fact that the assigned failure rates are not precise, making predictions less accurate. The latter means that the failure rates for individual components in a real situation are inconsistent and can vary over time depending on the circumstances of an operation. Dynamics fuzzy PSA is used to fill in the gaps in PSSs reliability assessments to address these problems. At the end the outputs of the fuzzy-PSA are used to feed fuzzy-FMEA to estimate the risk priority number for different failure modes.

The CAREM-25, a kind of iPWR SMR, demonstrates the abovementioned method. Assessing the reliability and safety of the PSSs in the CAREM-25 poses several challenges and uncertainties. This includes evaluating the reliability and performance of the Isolation Condenser System (ICS) and other safety-critical components and systems. The accurate and comprehensive assessment of the risks associated with the PSSs of the CAREM-25 is critical for ensuring the safety and reliability of the reactor. However, traditional methods for conducting PSA can be time-consuming, labor-intensive, and prone to errors and biases. This is where fuzzy logic and ANN can make a significant impact. By incorporating these technologies into the PSA process, we can significantly improve the accuracy, efficiency, and interpretability of the results and ensure that the PSSs of the CAREM-25 are robust, reliable, and effective.

1.4 Thesis Organization

This thesis is composed of six chapters which are organized as below:

Chapter 1:
Introduces the background information about the research, motivations for the using Fuzzy logic and ANN, the objectives of the research and organization of the thesis.

Chapter 2:
Contains a comprehensive literature survey on SMRs, PSSs, and traditional reliability and safety assessment methodologies.

Chapter 3:
Is the major component of this thesis where ANN-based FT analysis, dynamic fuzzy PSA, and fuzzy FMEA are proposed to address the deficiencies of the current PSA practice

Chapter 4:
Utilized the PRHRS system in the CAREM-25 SMR to demonstrate the implementation of the ANN-based FT analysis, dynamic fuzzy PSA and fuzzy FMEA developed in chapter 3. Lastly, in

Chapter 5:
Conclusions are drawn based on the comparative assessment and the potential use of the dynamic fuzzy PSA and fuzzy FMEA to impact the design of PSS is discussed. Finally, the potential future work is proposed.

Chapter 2

Literature Review

Small modular reactors are a promising technology for providing low-carbon energy, but as with any nuclear power technology, it is important to assess their safety risks. One approach to evaluating the safety of SMRs is through risk assessments, which involve identifying and analyzing potential hazards and developing strategies to manage them. Probabilistic safety assessments are a commonly used method for assessing the safety of nuclear power plants, including SMRs. Probabilistic safety assessments use probabilistic methods to estimate the likelihood of different types of accidents or incidents and the consequences of those events. This information can be used to identify potential safety vulnerabilities and develop strategies to mitigate them.

Another method for evaluating the safety of SMRs is Failure Mode and Effects Analysis (FMEA). Failure mode and effects analysis is a systematic approach to identifying and assessing potential failure modes in a system and developing strategies to prevent or mitigate them. Failure mode and effects analysis can be particularly useful for evaluating PSSs, as it can help identify potential failure modes and develop strategies to prevent them. However, there are also challenges associated with using PSAs and FMEA for evaluating the safety of SMRs. For example, the complex nature of these systems can make it difficult to accurately model their behaviour and assess the potential consequences of accidents or incidents.

Overall, while PSAs and FMEA can be useful tools for evaluating the safety of SMRs and their passive safety systems, it is important to recognize their limitations and approach safety assessments cautiously and carefully, considering all available data and information.

2.1 Small Modular Reactors

The use of nuclear energy, specifically SMRs, is crucial in combating the urgent issue of climate change. Small modular reactors have gained significant attention lately for their ability to supply power to remote locations and their deployment versatility - on the sea, underground, and under the sea. These features make SMRs an attractive solution for reducing global carbon dioxide emissions and breaking away from fossil fuels. The nuclear power sector and regulations worldwide are working towards achieving net-zero emissions by 2050, and implementing SMRs can accelerate this transition. Additionally, SMRs can offer a non-emitting alternative to diesel in isolated areas. Canada, with its growing SMRs market and a projected worth of $5.35 billion by 2040, is one of the most promising markets for SMRs.

Small modular reactors have diverse applications due to their compact and modular design. This flexibility makes them ideal for supplying power to remote areas and reducing reliance on fossil fuels. Furthermore, their safety features and ability to lower carbon dioxide emissions make them a feasible option for decarbonizing the electricity sector. The different SMR designs and objectives, as shown in Table 2.1, demonstrate the potential for the technology to be adapted and applied to meet the unique energy needs of various regions and industries [3].

Table 2.1: Small Modular Reactors Diversity [1]

	Applicability Small Modular Reactors	
On-grid SMRs	Advanced Reactors	Off-grid SMRs
150 to 300 MWe	10 to 150 MWe	1 to 10 MWe
Reliable, base-load power	Advanced reactors	Remote industrial
Displace coal	Heavy industrial applications	Off grid communities
Near term deployment	Deployed by 2030s	Commercial in the 2020s.
• GE BWRX 300	• ARC-100	• Global First Power MMR
	• Moltex	• Westinghouse eVinci
	• X Energy	

The evolution of SMRs has been instrumental in developing clean energy solutions. With core unit sizes ranging from 60 MWe to over 1600 MWe, and the creation of small and neutron sources, SMRs have proven to be a key player in the clean energy transformation. As defined by the International Atomic Energy Agency (IAEA), SMRs are further categorized as small (less than 300 MWe) or big (up to 700 MWe) based on their capacity [4]. This advancement in SMR technology has paved the way for their implementation in various applications. These small reactors can be assembled individually or as modules in a larger structure, allowing for incremental expansion. Compared to traditional NPPs, SMRs are viewed as more financially manageable investments as they often incur lower costs that do not exceed the utility's capitalization.

2.1.1 SMRs Design Features

Nuclear power plant accidents, thought inevitable, have increased public distrust of nuclear energy and eroded community confidence due to the growing concern about NPP safety. Consequently, future nuclear power facilities will be built with a stronger focus on hazard prevention and possible accident mitigation. As a result, it is believed that designing nuclear power facilities with purely passive safety systems is no longer a choice but a must. Additionally, passive safety solutions need to be considered more adequate. The following aspects are made possible by the design and operational characteristics of SMRs, which set them apart from existing LNPPs [5].

1. Passive safety systems (gravity, natural circulation);

2. Modular design, Modularity and Modularization;
3. Inherent Safety-By-Design

These design features differentiate them from traditional large-scale nuclear power plants and contribute to improved safety and efficiency and enhanced reliability and maintainability.

2.1.2 SMRs Passive Safety System

Small modular reactors have several unique design features that can contribute to their safety and efficiency, including using PSSs. Passive safety systems do not require operator intervention, external power, or cooling to maintain the reactor's safety and contain radioactive materials in the event of an emergency. The International Atomic Energy Agency (IAEA) categorizes PSSs into three main groups: natural circulation cooling systems, gravity-driven cooling systems, and passive containment cooling systems:

- Natural Circulation Cooling Systems (NCCS): A NCCS is a PSS that uses natural circulation to circulate cool water through the reactor in the event of a loss of coolant accident. The natural buoyancy of hot water drives it to rise to the top of the reactor, cool and then fall back down to the bottom, where it is re-circulated. This simple, reliable, fail-safe system can maintain the reactor's safety without requiring active interventions such as pumps or external power supply. Examples of SMR designs that utilize this type of PSS include the iPWR and the High-Temperature Gas-Cooled Reactor (HTGR) [6, 7].
- Gravity-Driven Cooling Systems (GDCS): Is a PSS that uses gravity to circulate cool water through the reactor in LOCA. The cool water is drawn from the bottom of the reactor and returns to the top, where it is cooled and re-circulated. This simple, reliable, fail-safe system can maintain the reactor's safety without requiring active interventions such as pumps or external power supply. Examples of SMR designs include iPWR, BWRX-300 [8, 9].
- Passive Containment Cooling Systems (PCCS): The PCCS typically consists of a pool of water, which acts as a heat sink, and various heat exchangers and passive components that transfer heat from the reactor to the pool. The PCCS aims to remove heat released inside the containment vessel following postulated design-basis accident (DBA) such as LOCA or main steam-line break (MSLB). Examples of SMR designs that utilize this type of PSS include the NuScale, Westinghouse SMR [10, 11].

These passive safety systems focus on ensuring reliable and safe operation, improving incident control, minimizing consequences, and eliminating the need for off-site emergency response from a technological standpoint. The reliability assessment of PSS is of utmost importance as the safety of SMRs is dependent on multiple passive characteristics. To fulfill the safety and reliability objectives, the following fundamental safety functions, known as the 3Cs (cooling, containment, and control), must be implemented.

- Passive Controlling: control rod insertion, boron dilution, and coolant-based reactivity feedback are utilized for reactivity control. The reliability of these systems in controlling reactivity is contingent on design, configuration, and interdependent component factors.
- Passive Cooling: including passive heat removal systems and functions such as; natural circulation cooling, passive heat exchanger, gravity-driven cooling, and passive containment cooling are assigned to cool the reactor core during normal and abnormal operation;
- Passive Containing: underground containment, passive containment isolation, helping to radioactive materials containing, regulating operating emissions, and preventing unintentional releases.

To ensure that the above 3Cs are achieved, Defense-In-Depth (DID) strategy is defined as a safety approach. This safety approach, including accident prevention, accident mitigation, and accident accommodation, is characteristic of the design of the entire plant. Defence-in-Depth has military origins and protects systems via overlapping series of physical barriers. The concept is based on the failure of one barrier shall not fail other barriers and mitigating systems, eventually leading to a disaster. Two models of nuclear reactor DID concepts are physical barriers, where multiple physical barriers are used to confine radioactive material. The system-specific design varies based on the material's behaviour and any deviations from routine operations that could cause the barrier to collapse. Distinct physical barriers comprise the fuel matrix, the fuel cladding (sheath), the border of the reactor coolant system, and the containment. Moreover, overlapping processes refer to implementing multiple layers of control to ensure a backup is in place if a failure in the first line of defence occurs. These processes may include emergency response plans, training, and contingency planning.

By overlapping the physical and process-based defence, the DID strategy creates a comprehensive approach to managing risk and reducing the potential impact of an incident.

2.1.3 Modular, Modularity and Modularization

The **3 "M"** concept - **M**odular, **M**odularization and **M**odularity - plays a crucial role in defining the characteristics of SMRs. This concept refers to the design and implementation of these reactors, which are built into modules and can be assembled individually or in a larger structure. The modular design allows for flexibility in expanding capability as needed, making SMRs a more manageable investment than traditional NPPs, where expenses often exceed the utility's capitalization.

- A *module* is a system or component that is constructed, integrated, and validated in a laboratory or factory prior to being transported to the job site. Various modules, such as functional, production, and equipment, are independently assembled and fabricated in a factory to reduce completion time and expenses, enable independent parallel operation, and enhance safety.

- *Modularization* is the process of transforming a system or design into a modular format. In the context of SMRs, modularization refers to the engineering and design efforts to break down the reactor system into smaller, standardized, and manageable modules or components. This process aims to improve the efficiency of manufacturing, transportation, and on-site construction by streamlining the overall design and assembly process.

- *Modularity* refers to the degree to which a system component can be detached or use a standard component to produce products or systems. According to the IAEA, scale modularity refers to developing a large NPP in small components or module installations.

SMRs utilize modularity to minimize size and improve safety by incorporating or separating modules to prevent a domino effect in the event of a malfunctioning module. The reactor core and primary coolant system are incorporated into a single Reactor Pressure Vessel (RPV) as part of an integrated design (Nuscale, CAREM-25). Modularity in SMRs imposes additional constraints regarding well-defined interactions and predefined bounds. Design modularity needs more effort to create a practical module and demands decisions on methods, connections, and integrations. First-of-kind SMRs are more expensive due to the lack of OPEX [12, 13].

2.1.4 Safety-By-Design

Safety-by-design is a design philosophy that considers accident mitigation and prevention approaches in the design of SMRs. Implementing the safety-by-design concept Minimizes plant accidents by design or drastically minimize their likelihood; for instance, the integrated layout of SMRs removes extra coolant loop piping, leading to eliminating the Loss Of Coolant Accident (LOCA). Therefore, for SMRs, the Core Damage Frequency (CDF) for internal events is commonly estimated to be between 10^{-6} and 10^{-8} per year. Consequently, safety-by-design measure decreases the risk of accidents and lessens their effects. Resulting in simpler, safer, and more cost-effective designs [14]. Seven Class IV accidents for the Integral Pressurized Water Reactor (iPWR) design are indicated in Table. 2.2.

Table 2.2: Safety advancements by applying the safety-by-design concepts [15]

Design Basid Accidents	**iPWR Safety-by-Design Result**
Loss Of Coolant Accident	Eliminated
Control Rod Ejection	Eliminated
Reactor Coolant Pump Shaft Break	Eliminated
Reactor Coolant Pump Seizure	Downgraded
Steam Generator Tube Rupture	Downgraded
Steam System Piping Failure	Downgraded
Feed-water System Pipe Break	Downgraded

Safety-by-Design aims to minimize potential hazards and ensure the safe operation of SMRs by implementing reliable safety systems, risk-informed decision-making, and continuous design improvement. Effective Safety-by-Design requires a systematic and integrated approach to hazard identification, assessment, and control to enhance the overall safety performance of SMRs.

2.1.5 Challenges with SMRs

Even though substantial breakthroughs have been discussed in earlier sections, several technological challenges persist in multi-module concepts of SMRs, including:

- Control room staffing:

  Small modular reactors' innovative design requires control rooms' crew responsibilities, composition, and size changes. The safety and reliability of SMRs rely on having the proper control room operators, and optimal control room staff composition will vary from the current operating fleet of LNPP (due to adding passive features and design simplicity) [16].

- Human Factor Engineering (HFE):

  Operating procedures must be established (between supervisors) to avoid human error leading to isolating equipment in the faulty module or to ensure that substantial modifications to operation in one module do not compromise the safe functioning of others. To counteract this shortcoming, plant designers are investigating alternative operating strategies, such as a single operator monitoring multiple modules or reactors controlling remotely. Small modular reactors require a systematic HFE evaluation to establish the minimal staff complement based on operational tactics, essential staff engagements, and competency (not only qualification) [17].

- Neutron leakage[1]:

  Small modular reactors will have more neutron leakage than Large Nuclear Power plants (LNPP) (SMRs produce nine times as much neutron-activated steel) due to their diminutive size, leading to increasing leakage impacts on their waste streams' quantity and structure [18].

- Developing new codes, standards and licensing:

  The unique design characteristic of SMRs creates additional barriers when applying codes and standards. For instance, gravity-driven injection and passive cooling systems, which are innovatively connected to LNPP, operate using natural circulation; therefore, safety assessments for regulators and licensees are very demanding because of the naval design elements and lack of new design coverage in current codes and standards. On the other hand, the Operating Experience (OPEX) scarcity for each innovative feature raises uncertainty, each of which is subsequently taken into account in safety evaluations and influences final results.

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[1] Neutron leakage is the issue that results from certain neutrons that escape from the core when a chain reaction occurs there.

- Determining Emergency Planning Zone (EPZ):

  The emergency planning zone for SMRs may be scaled based on the findings of the risk evaluations, the innovation, unique attributes, and specific design requirements. The size of the EPZ may vary based on the legislation, security plan, dosage limits, policy considerations, and social acceptability when the same SMR design is applied in various countries.

As mentioned, the design and operation of SMRs present several challenges, including issues with control room staffing, human factors engineering, neutron leakage, difficulties in applying codes and standards, and determining the emergency planning zone. A reliable passive safety system is essential to guarantee the safe operation of SMRs, which have limited redundancy due to their small size. A comprehensive reliability assessment must account for the technology, interdependence of different modules, and external factors such as natural disasters, human errors, and cyber-attacks. Therefore, the importance of reliable passive safety systems in SMRs emphasizes the need for ongoing research and development in the reliability assessment of SMRs.

2.2 Reliability Analysis Methods

The increasing incidents of Nuclear Power plants (NPP) accidents, such as the Chernobyl disaster, the Fukushima Daiichi nuclear disaster, and the Three Mile Island accident, have heightened public concern regarding the safety and reliability of nuclear power generation. To mitigate these concerns, the discipline of reliability engineering has been established. This nascent field of engineering examines the fundamental reasons for system and component failures during the preliminary and final design phases and provides plant engineers with data that can be utilized to avoid such failures proactively [19].

Reliability, as defined in [20], is the ability of a system or component to perform its intended mission over specified circumstances for a specified period. The essential elements of reliability are capability, functionality, conditions, and time, which estimate the mission time. The mathematical definition of reliability is the probability that the time of unexpected failure (T) is greater than or equal to the mission time (t), as expressed in the following equation:

$$R(t) = P(T \geq t) \tag{2.1}$$

Reliability is evaluated using measures such as failure rate and failure interval, although it should be noted that reliability provides a relative, rather than absolute, assessment of system performance. For example, reliability assessment is used to improve the Safe Operating Envelope (SOE)[2]concept when defining the constraints and requirements for NPP to ensure compliance with safety analysis [21].

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[2] "Based on [21], the Safe Operating Envelope refers to the set of limits and conditions within which the station must be operated to ensure conformance with the safety analysis upon which reactor operation is licensed and which can be monitored by or on behalf of the operator"

Failures, even in highly-technical systems, are inevitable. These failures can result in discomfort, expenses, human harm, lost revenue, ecological damage, and fatalities. Reliability and safety engineering provides a numerical measure of efficiency, identifies contributing factors, and offers valuable insights for enhancing system productivity, such as reducing failures and adverse effects [22]. Analyzing, describing, measuring, and evaluating failures is an important aspect of reliability. Based on the examination of failures, there are two main ways in which NPPs can encounter difficulties:

- ***Equipment Failure***; The assessment of equipment failure probability and unavailability is based on reliability modelling. This framework predicts the likelihood of element failure to perform its desired function and depends on the system's stage of operation (standby and operating components).
- ***Human Error***; Human error can contribute to initiating accident scenarios. Most human actions that occur during the conceptual design and final stages are included in this study, as they can impact the organization and outcome of the model. The consideration of human performance in terms of reliability is a continually evolving field due to the complexity of human behaviour and the scarcity of critical information [23]. A method for understanding the human reliability analysis (HRA) and using current HRA approaches in SMRs was proposed in [24], where human intervention is minimal due to innovative design concepts, such as PSSs.

Predictable outcomes are essential for the design of NPPs, where SSCs are managed and maintained (and are not vulnerable to human error) to meet all safety criteria, reliability assumptions, and environmental release requirements for the entire plant lifetime. Various techniques, including safety design concepts, are proposed to enhance system reliability: redundancy (having alternative SSCs), diversity, independence, fail-safe design, and equipment qualification. Passive safety systems improve the reliability of NPPs by automatically activating during emergencies without human intervention or external power. These systems, such as passive cooling, prevent fuel damage and reduce the release of radioactive materials, mitigating the consequences of accidents. By enhancing plant reliability, PSSs increase public confidence and address concerns about nuclear power generation.

2.2.1 Reliability Assessments of Passive Safety Systems

Passive safety systems in NPPs rely on physical processes, such as gravity, natural convection, and conduction, rather than human intervention or activators. As a result, they are considered to be more reliable than active systems. However, it is essential to note that passive systems may be subject to structural failure, physical degradation, and clogging. To ensure the ongoing reliability of these systems, it is imperative to conduct continuous evaluations, especially for novel designs with limited operational experience [25]. The reliability of PSSs is impacted by various factors, including operating conditions, the physics of the associated phenomena, and the reliability of individual components, which can be influenced by factors such as design, materials, manufacturing, and testing. The challenges of evaluating the reliability of PSSs are depicted in Fig. 2.1.

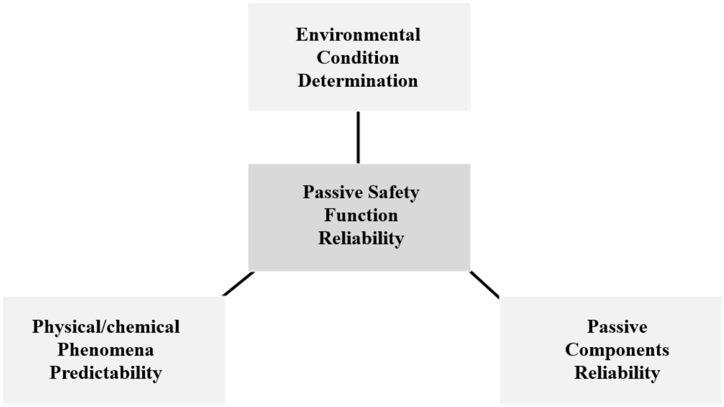

Figure 2.1: Factors Affecting the Reliability of Passive Safety Systems

Reliability assessment methods for PSSs are essential because they help ensure critical systems' safe and reliable operation. Engineers can identify and evaluate potential failure modes and determine their impact on system performance by conducting reliability assessments. This information can then be used to make design improvements or implement mitigation strategies, reducing the risk of system failure and ensuring public safety.

2.2.2 Reliability Assessment Methods for PSSs

The reliability of PSS in NNP is crucial for ensuring safe and efficient operation in emergency scenarios. Reliability assessment of PSSs involves evaluating key factors such as operating conditions, physics of phenomena, and the reliability of single components. This assessment is vital for established and novel designs to guarantee performance in real-world scenarios.

In reviewing the methods commonly used for conducting reliability assessments of passive safety systems for NPPs, five stand out: Reliability Evaluation of Passive Systems (REPAS), Reliability Methods for Passive Safety Functions (RMPS), and Assessment of Passive System Reliability (APSR), Probabilistic Safety Assessment (PSA) and Failure Mode and Effects Analysis (FMEA). The choice of a reliability assessment method for PSSs depends on the evaluation's objectives and specific requirements. Each method has its unique emphasis and advantages, making it essential to consider its suitability for the desired assessment outcomes. Hence, a comprehensive understanding of the available methods and their strengths is crucial for determining the most appropriate method.

The Reliability Evaluation of Passive Systems method is utilized to assess the reliability of PSSs. This method boasts several advantages, including a systematic approach, provision of quantitative results, consideration of both design and operational factors, integration with other reliability assessment methods, and user-friendliness. The Reliability Evaluation of Passive Systems method adopts a systematic approach in its evaluation, ensuring the accuracy and completeness of the assessment process. The method provides quantitative results, allowing for a detailed analysis of PSS reliability and its components. Furthermore, REPAS can be integrated with other methods, such as fault tree analysis, to provide a more comprehensive reliability assessment. The user-friendly nature of REPAS, with its clear guidelines and procedures, makes it a valuable tool for evaluating the reliability of PSSs. Jafari et al., in their publication [26], have investigated the reliability of Nuclear Cooling (NC) systems. The proposed methodology for the study was the REPAS approach, which aimed to optimize the information for a single-phase NC loop and to manage the propagation of uncertainty through the Thermal-Hydraulic-Reliability (TH-R) model. The result of the study indicated that the proposed TH-R approach was more reliable than other TH-R approaches, such as that proposed by Bianchi et al. [27], when comparing the single-phase NC system to a two-phase system. The numerical values obtained from the study could be employed in more complex safety assessment studies, such as PSA studies, to optimize passive systems.

The Reliability Methods for Passive Safety Functions (RMPS) is a widely recognized technique utilized to evaluate the reliability of PSSs. The Reliability Method for Passive Safety Functions method aims to assess the dependability of passive safety functions, which are crucial in ensuring the system's secure operation. This method examines the reliability of components that make up the PSS, including design, materials, manufacturing processes, and operational conditions. The Reliability methods for passive safety functions approach considers numerous factors, such as failure probabilities, system redundancy, and performance, to establish the overall reliability of the PSS. The outcomes of the RMPS assessment can be employed to identify potential areas for improvement, optimize the design and operation of passive safety systems, and augment the overall safety of SMRs. Marquès et al. [28] proposed the RMPS method, which aims to evaluate the reliability and sensitivity analyses of passive systems, specifically the Residual Passive Heat Removal system on the Primary circuit (RP2), during a Total Loss of Power Supplies (TLPS) accident scenario. This method has been successfully applied to several passive systems, including the In-Containment Refueling Water Storage Tanks (IRWSTs) of Boiling Water Reactors (BWRs) and the Hydro-Accumulators of the Pressurized Water Reactors (PWRs) [29]. The passive system is modelled using the CATHARE code. The numerical results are fed into the PSA to define TLPS as an initiating event for the event tree analysis in estimating the frequency of occurrence and the accident sequences leading to core damage. The proposed technique addresses the issues of identifying uncertainty contributors, the uncertainty of Thermal-Hydraulic (T-H) models, and incorporating the unreliability of the passive system into the accident sequence analysis.

Assessment of Passive System Reliability (APSR) aims to identify the potential failure modes and causes and assess the reliability of PSSs. The results of the APSR assessment can provide valuable insights for improvement, optimization of the design and operation of passive safety systems, and enhancement of the system's overall safety. Nayak et al. [30] conducted a study evaluating the reliability of PSSs using the APSRA method. The study focused on the boiling natural circulation system in the central heat transport system of the Indian Advanced Heavy Water Reactor (AHWR) concept. The authors developed a failure surface by considering the deviation of all critical elements that affect the system's efficiency. Root cause analysis was then performed to determine the sources of deviation, which were linked to mechanical component failures such as pumps and valves. Finally, traditional PSA was applied to calculate the probability of component failure.

The distinction between the Reliability Methods for Passive Safety Functions (RMPS), the Reliability Evaluation of Passive Systems (REPAS), and the APSR methodologies are rooted in their respective principles and techniques for the reliability assessment of PSSs.

The selection of an appropriate method would depend on the particular objectives and demands of the reliability assessment and the unique characteristics of the PSS under examination.

The Reliability Methods for Passive Safety Functions approach was employed to provide a quantifiable method for evaluating the reliability of Category B passive systems. The primary objective of RMPS was to establish a mechanism for quantifying the reliability of thermal-hydraulic passive systems. The study using RMPS evaluated three passive safety systems: the Injection Cooling System (ICS), the Pressure Relief System (PR), and the Hydro-Accumulator of a VVER.

In the RMPS study, there was a need for a transparent agreement on integrating the reliability of PSSs with the PSA; however, some contributors only provided theoretical ideas. The reliability Methods for Passive Safety Functions method does not explicitly incorporate active components and only analyzes the reliability of passive systems based on mechanical component failures. In a realistic PSA, the interaction between passive and active components must be considered, as a failure of an active system may fail the passive system. Figure 2.2 presents a simple fault tree to demonstrate how both types of failures may contribute to the breakdown of the complete passive system [31].

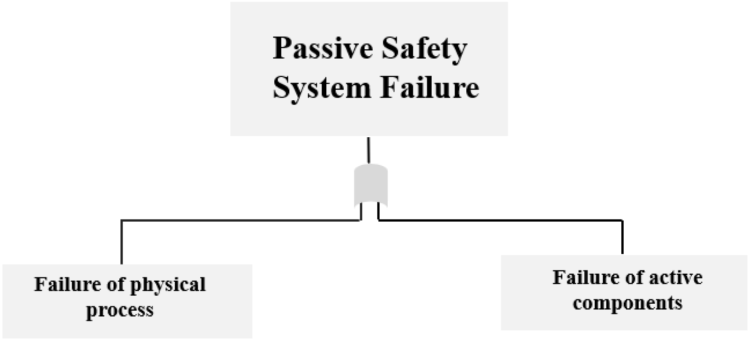

Figure 2.2: Combination of active components failure and physical process failure to describe passive system failure

Probabilistic safety assessment is a comprehensive and systematic approach that can be utilized in conjunction with REPAS, Reliability, RMPS, and APSR methods for evaluating the reliability of PSSs. This quantitative method employs probabilistic models to assess different events' probabilities and consequences. The results from REPAS, RMPS, and APSR can be utilized to inform the PSA model, and conversely, the outcomes from the PSA can be used to refine the other three methodologies.

2.3 Probabilistic Safety Assessment

Probabilistic safety assessment is a well-established methodology for evaluating the safety of complex technological systems, including NPPs. The primary objective of PSA is to provide a quantifiable evaluation of the likelihood and consequences of potential accidents to support informed decision-making during the design and operation of these systems.

Using PSA in the context of PSS allows for a comprehensive evaluation of the safety performance, provides valuable insights into the safety margins and vulnerabilities, considers a range of potential scenarios and uncertainties and can help identify potential areas for improvement. The results of a PSA can be used to inform the development of design and operating criteria and support risk-informed decision-making and regulatory oversight.

Before the 1975 Reactor Safety Study (WASH-1400) publication, licensing nuclear power reactors relied solely on deterministic methodologies. These methodologies were limited by insufficient plant modelling and uncertainties from conservative design and operation practices; Probabilistic safety assessment provides a more comprehensive assessment of the safety of a system by considering both deterministic and probabilistic approaches. WASH-1400 introduced PSA to the US nuclear power sector, presenting a comprehensive risk analysis of a Pressurized Water Reactor (PWR) and a Boiling Water Reactor (BWR) [32]. The integration of PSSs into PSA offers a systematic approach to evaluating the safety and reliability of nuclear power plants.

Integrating PSSs into PSA is crucial for evaluating the safety and reliability of SMRs, where utilizing PSSs provides safe operation and meets high safety standards. Here is a summary of some research on PSA for passive safety systems in Table 2.3:

Table 2.3: PSA implementation for PSSs

References	**Proposed approaches**
Johnson, T. A. and et al. [2015]	The authors performed a probabilistic safety assessment on SMRs to evaluate their safety margins and the reliability of their PSSs.
Zhang, Y. and et al. [2019]	This work carried out a safety assessment of PSSs in SMRs to understand their behaviour in case of a design-basis accident or a beyond-design basis accident.
Kim, Y. W. and et al. [2020]	The authors conducted a probabilistic safety assessment of the PSSs in SMRs to identify the potential failure modes and evaluate the performance of these systems under different scenarios.
Kim, J. and et al. [2017]	Integrated various safety analyses and carried out a probabilistic safety assessment of the PSSs in SMRs to assess the overall safety margins of these systems.
Ma, X. and et al. [2016]	Performed a probabilistic safety analysis on PSSs in SMRs to understand the potential risk levels and the uncertainties associated with these systems.
Lee, H. and et al. [2018]	The authors conducted a probabilistic safety assessment of the passive cooling systems in SMRs to evaluate the reliability and the performance of these systems under different scenarios.
Chen, L. and et al. [2020]	Performed a probabilistic safety assessment of the passive residual heat removal systems in SMRs to evaluate their performance and to identify the potential failure modes.

The main components of PSA are the FT and ET, which analyze the progression of events leading to potential accidents in a system. Fault trees are graphical representations of the logical relationships between the failures of system components that can lead to an undesired event. However, ETs represent the progression of events following the initiation of an undesired event by illustrating the different paths the event can take and the consequences of each path. Both FTs and ETs play an essential role in PSA by providing a structured and systematic approach to analyze the events leading to an accident and to evaluate the overall risk associated with the system. Integrating FT and event tree analysis into the PSA process makes it possible to produce a comprehensive and systematic risk evaluation that supports effective risk management and decision-making.

Fault Tree Analysis (FTA)

Fault trees are diagrams that depict the combinations of faults that may result in a system failure, as shown in Fig. 2.3. They are constructed in a logical, deductive, and top-down manner and are used to identify the causes of a system's failure and develop strategies to mitigate it. The diagrams are created using Boolean operators[3], such as AND and OR gates, to represent the relationships between system faults and the events that cause the failure.

Table 2.4: "OR" and "AND" gates probabilities equations

Gate	Inputs	**Probability**
OR	2	$P(A) + P(B) - P(A)P(B)$
OR	3	$(P(A) + P(B) + P(C)) - (P(AB) + P(AC) + P(BC) + P(ABC))$
OR	4	$(P(A)+P(B)+P(C)+P(D))-(P(AB)+P(AC)+P(AD)+P(BC)+P(BD)+P(CD))+$ $(P(ABC)+P(ABD)+P(BCD)+P(ACD)+P(ABCD))$
AND	2	$P(A)P(B)$
AND	3	$P(A)P(B)P(C)$

The critical component of an FT is the Top Event (TE), which represents an unfavourable outcome, such as an Incomplete System Failure, depicted in Fig. 2.3. The top event results from a combination of BEs identified as contributing causes. OR and AND logic gates are utilized to establish a logical relationship between the TE and its BEs. The probability of failure $Pr_C(t)$ is calculated as follows:

$$\text{Failure probability} = \text{Failure Rate} \times \text{Demand} \tag{2.2}$$

$$Pr_C(t) = 1 - \exp^{-\lambda t} \tag{2.3}$$

In the expression, λ and t represent the failure rate and mission time, respectively. The Fault Tree (FT) logic gates, AND and OR, are fundamental components of Boolean logic.

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[3] AND gate, the output event occurs if all input events occur.

[3] OR gate, the output event occurs if at least one of the input events occurs.

An AND gate produces an output if all inputs occur, and an OR gate produces an output if at least one of its inputs occurs (Equations 2.4 and 2.5 show the equations for AND and OR, respectively [40]). The equations for the logic gates are based on the contents of Table 2.4; the probabilities of intermediate events and the TE are estimated by considering the Table's contents [41].

$$P = \prod_{i=1}^{m} P_i \tag{2.4}$$

$$P = \prod_{i=1}^{m} (1 - P_i) \tag{2.5}$$

The failure of the Isolation Condenser System (ICS), as shown in Fig. 2.3, is recognized as a critical factor that contributes to the failure of other components and systems. For example, a combination of natural circulation failure, ICS failure, and pipe rupture is a significant cause of ICS failure. Qualitative analysis is paramount in determining the root cause of ICS failure, such as failure of the Heat Exchangers (HXs) and condensation valves. Furthermore, multiple pipe ruptures and plugging can also lead to HX failure. This interplay of system and component failures ultimately fails the ICS [42].

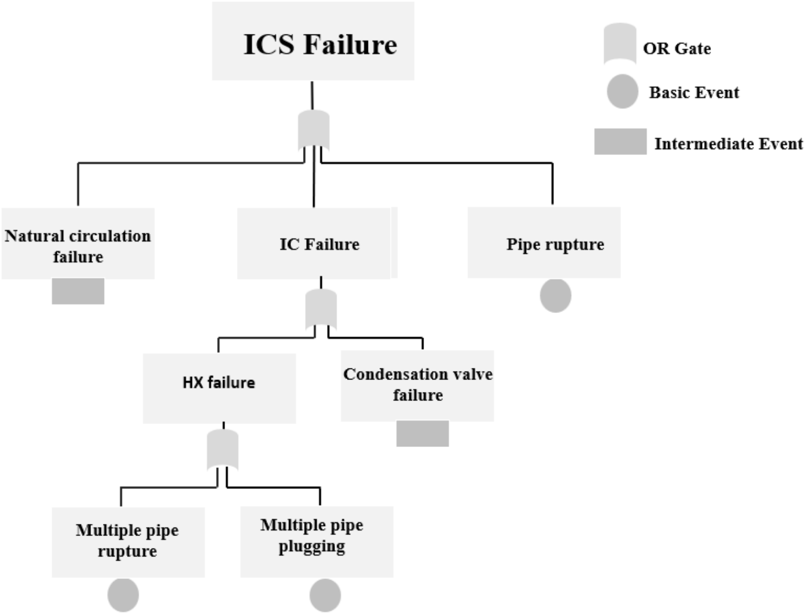

Figure 2.3: Fault tree for ICS failure

Event Tree Analysis (ETA)

Event tree is a diagram that illustrates the progression of events, beginning with an initiating event, which is an unfavourable state that endangers the efficient operation of the facility and culminates in a final stage. The event tree diagram is constructed using inductive reasoning and presented in a left-to-right format, depicting the event sequence's qualitative and time-dependent mitigation function.

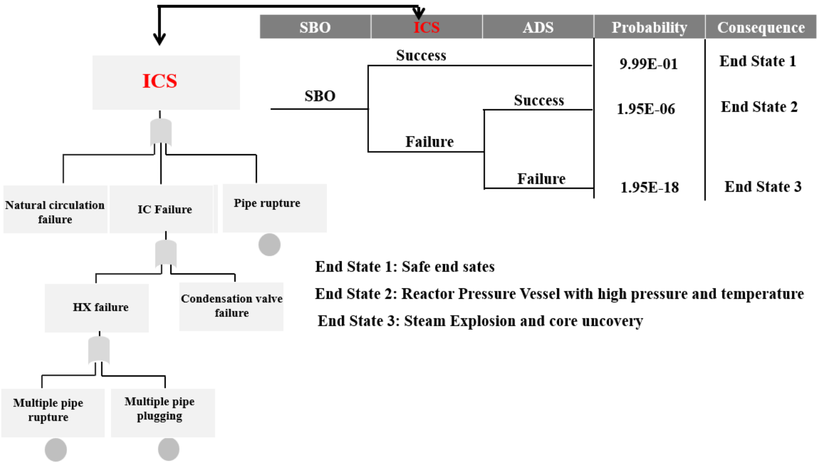

Figure 2.4: Fault tree and related event tree for ICS failure

The event tree for the ICS is constructed to demonstrate the sequences of potential accidents and their probabilities, as assessed through FTA. Suppose a Station Blackout (SBO), the ICS and the Automatic Depressurization System (ADS) are considered mitigating systems. The event tree of the ICS is initiated with the SBO event, and the failure of both the ICS and the ADS is treated as distinct events. As shown in Figure 2.4, the event tree displays various alternative scenarios and their associated probabilities [42].

The outcomes of PSA (by conducting the FT and ET) reflect its various levels (three levels); These levels provide increasing detail and accuracy in assessing risk, from a broad overview to a detailed and comprehensive analysis. The choice of level depends on the specific objectives and requirements of the PSA study.

1. **Core damage frequency (Level 1):** Figure 2.5 illustrates that Level 1 of PSA covers the stage referred to as “Accident Frequency Analysis”; This stage evaluates the various plant conditions that could lead to core damage.

2. **Release frequencies (Level 2):** Level 2 of a PSA encompasses two parts: “Accident Progression Analysis” and “Source Term Analysis”; The former predicts the timing and mechanism of containment failure, while the latter evaluates the magnitude of a radioactive release in various transients, as per Fig. 2.5.

3. **Radiological consequences (Level 3):** Level 3 analysis, as depicted in Figure 2.5, encompasses the “Consequences Analysis” section. Its objective is to evaluate the off-site effects resulting from the outcomes of Level 2.

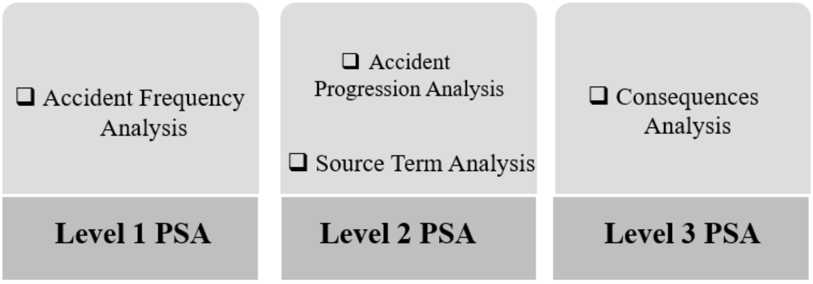

Figure 2.5: 3-Level PSA

The outcomes of these levels provide increasing detail and accuracy in assessing risk, from a broad overview to a detailed and comprehensive analysis.

The standard methodology for PSA, as delineated in NUREG-1150[4], has several inherent limitations that may result in an unreliable evaluation of risk in complex, dynamic systems [43, 32].

1. Traditional PSA is static and cannot model dynamic risk assessment;
2. The standard PSA does not encompass the evaluation of partial component failures. The conventional approach assumes that partially functioning equipment is entirely defective. Furthermore, it does not account for sequence-dependent functioning, in which the failure of certain components may occur prior to others (e.g. valve 1 fails before valve 2). Implementing redundancy and diversity measures for enhancing safety results in varying failure rates for different components, which is a crucial consideration for dynamic risk analysis.
3. Ignoring system interactions and interdependencies since all BEs are seen as independent;
4. The knowledge and judgment of experts may be insufficient or flawed. In such cases, the fuzzy logic approach proposed using expert judgment as a basis for aggregating subjective quantitative data from experts to produce absolute quantitative data, thus facilitating consensus among all basic events. [44, 45, 46].
5. The evaluation of a sophisticated system through conventional PSA presents a significant challenge due to the multitude of basic events, intermediate events, logic gates, and failure paths involved.

Various approaches have been proposed to address classical PSA limitations, including using advanced modelling and simulation techniques, incorporating new data sources, and integrating multiple analysis methods to evaluate risk comprehensively.

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[4] NUREG-1150 is a report produced by the U.S. Nuclear Regulatory Commission (NRC) that provides guidance and standards for conducting PSA studies in the nuclear power industry

2.4 Failure Mode and Effects Analysis (FMEA)

Failure Mode and Effects Analysis (FMEA) is a bottom-up methodology performed at the system level. This technique evaluates each failure mode to identify the causes and strategies for mitigating the impact and to prioritize the consequences of potential accident scenarios. By identifying potential operational issues and minimizing the likelihood of cascading failures, FMEA can lead to cost and time savings, primarily when implemented during the preliminary and conceptual design phases. However, conducting a comprehensive FMEA requires significant time, resources, and budget. To ensure that the FMEA is accurate, it is essential to have a precisely outlined process and criteria. Specifying standards can provide an appropriate approach and structure but only guarantee an adequate FMEA. Various reference standards and guidance documents are available (most common [47, 48, 49]) and guidance documents, for instance, IMCA M166, Guidelines for FMEA applied to a specific system and IMCA M178, FMEA management that can assist with conducting a satisfactory FMEA [50].

Whenever an FMEA is required for a design, it serves as a verifying report to ensure that the design under evaluation satisfies the established standards and design principles. For example, a fundamental design concept for categorization is that a single failure must not result in an unfavourable outcome or a dangerous scenario with potential personal, component, or environmental harm. Avoidable outcomes encompass the loss of system functionality (or degradation) or loss of control beyond an acceptable level. To mitigate these risks, specific design modifications can be made, such as implementing redundancy and diversity concepts, safe and controlled shutdown procedures, and minimizing the probability of failure through risk management strategies [51].

Human error and component failure are two scenarios that can lead to NPP accidents. To minimize system vulnerabilities, risk assessment and evaluation methods using either top-down or bottom-up techniques can be used to evaluate the Structures, Systems, and Components (SSCs) and the influence of human factors.

Several hazard evaluation methods have been proposed to design out vulnerabilities, reduce the likelihood of failure, and increase the ability to detect and address issues before they cause adverse effects. For instance, the FMEA described by [52] compares the components of Large Advanced Pressurized Water Reactors (mPower, Nuscale design), such as Steam Generators, Control Rod Drives, Reactor Internals, and Vessel Components, to identify the importance of FMEA in enhancing the ability of the industry to assess and prioritize any degradation that may occur. [53] combined FMEA with fuzzy logic methodologies to address the challenges posed by the absence of operating experience (OPEX) data and the availability of dependability data for the High-Temperature Gas Reactor (HTGR). [54] used FMEA to perform safety assessments for the helium-cooled solid breeder (HCSB), conducting a comprehensive examination of the various factors that could trigger unit failures or interrupt operations. [55] integrated FMEA as an informational resource into the MFM-SC approach to increase the efficiency of operation analysis under uncertainties for the PSSs of SMRs, thus generating essential data for decision-making.

[56] proposed a PSA for nuclear-powered icebreaker operations in ice-covered waters by using FMEA as a qualitative hazard identification method and feeding the results into a functional resonance analysis method (FRAM) to obtain critical accident scenarios. [57]

implemented a new FMEA-based Gradual Screening Approach for the Electrical failure (unplanned outages) in the High-Temperature Engineering Test Reactor (HTTR). The objective was to determine the frequency of system failures and the most critical failure modes. [58] developed GO-FLOW assessment methods to evaluate the reliability of the AP1000 passive core cooling system (PXS) and passive containment cooling system (PCCS), using FMEA to identify possible failure modes and characteristics deemed crucial for the functioning of the PSSs. [59] combined FMEA with Fault Tree Analysis (FTA) methods to evaluate the LOCA in the Brazilian TRIGA IPR-R1 reactor. The FMEA framework was used to identify failure modes and prioritize risk management based on the Risk Priority Number (RPN). In contrast, FTA was used to develop the logical connections between failure modes and identify the minimum cut sets. FMEA is an effective strategy for identifying, evaluating, and managing risks in nuclear power plants. However, the input variables in this method are defined based on experts' judgment, which can be challenging in the presence of uncertainties due to a lack of OPEX data and information.

The outcome of an FMEA is the Risk Priority Number (RPN). The risk priority number is a numerical value calculated based on the information provided regarding the Severity (S) of the effect, the Occurrence (O) probability, and the Detectability (D) of the failure modes. Severity reflects the potential for damage in a given scenario, Occurrence represents the probability of failure, and Detectability illustrates the extent to which the failure can be detected [60]. By multiplying these three factors (S, O, and D), as specified in Eq. 2.6, it becomes evident that a higher RPN score indicates a failure mode with high risk

$$\text{RPN} = \textbf{Severity}\,(S) \times \textbf{Occurrence}\,(O) \times \textbf{Detectability}\,(D) \tag{2.6}$$

Gargama et al. [2011] outlined various disadvantages of the conventional FMEA, which for practical purposes, make evaluating S, O and D complicated, as follows:

1. The risk priority number is generated from various combinations of risk variables, as shown in Eq. 2.6; however, it should be noted that while the RPN number may be the same, the associated risk consequences can vary greatly.

2. The risk priority number parameters (S, O, D) are often assumed to have equal weight, leading to an invalid risk analysis [62]. A technique for combining FMEA with FTA was developed by Shafiee et al. [2019] for the risk assessment of the Blowout Preventer (BOP) system. This approach assigns weights to RPN numbers determined using FTA, which are then used to modify RPNs obtained through traditional FMEA methods.

3. The risk priority number primarily focuses on only three safety-related factors. Other factors, such as economic considerations, should be taken into account. In [63], a comprehensive FMEA is proposed that utilizes fuzzy logic to consider additional RPN variables. The methodology includes a pre-assessment using fuzzy logic systems to analyze incoming factors affecting the severity, occurrence, and detectability variables. Instead of a single severity rating, the consequences on assets, people, the environment, and reputation are considered. Additionally, detectability comprises three components: process management, manual or automated judgments, and data-driven decision-making.

4. The mathematical method used to determine the RPN has been criticized for lacking a solid scientific foundation.

One limitation of the traditional FMEA method is the lack of consideration for each independent variable's relative significance, and the scale's qualitative importance, as noted in [64]. The computation of RPN in FMEA assumes a linear interaction between the parameters (Severity, Occurrence, and Detectability), meaning these factors are calculated using the same scale without considering their relative significance. This approach needs to consider the relative importance of each independent variable, resulting in a lack of nuanced analysis. For example, a high severity score indicates a high risk due to the severe consequences to operators or equipment. However, if there is a threat to human life, the other variables should not be allowed to lower the overall RPN value. To address these limitations and improve the accuracy of risk assessment, there is a need for a more comprehensive analysis that considers the relative significance of each independent variable.

2.5 Conclusion of Chapter 2

The reliability of passive safety systems in SMRs is essential for a safe operation of the plant, and reliability evaluation of PSSs is a complex process that involves several factors. Firstly, SMRs are smaller and have lower power levels, meaning they have less redundancy. This challenges traditional safety analysis and makes it even more critical to have reliable passive safety systems and accurate assessments. Secondly, using new technologies in SMRs can make it challenging to understand their behaviour and performance during routine operations and emergency situations, affecting the accuracy of reliability assessments. Thirdly, the modular design of SMRs means that different modules with different reliability characteristics must be integrated, making it challenging to predict overall system reliability. Fourthly, external factors such as natural disasters, human error, and cyber-attacks must also be considered when evaluating the reliability of passive safety systems in SMRs.

Given these challenges, there is a need for further research and development in the field of reliability and safety assessment for PSSs in SMRs. This can involve advanced techniques like ANN and fuzzy logic to support decision-making by providing more accurate and comprehensive risk assessments. In conclusion, incorporating innovative techniques is needed to address the limitations of classical PSA, and a more integrated and comprehensive approach to risk assessment is needed. This will be discussed in the next chapter.

Chapter 3

Literature Survey on Fuzzy Logic and Artificial Neural Network in Safety Assessment

Reliability analysis is crucial to the safety systems' design and development process. It identifies potential threats and assesses the system's ability to perform its intended function confidently, thereby protecting people and the environment during normal and abnormal operations. Classical methods such as PSA and FMEA have traditionally been used for the reliability analysis of safety systems. However, these methods have several limitations, as highlighted in literature [65, 66]. One limitation is their dependence on expert knowledge and assumptions about the system, which may only sometimes be accurate or comprehensive, particularly in cases where consensus among multiple experts is difficult or in the investigation of innovative systems. This can lead to oversimplification and incorrect results, especially in complex systems with hundreds of subsystems. Probabilistic safety assessment and FMEA also do not effectively incorporate uncertainty into reliability analysis, leading to a limited understanding of the system's behaviour under different conditions, resulting in a lack of confidence in the results and limiting their utility in the design and development process. Additionally, PSA and FMEA are primarily static methods, making it challenging to model the system dynamic and predict its behaviour over time. Furthermore, they can be time- and resource-intensive, requiring significant data collection, modelling, and analysis, making them impractical in fast-paced or resource-constrained environments.

The following sections examine ANNs and fuzzy logic as alternative techniques to address the limitations mentioned by conventional methods (PSA and FMEA) in the reliability analysis of passive safety systems. The objective is to investigate the potential benefits of these novel methods in incorporating uncertainty into the analysis, modelling the behaviour of dynamic systems, and enhancing efficiency in terms of time and resources. A comprehensive review of the existing literature and practical applications is performed to demonstrate the improvement in accuracy and confidence that can be achieved through the implementation of ANNs and fuzzy logic in reliability analysis, thereby contributing to the advancement of the design and development of safety systems.

3.1 Fuzzy Logic

Fuzzy logic is an annex of Boolean Logic and first appeared in 1965 with the publication of a work titled "Fuzzy sets" by Berkeley professor Lotfi A. Zadeh. Fuzzy logic is a mathematical approach that deals with uncertainty and imprecision. It represents and manipulates vague, ambiguous, or uncertain information that cannot be easily expressed in numerical terms. Fuzzy logic is a mathematical framework for modelling complex, uncertain systems that operate on degrees of membership rather than binary truth values. It offers advantages in the reliability analysis of safety systems by incorporating uncertainty, modelling dynamic behaviour, and being more time and resource-efficient. Resulting in enhanced accuracy and confidence in reliability analysis [67]. Probability distributions are the most popular method for expressing uncertainty about numerical values, whether epistemic or aleatory. In Interval analysis based on fuzzy representation, the variable's uncertainty is specified as an interval integer. The interval should indicate the uncertain parameters' maximum, minimum, and best estimates. The suggested method can predict probable ranges on model outcomes by employing boundaries (intervals) to express uncertainty about model inputs and variables [68]. Almost every real-world situation has an element of uncertainty either in inputs, process, or output data. In essence, measurement is inseparable from uncertainty and comes from integrating the instrument's measurement limitations and unavoidable measurement errors [69]. There are two basic categories of uncertainty to distinguish:

1. **Aleatory uncertainty** [1]**;** Is attributed to the real, stochastic nature of some physically quantifiable parameter, such as temperature fluctuations, component failure changing during the test, and failure and repair times of components [70, 71].
2. **Epistemic uncertainty** [2]**;** Is a lack of clarity, natural stochasticity or accuracy in an assessment or quality statement. This feature necessitates PSA analysts to assign probability distributions using Expert Judgment (EJ) as their primary source of information [70].

Therefore, uncertainty is a major concern that can significantly impact the accuracy of the results. Fuzzy logic addresses uncertainty in the risk analysis process by representing uncertainty through fuzzy set theory.

3.1.1 Fuzzy Sets and Operations

The standard set identifies with a crisp boundary, meaning that a member either belongs or does not belong to the set. The transition from a member in the universe of discourse to a specific set in classical sets is fast-changing and crystal clear. In contrast, this change might be continuous in fuzzy sets without crisp boundaries. This transition amongst degrees of membership might be interpreted as complying that the boundaries of the fuzzy sets are vague and ambiguous [72]. The definition of fuzzy sets based on partial membership is that

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[1] "Aleatory uncertainty also known as Randomness, variability, stochastic uncertainty, objective uncertainty, dissonance, or irreducible uncertainty"

[2] "Epistemic uncertainty also known as Incertitude, ignorance, subjective uncertainty, non-specificity, or reducible uncertainty"

each element belongs partially or gradually to the specified fuzzy sets. The boundaries of each fuzzy set (Fig. 3.1) are not "sharp" but rather gradual; therefore, in contrast to a conventional set, fuzzy sets permit elements to have a soft edge. According to Fig. 3.1, x belongs neither to set A nor set B, y belongs totally to set A, z totally belongs to set B, but t partly belongs to set B.

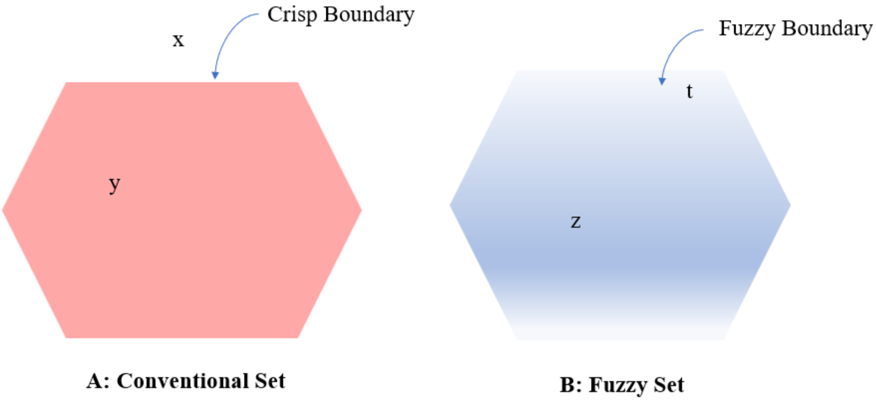


Figure 3.1: Comparison of Conventional Set A and Fuzzy Set B, showing the sharp boundaries of Set A and the gradual boundaries of Set B.

The degree of belonging of an element to a set (A, B) is used to represent the uncertainty and vagueness in real-world systems. This degree of belonging is determined by the Membership Function (MF), which maps the elements of a universe of discourse to a degree of membership within a fuzzy set.

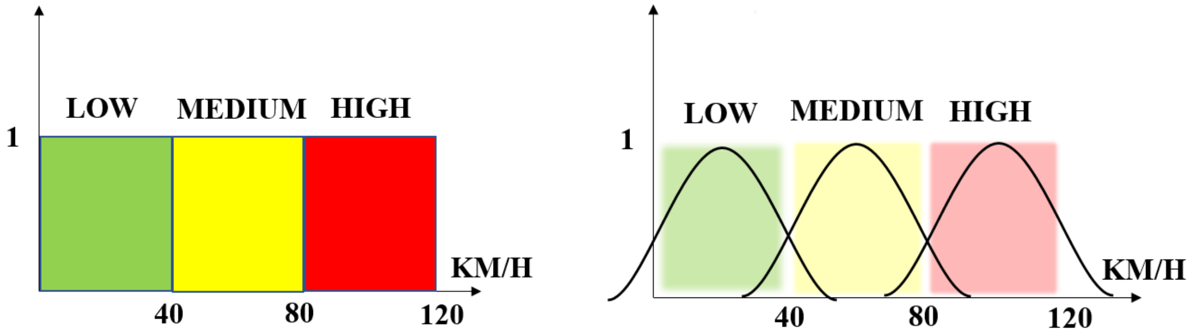
Membership Function

In fuzzy logic, a membership function is used to quantify an element's membership degree in a fuzzy set. This function assigns a value between 0 and 1 to each element in the set, where 0 indicates that the element is not a member of the set, and 1 indicates that the element is a fully-fledged member. The membership function outlines the limits of the fuzzy set and establishes the element's membership level in the set. A fuzzy set allows elements to have partial membership, with values ranging between 0 and 1. For example, consider a fuzzy set A in the universe X, represented by a membership function $\mu_{A(x)}$:

$$\mu_A(x) : X \to [0, 1] \tag{3.1}$$

Where $\mu_A(x)$ accounts for the membership degree of x in a set A. Therefore, each fuzzy set has a unique MF graphically representing its fuzzy boundary and characteristics.

Denition 1.
Let X be a set. A membership function characterizes a fuzzy subset A of X. f^a: X $\to$ *[0; 1]. (In theory, it is possible that the output is greater than 1, but in practice, it is rarely used.)*
Note: This membership function is equivalent to the identity function of a classical set.



(a) Classical Set **(b)** Fuzzy Set

Figure 3.2: Comparison of classical and Fuzzy Sets; the boundary of the classical set (3.2a) is sharp and clearly defines the speed boundaries, while the boundary of speed in the fuzzy set (3.2b) is smooth and gradual.

According to Fig. 3.2, classical set 3.2a has a crisp and sharp boundary compared with a smooth one in fuzzy set 3.2b. In other words, a fuzzy set utilizes MF's degree to allow a member to partially belong to a set in the context of fuzzy logic. For instance, the vehicle speed ranges are shown in Fig. 3.2. For the classical set, illustrated in Fig. 3.2a, the speed is separated into three varieties: LOW ($0 \sim 40\,\mathrm{km/h}$), MEDIUM ($40 \sim 80$ km/h), and HIGH ($80 \sim 120\,\mathrm{km/h}$); from the perspective of the classical set, the speed range is obviously defined, but in the fuzzy set, the border is fuzzy and devoid of any distinct edges, meaning that one speed in the fuzzy concept belongs simultaneously to two or more subsets. For instance, a speed of 50 km/h can be deemed LOW to a specific degree of around 0.5 degrees and MEDIUM to a great extent of around 0.7. Therefore, as the quantity of A(x) increases, so does the membership degree of x in A.

Different MF shapes are used to model different system characteristics being analyzed, such as uncertainty, imprecision, or non-linearity. Some of the commonly used shapes of MF (Fig. 3.3) based on application and purpose are Triangular, Trapezoidal, Piecewise linear, Gaussian, and Singleton.

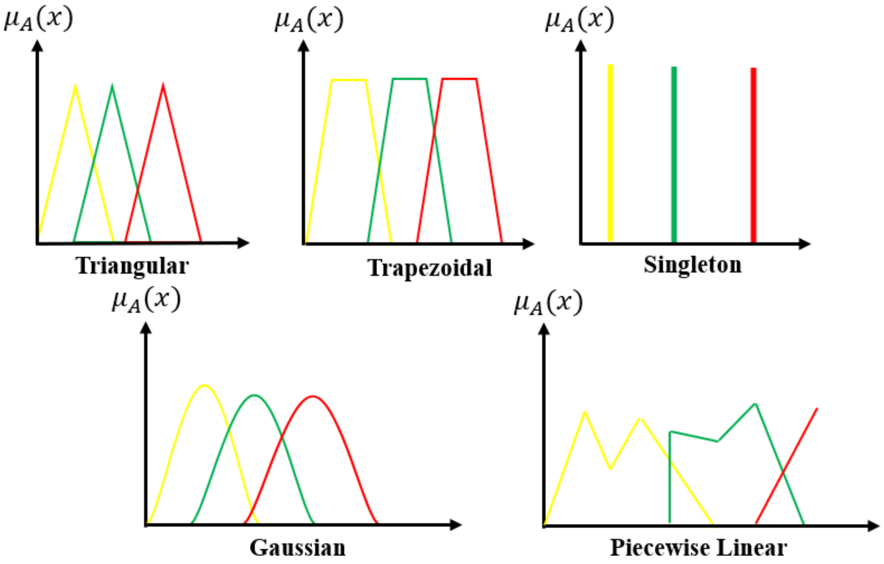


Figure 3.3: Various shapes of MF are employed in modelling different system characteristics. Some MF shapes, including Triangular, Trapezoidal, Piecewise linear, Gaussian, and Singleton, are frequently used in various applications and purposes.

Following Fig. 3.3, several fuzzy MFs are defined, each with a unique identifier and set of attributes. Triangular Fuzzy Number (TFN) and Trapezoidal Fuzzy Number (TZFN) are two valuable forms of these numbers, particularly for engineering and assessment operations which will introduce in the following sections [73].

Trapezoidal Fuzzy Number

Trapezoidal fuzzy number is a mathematical representation of a fuzzy set that utilizes a trapezoidal MF. This type of fuzzy number is described by Eq. 3.2, and the MF $\mu_{\tilde{A}}(x) : R \rightarrow [0,1]$ maps a real number to a value between 0 and 1, representing the degree of membership of the element in the fuzzy set.

$$\mu_{\tilde{A}}^{TZFN}(x) = \begin{cases} \mu_{\tilde{A}}^{L}(x) \equiv \dfrac{(x-a)}{(b-a)}, & \text{a} \leq x \leq b \\ 1, & \text{b} \leq x \leq c \\ \mu_{\tilde{A}}^{R}(x) \equiv \dfrac{(c-x)}{(c-b)}, & \text{c} \leq x \leq d \\ 0, & \text{otherwise} \end{cases} \tag{3.2}$$

The membership degrees of TZFN are defined by four parameters, denoted as $\tilde{A} = (a, b, c, d)$ as depicted in Fig. 3.4. The lower and upper bounds of the MF are represented by the values of a and d, respectively, while the best estimate value falls within the tolerance interval of b to c. The characteristics of the MF have displayed in Fig. 3.4 for the fuzzy set $\tilde{A}$ as listed in Table 3.1.

Table 3.1: Features of membership functions

Features	**MF range**	**Description**
Core	$\mu_{\tilde{A}}(x) = 1$	An area of the universe that contains the entire membership in the set.
Support	$\mu_{\tilde{A}}(x) > 0$	The portion of the universe whose membership in the set is greater than zero.
Boundary	$1 > \mu_{\tilde{A}}(x) > 0$	The segment of the universe whose membership in the set is nonzero but incomplete.
Alpha-cut ($\alpha - cut$)	$\tilde{A}_\alpha = \{X \mid \mu_{\tilde{A}}(x) \geq 0\}$	It is the collection of all x where $\mu_{\tilde{A}}(x)$ surpasses α.

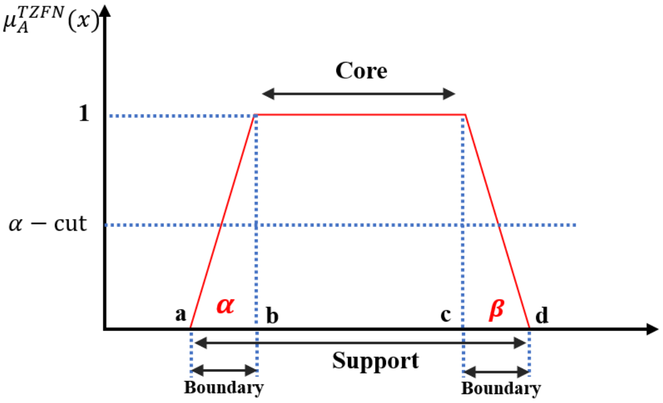


Figure 3.4: Representation of trapezoidal fuzzy number shape, depicts the membership degrees of a TZFN, defined by three parameters, $\tilde{A} = (a, b, c, d)$.

Triangular Fuzzy Number

Trapezoidal fuzzy number ($= [a, b, c, d]$, with $c = b$) can be transformed into a Triangular Fuzzy Number, mathematically represented as $= [a, b, c]$. The triangular fuzzy number is defined by its MF, which is a triangular shape and defines as Eq. 3.3:

$$\mu_{\tilde{A}}^{TFN}(x) = \begin{cases} \dfrac{(x-a)}{(b-a)}, & \text{a} \leq x \leq b \\ \dfrac{(c-x)}{(c-b)}, & \text{b} \leq x \leq c \\ 0, & \text{otherwise} \end{cases} \tag{3.3}$$

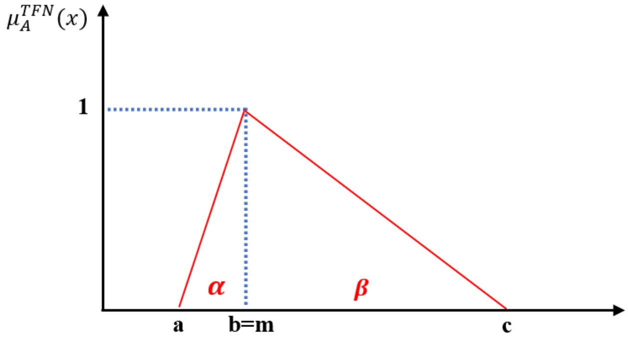


Figure 3.5: Representation of Fuzzy triangular number shape; depicts the membership degrees of a TFN, defined by four parameters, $\tilde{A} = (a, b, c)$.

These two forms of MF can be used in fuzzy set operations such as union, intersection, and complement to create new fuzzy sets and obtain new information. These operations are essential in many applications, such as decision-making, control systems, and pattern recognition. Due to their simple mathematical representations and flexible shapes, the triangular and trapezoidal fuzzy numbers provide a convenient and effective way to represent uncertainty in fuzzy set operations.

Fuzzy set operations apply to linguistic variables, which are variables that take on values described in natural language terms, such as “hot”, “cold”, or “warm”. The uncertainty and imprecision in these natural language terms can be mathematically represented using fuzzy set operations. Triangular and trapezoidal fuzzy numbers are common ways to represent linguistic variables in fuzzy set theory.

Linguistic Variables

According to Zadeh [74], in complex systems, it is natural to utilize linguistic variables, meaning variables whose values are not numbers but words or sentences in a natural or artificial language. The use of linguistic variables, as opposed to numerical ones, is driven by the observation that linguistic characterizations are generally less specific than numerical ones. Linguistic variables are natural language expressions that introduce uncertainty to specific features. For example, if we consider the concept of “speed” as a linguistic variable, then the set $\Gamma(speed)$ should be:

$$\Gamma = \{\text{very slow, reasonably slow, slow, medium, fast, reasonably fast, very fast}\} \tag{3.4}$$

Where there is a fuzzy set for each member of Γ set in a universe of discourse, for instance, $\Theta = [0, 150]$ km/h; in defined Θ set, “fast” is interpreted as a speed exceeding 120 km/h. these terms can be indicated in Fig. 3.6 with certain MF of fuzzy set[1].

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[1] The MFs’ patterns and degrees of overlap are entirely arbitrary.

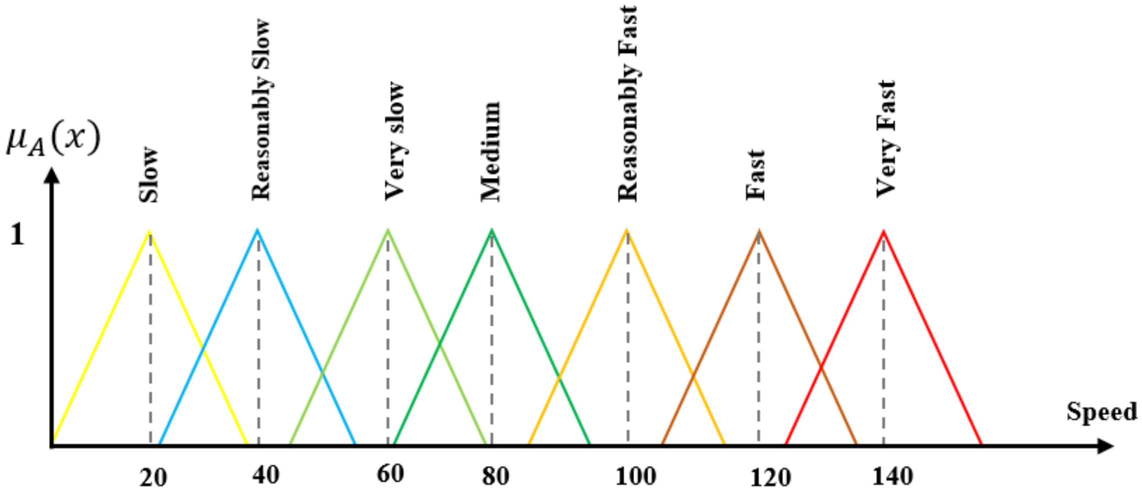

Figure 3.6: The Linguistic variable and its associated MFs are visualized, demonstrating the pattern of the fuzzy set's degree of membership for a given linguistic term.

Standard linguistic variables values, such as "fast", and "medium", are basic definitions that are combined with hedge or quantifier terms, such as "very", "less", and "reasonable" in order to convey a distribution of possibility, rather than a crisp value. Using these linguistic variables and hedge terms allows for a more nuanced representation of uncertainty instead of a purely numerical representation [75].

Fuzzy logic systems are composed of linguistic rules expressed in a natural language format and employed to model relationships between input and output variables. The processing of these rules is accomplished by applying fuzzy inference algorithms, which result in the generation of a fuzzy set. The fuzzy set represents the degree of truth of the proposition being analyzed and can be transformed into a single, precise output value through a process known as defuzzification. The defuzzified output can be utilized for various purposes, including controlling dynamic systems, making decisions based on incomplete information, and facilitating human-like communication in natural language processing applications.

3.1.2 Fuzzy Logic Systems

Fuzzy logic systems are an integral sub-discipline within the field of computational intelligence. As suggested by studies in ANNs, the representation of knowledge concerning intricate or ambiguous processes through the use of natural language expressions is a widely employed technique for conveying human knowledge. This approach uses fuzzy logic to emulate human decision-making processes by incorporating human reasoning into the computational framework [76]. In classical logic, reasoning has the following form:

$$\textbf{Classical logic reasoning} \Longrightarrow \begin{cases} \text{If A then B} \\ \text{If A true then B true} \end{cases}$$

The IF-THEN "rule-based" approach is a standard method used in fuzzy logic systems, comprising a series of linguistic rules that express the relationships between inputs and outputs. However, this approach may not represent more complex object structure and behaviour knowledge. In such cases, more profound forms of knowledge, such as object-oriented knowledge, may be more appropriate for capturing the relationships and information needed to make accurate decisions. This is because object-oriented knowledge considers the underlying structure of the objects being modelled and their behaviour, providing a more comprehensive representation of the modelled system [77].

$$\textbf{IF premise (hypothesis, antecedent)} \rightarrow \textbf{THEN conclusion (consequent)} \tag{3.5}$$

The fuzzy inference system frequently uses this IF-THEN rule (antecedent-consequent linguistic rules), as shown in Expression 3.5, to compute the degree to which the incoming information fulfills the criteria of a rule. Therefore, based on the deductive form of procedure, there is the given fact as a conclusion for the given antecedent 3.5. This antecedent-consequent linguistic rule, first developed by Mamdani (1976) to control the control steam engine and boiler combination, is often referred to as a Mamdani-type rule, and it is acquired by applying the aforementioned prior knowledge to build the frame rule base list as following [78]:

- Scientific principles (physical laws);
- System and controller data;
- Expert knowledge and judgments.

Like classical expert systems, fuzzy logic systems rely on a knowledge base derived from human expertise. However, there are essential differences between the two approaches regarding their features and knowledge-processing capabilities, as summarized in Table 3.2. For example, classical expert systems typically represent knowledge with crisp logic and binary values (true or false). In contrast, fuzzy logic systems use a graded membership representation, where the degree of truth of a proposition is expressed as a value between 0 and 1. Additionally, classical expert systems often use forward chaining to process knowledge, while fuzzy logic systems use fuzzy inference algorithms. These differences in features and knowledge processing capabilities result in fuzzy logic systems better suited for modelling complex, uncertain, and vague systems. In contrast, classical expert systems are better suited for modelling systems with well-defined rules and relationships. In either case, it is essential to carefully consider the strengths and limitations of each approach when selecting the best method for a particular problem.

Table 3.2: Fuzzy rule base and conventional rule base [79]

Classical Set	**Fuzzy set**
Classes of objects with sharp boundaries	Classes of objects with vague boundaries
Boolean processing	Gradual processing
Sequential rules processing	Parallel rules processing
No interpolation, no contradiction	Interpolation between rules

The Mamdani-style fuzzy inference process is a commonly used method in fuzzy logic systems and is composed of three major steps: fuzzification, inference, and defuzzification. These steps are illustrated in Fig. 3.7. In the fuzzification step, crisp input values are transformed into fuzzy set values, representing the degree of truth of the proposition being evaluated. In the inference step, the system uses a set of fuzzy rules to define the degree of truth of the conclusion based on the fuzzy input values. Finally, in the defuzzification step, the fuzzy output is transformed into a single output that can be used to control a system or make a decision. These three steps work together to provide a flexible and robust method for modelling complex and uncertain systems.

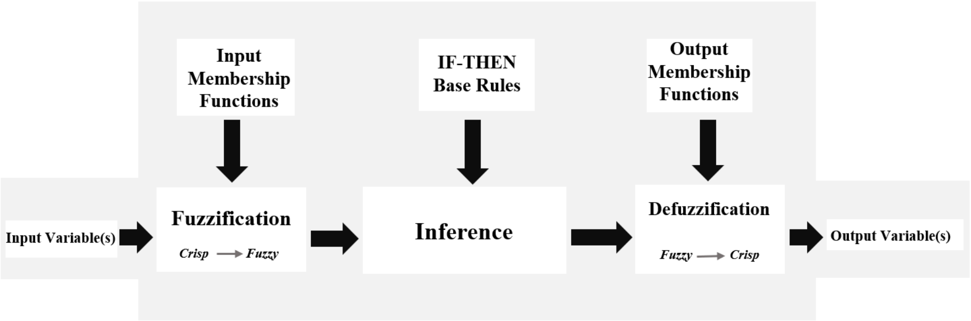

Figure 3.7: Depiction of the three major steps in the Mamdani-style fuzzy inference process - Fuzzification, Inference, and Defuzzification.

The following section will delve into the three critical components of fuzzy logic systems: fuzzification, inference, and defuzzification. These components collectively form the backbone of fuzzy logic systems, and understanding their role and functioning is crucial for a comprehensive understanding of these systems.

Fuzzification

The fuzzification step is an integral part of the fuzzy inference process, as it helps to convert crisp input values into fuzzy variables. Crisp inputs are only sometimes deterministic and often contain significant uncertainty, which could be due to inaccuracy, confusion, or ambiguity. By representing these uncertain values as fuzzy variables, the system can better capture the inherent uncertainty in the inputs using an MF.

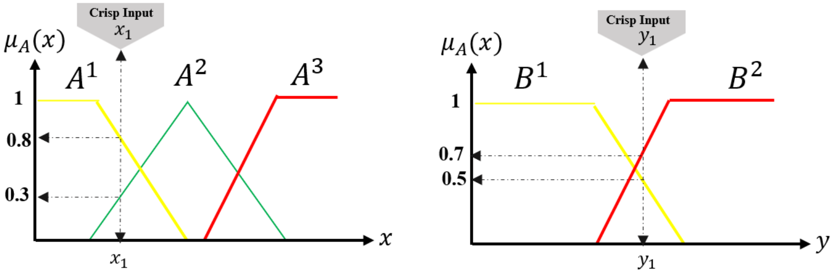

Figure 3.8: Conversion of crisp inputs (x_1 and y_1) to fuzzy variables in the fuzzification step

In the first stage, as shown in Fig. 3.8, x_1 and y_1 are plugged in as crisp inputs, and their belongingness degree to suitable fuzzy sets (A and B)[2] is ascertained. Therefore, for a given x_1 and y_1 as inputs the degree of MFs are,

$$\text{Degree of MFs} = \begin{cases} \mu_{x=A^1} = 0.8; \\ \mu_{x=A^2} = 0.3; \\ \mu_{x=A^3} = 0.0; \\ \mu_{y=B^1} = 0.1; \\ \mu_{y=B^2} = 0.7. \end{cases} \tag{3.6}$$

This flexible and robust representation of uncertain inputs is one of the critical strengths of fuzzy logic systems, as it allows them to handle complex and uncertain systems effectively. By considering the inherent uncertainty in the inputs, fuzzy logic systems can better represent the modelled system and make more informed decisions.

Inference

The inference is reasoning and making conclusions based on data, information, or evidence. In the context of fuzzy logic systems, inference refers to the process of using the knowledge base and rules of the system to make decisions or draw conclusions based on the input data. The inference process in a fuzzy logic system typically consists of several steps, including mapping the input data into a fuzzy set, making logical inferences based on the knowledge base and rules, and aggregating the results of the inferences to form a single output. In the subsequent section on fuzzy FMEA, a more in-depth discussion of the inference process will be provided.

Defuzzification

The fuzzy set output is established as the final inference stage but cannot be utilized to give the operation accurate information or a control command. For instance, a variable cannot be commanded to open partially or entirely; accordingly, the input order must be modified to a specific quantity; hence, defuzzification is required. A defuzzifier generates unambiguous output from a system employing fuzzy logic [80]. A variety of defuzzification techniques were established. Even though the "Center of Gravity" and "Weighted Mean of Maximum" methods are extensively employed, no one approach is optimal for all situations (the best defuzzification techniques are discussed in [81]). The computation of the "center of gravity" of the fuzzy set is the most frequent.

The greyed area in Fig. 3.9 represents the region where the fuzzy numbers $\tilde{A} = (a, b, c, d)$ are defuzzified into a crisp value using the Area Defuzzification Technique (ADT). The ADT is a popular defuzzification method that utilizes the centroid point of the MFs on the vertical axis and its intersection with the left and right MFs. The centroid point of the MFs is calculated as the weighted average of the MFs, with the weights being proportional to the area under the MFs. By taking into account the shape and spread of the MFs, the

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[2] A and B could be any set of hedge or quantifier

ADT provides a more accurate representation of the degree of truth of the proposition being evaluated. The output of the defuzzification step is a crisp value that can be used to control a system or make a decision. This crisp output value is a numerical representation of the degree of truth of the proposition, which can be easily interpreted and used by other systems or processes.

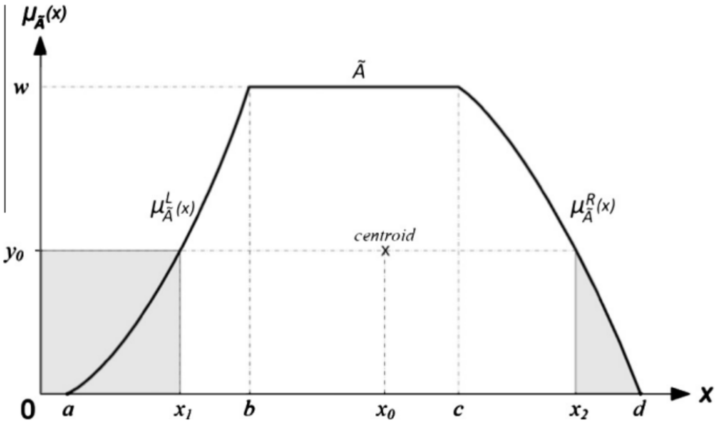

Figure 3.9: Illustration of the area defuzzification technique for determining crisp output from fuzzy number $\tilde{A}$, with intersection projection on the horizontal axis (x_1 and x_2) [44].

$$\text{ADS} = d(\mu_A(x)) = x_1 y_0 + \int_{x_2}^{d} \mu_A^R(x)dx \tag{3.7}$$

Where y_0, represent the central point between 0 and fuzzy number $\tilde{A}$, x_1 and x_2 are projection of intersection y_0 on $\mu_A^L(x)$ and $\mu_A^R(x)$ on horizontal axis, respectively. To estimated the y_0, x_1, and x_2:

$$y_0 = \frac{\int_0^w y \cdot \mu_A^R(y)dy - \int_0^w y \cdot \mu_A^L(y)dy}{\int_0^w \mu_A^R(y)dy - \int_0^w \mu_A^L(y)dy} \tag{3.8}$$

$$x_1 = \mu_A^L(y_0), \text{ and } \qquad x_2 = \mu_A^R(y_0) \tag{3.9}$$

For TFN where $b = c$, $\tilde{A} = (a, b = c, d)$, the ADT is rewrite as:

$$\text{ADT} = \frac{1}{18}(4a + b + d) \tag{3.10}$$

The area defuzzification technique was validated as the optimal method for decoding membership functions into the relevant failure probability, which is then utilized to generate failure likelihoods of BEs in the FT.

Fuzzy logic can be applied in PSA to support the decision-making process. The uncertainty and vagueness inherent in the probabilistic analysis results can be represented and handled effectively by fuzzy logic. The main idea behind integrating fuzzy logic in PSA is to incorporate subjective judgment, dealing with input uncertainty and expert knowledge into the analysis process to enhance the accuracy and robustness of the results. This is achieved through fuzzy sets, MFs, and fuzzy inference systems.

3.2 Fuzzy Probabilistic Safety Assessment (FPSA)

The fuzzy PSA proposed in this thesis is a hybrid approach encompassing fuzzy logic and PSA principles. This methodology provides a framework for evaluating the reliability of complex systems, considering the inherent uncertainty and imprecision associated with the data and parameters used in the analysis. Unlike traditional PSA, fuzzy PSA allows for the modelling and analysis of vague and uncertain information using MFs and fuzzy sets. This approach offers a more comprehensive representation of the system's behaviour, which results in a more realistic evaluation of the system's risk and safety.

The following sections will propose the fuzzy Fault Tree (FFT) and Fuzzy Event Tree (FET) as two computational intelligence techniques for analyzing PSSs in an iPWR reactor. The conventional FTA and ETA methods assume that component failure rates remain constant during quantitative analysis. However, this assumption may only sometimes be valid, particularly in cases with limited knowledge, insufficient statistical data, or vagueness in the performance of components. In such situations, fuzzy logic can provide a promising solution to these challenges. Using an FFT and FET allows for incorporating uncertainty and imprecision in the analysis, providing a more comprehensive evaluation of the system's reliability and safety.

3.2.1 Fuzzy Fault Tree Analysis (FFTA)

Fuzzy fault tree is a computational intelligence technique that is commonly utilized in the field of risk analysis and safety assessment. Fuzzy fault tree has been introduced as a promising alternative to classical FTA to overcome its limitations related to the availability of statistical data and information uncertainty. The main objective of FFT is to provide a more precise evaluation of the failure probabilities and risk assessments of complex systems by incorporating the uncertainty and vagueness of the data into the analysis. In the FFT methodology, the uncertain data is represented by fuzzy numbers and membership functions, which provide a flexible and intuitive way of expressing imprecise information. Several studies have explored the applications of FFT in various domains, including the reliability analysis of electrical power systems [82], the assessment of system safety in chemical processes [83], and the evaluation of fire risk in underground mines [84]. The literature has also highlighted the advantages of FFT, including its ability to incorporate subjective knowledge and to handle uncertainty in system performance [85]. Tanaka et al. [1983] initially employed FFT theory for evaluating the likelihood of the undesirable top event failure. Several authors recently established various FFT approaches for system safety and reliability assessments. Additional scientists have used similar approaches in many technology domains, like NPP and the process industries. Table 3.3 outlines several studies on the risk analysis method employing a combination of fuzzy logic and FT.

Table 3.3: Risk Analyses methods based on fuzzy fault tree

References	**Proposed approaches**
In [87]	Failure probabilities of the Combustion Engineering Reactor Protection System (CERPS) and the ECCS were transformed from discrete values to fuzzy numbers to assess system failure probability with the greatest precision (lower and upper bound).
In [88]	Integrating FFTA with Bayesian networks, a unique technique is provided for obtaining modified probabilities of BEs and the TE of the leak in the submarine pipeline fault tree facing upgraded new failure rates.
In [89]	The work employed an FFTA to acquire statistical data regarding the impact and recognition of human factors in maritime shipping accidents.
In [90]	To compare response time between two reactors, a FIS was implemented to CDF, recovery and sensor time data about accident scenarios in AP-1000 and VVER-1200 nuclear reactors.
In [91]	A FFTA is utilized to conduct a systematic risk analysis on ship mooring operations based on the expert rankings of the BEs. The FFTA is capable of managing of uncertainty to have a better output.
In [92]	Utilizing FFTA, analyze the risk of a leak from Permanently Abandoned oil and natural gas wells in the drilling sector. The study benefited both ethically and practically to marine safety and natural preservation.
In [93]	Integrating expertise judgments and FFTA with temporal analytical gates enables examination of the reliability of a ship's fault-tolerant fuel distribution system with ambiguous failure probability information.
In [94]	Passive decay heat removal system PDHRS (NC) reliability evaluation adopting the integrating RELAP and FFT method to analyze the CFD.
In [44, 45, 95]	A fuzzy reliability of the BEs of FT is based on qualitative information analytics that converts expert opinions and language factors into fuzzy numbers.
In [96]	Combining FFTA and expert judgment to determine the likelihood of equipment breakdown (lack of previous data) owing to natural and technological accidents.
In [97]	Combination of fuzzy FT and ET to determine the chance that danger may arise while building a bridge. Then comparing and confirming the outcome using Monte Carlo simulation
In [98]	Probabilities are substituted for probabilistic examination of basic events, resulting in FFTA. Because systems could be subjected to varying operational situations during the development and evaluation phases, triangular and trapezoidal fuzzy numbers show the failure probability of basic events comparison; this study will assist in selecting the optimal fuzzy number.

In an FTA context, gates represent the logical relationships between a system's different events or components. In a traditional FTA, gates are typically binary and modelled as either AND or OR gates. However, in an FFT, gates can be modelled as fuzzy operators that can handle uncertainty in the event probabilities. Fuzzy operators in FFTs introduced in the following section.

3.2.2 Fuzzy Operators for the Fault Tree Gates

The fuzzy fault tree can provide a more comprehensive and realistic representation of system reliability and risk by using fuzzy operators, where time and occurrence sequence is considered. After acquiring the fuzzy failure probabilities of all the BEs as a fuzzy set, the results characterize the top event failure probabilities. Nonetheless, specifying the fuzzy operators for each FFT gate is essential in the area of dynamic FFT. Notably, all fuzzy operators are defined for exponential failure rate distribution and continuous time domain.

AND gate fuzzy operator

The AND gate is a central FTA component that models the logical relationship between events. It represents the simultaneous occurrence of multiple events that lead to a top event. The output of an AND gate is considered to be true if all of its inputs are true. An AND gate's output probability with N inputs is calculated as the product of the probabilities of each of its N inputs. When the inputs are statistically independent events at time t, the probability of the output is [99]:

$$P\Bigg\{BE_1 \wedge BE_2 \wedge BE_3 \wedge \cdots \wedge BE_{n-1} \wedge BE_n\Bigg\}(t) = \prod_{i=1}^{N} P\{BE_i\}(t) \tag{3.11}$$

Where $P\{BE_i\}(t)$ is BE_i failure probability at time t.

If the MF of the fuzzy number is considered triangular, defined in 3.1.1, we have fuzzy possibility rather than the fuzzy probability for each BE. Therefore, AND fuzzy gate operator is as follows for a triangle illustration of the failure possibilities $P_i(t) = \{a_i(t), b_i(t), c_i(t)\}$:

$$\begin{aligned} P_{AND^{F}[3]}(t) &= AND^F\Bigg\{P_1(t), P_2(t), \ldots, P_N(t)\Bigg\} \\ &= \Bigg\{\prod_{i=1}^{N} a_i(t), \prod_{i=1}^{N} b_i(t), \prod_{i=1}^{N} c_i(t)\Bigg\} \quad (i = 1, 2, \ldots, N) \end{aligned} \tag{3.12}$$

OR gate fuzzy operator

The output of an OR gate is true if at least one of its inputs is true. The probability of an OR gate output with N inputs may be calculated as the sum of the probability of each input occurring. Suppose there are N statistically independent input events at time t in an OR gate. In that case, the probability of the output is given by the union of the probabilities of each event occurring. In fuzzy fault tree analysis, the OR gate fuzzy operator is used to model the occurrence of alternative events that can cause a TE.

$$P\Bigg\{BE_1 \vee BE_2 \vee BE_3 \vee \cdots \vee BE_{n-1} \vee BE_n\Bigg\}(t) = 1 - \prod_{i=1}^{N}(1 - P\{BE_i\}(t)) \tag{3.13}$$

---

[3] AND^F means Fuzzy AND

In the unavailability of the failure probability, if the failure probability of BE_i is provided as a TFN, then the likelihood of failure can be approximated. Therefore, OR fuzzy gate operator as follows for a triangle illustration of the failure possibilities $P_i(t) = \{a_i(t), b_i(t), c_i(t)\}$:

$$\begin{aligned} P_{OR^{F}{}^{4}}(t) &= OR^F\left\{P_1(t), P_2(t), \ldots, P_N(t)\right\} = 1 - \prod_{i=1}^{N}(1 - P_i(t)) \\ &= \left\{1 - \prod_{i=1}^{N}(1 - a_i(t)), 1 - \prod_{i=1}^{N}(1 - b_i(t)), 1 - \prod_{i=1}^{N}(1 - c_i(t))\right\} \quad (i = 1, 2, \ldots, N) \end{aligned} \tag{3.14}$$

If the MF is considered trapezoidal, one element adds to Eqs 4.3 and 4.4.

The traditional fuzzy AND and OR gates, which transfer crisp values into fuzzy numbers, do not adequately capture the uncertainty in system inputs. This is because they do not account for influential factors such as the sequence of events and the exponential increase in failure rate over time. This results in less precise modelling of system behaviour. To address this limitation, fuzzy fault tree analysis introduced Priority-AND (P-OR) and Priority-OR (P-OR) gates. The main difference between the traditional fuzzy AND and OR gates and the P-AND and P-OR gates is the incorporation of the occurrence sequence of the basic events and their effect over time.

Pandora Temporal Fault Tree Analysis

Priority-AND and Priority-OR gates are commonly used in FTA to model the interdependency of events in complex systems. Priority-AND and Priority-OR gates are extensions of the traditional AND and OR gates, respectively, that can handle uncertainty in event occurrence. Pandora enhances FT with new temporal gates and laws to enable qualitative estimation, consequently addressing the constraints of FTA in representing a sequence-dependent function. This method estimates the failure likelihood for the TE. Pandora implies that the occurrence of the events is immediate; for instance, they transition from “non-fail” to “fail” without latency, and permanent, say, they stay in a ’true’ state forever after they have occurred. Consequently, there are three potential temporal relationships among X and Y [100]:

- **Before** $\longrightarrow$ X occurs before Y;
- **After** $\longrightarrow$ X occurs after Y, or equivalently, Y occurs before X;
- **Simultaneous**$\longrightarrow$ X and Y occur simultaneously.

Based on the logic gates proposed by Edifor et al. [2012] and Edifor et al. [2013], Pandora offers three temporal gates:

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[4] OR^F means Fuzzy OR

Priority-AND gate (PAND)

- Symbol: $<$, means (X PAND Y) where X and Y are both failure events, the fault tree symbol of the PAND gate is shown in Fig. 3.10
- Sequence Value: $S(A < B) = S(B)$
- Meaning[5]: A occurs before B occurs. Both A and B must occur

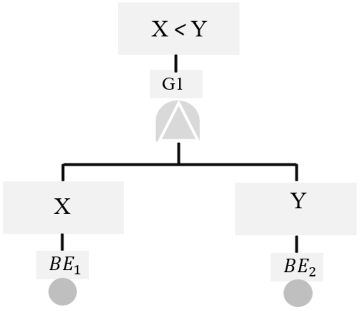


Figure 3.10: Priority-AND (PAND)

Priority-OR gate (POR)

- Symbol: $|$, means (X POR Y) and the fault tree symbol of the POR gate is shown in Fig. 3.11
- Sequence Value: $S(A \mid B) = S(A)$
- Meaning: A occurs before B occurs. Both A and B must occur

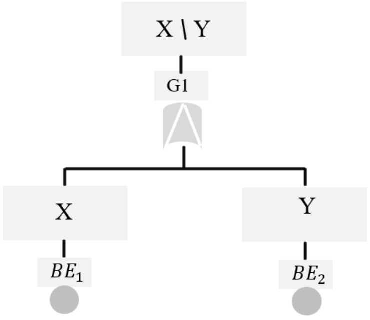


Figure 3.11: Priority-OR (POR)

Simultaneous-AND (SAND)

- Symbol: &, is used to represent the SAND gate in logical expressions and the fault tree symbol of the SAND gate is shown in Fig. 3.12
- Sequence Value: $S(A \& B) = S(B)$
- Meaning: B occurs at the same time as A occurs. Both A and B must occur.

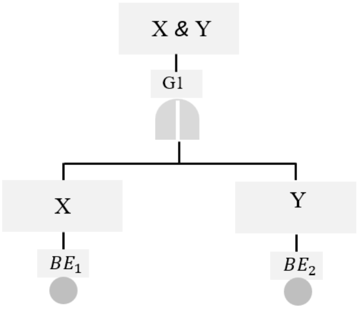


Figure 3.12: Simultaneous-AND (SAND)

Employing P-AND and P-OR gates in fuzzy fault tree analysis enhances the accuracy of modelling system behaviour, enabling more precise assessments of the system's reliability.

Mathematical Formulation of Pandora Gates

The mathematical formulation of Pandora gates, specifically the P-AND and P-OR gates, involves the utilization of mathematical expressions and equations to describe the operation and behaviour of these gates in the context of FFTA. This formulation aims to provide a more precise and accurate representation of the relationships between the events within

---

[5] By "nesting" method, the above definitions may be expanded to accommodate any quantity of BE.

the FT, considering factors such as occurrence sequence and an exponential increase in failure rate over time.

According to the literature [99, 103, 104], the mathematical formulation of a Fuzzy Temporal gate can be defined as follows: Given N statistically independent basic events, each with a triangular fuzzy number $\lambda_i = (a_i, b_i, c_i)$, an algebraic model representing a P-AND gate with the notation $\lhd$ can be calculated as follows:

$$P\left\{BE_1 \lhd BE_2 \lhd BE_3 \lhd \cdots \lhd BE_{n-1} \lhd BE_n\right\}(t) = \prod_{i=1}^{N} \lambda_i \sum_{k=0}^{N} \left[\frac{e^{u_k t}}{\prod_{\substack{j=0 \\ j\neq k}}^{N}(u_k - u_j)}\right] \tag{3.15}$$

Where the $\lambda_i(t) = (a_i(t), b_i(t), c_i(t))$ represents the triangular fuzzy number representing the failure rate of the i^{th} component, and t denotes the mission time. Additionally, certain criteria must be met, including $\begin{cases} \mathrm{u}_0 = 0 \\ \mathrm{u}_m = -\sum_{j=1}^{m(m>0)} \lambda_i \end{cases}$.

Similar to the PAND gate, for N statistically independent BEs with a TFN $\lambda_i(t) = (a_i(t), b_i(t), c_i(t))$, the algebraic model representing a POR gate with the notation $\wr$ can be calculated as follows:

$$P\left\{BE_1 \wr BE_2 \wr BE_3 \wr \cdots \wr BE_{n-1} \wr BE_n\right\}(t) = \lambda_1 \cdot \left[\frac{1 - e^{-(\sum_{i=1}^{N} \lambda_i t)}}{\sum_{i=1}^{N} \lambda_i}\right] \tag{3.16}$$

Where λ_1 represents the failure rate of BE_1, it is crucial to note that, in contrast to the conventional gates utilized in FTA, the use of priority gates (POR and PAND) requires consideration of the sequence of component or system failures, to accurately incorporate their failure rates based on their order of occurrence.

In conclusion, the quantitative analysis of a temporal fault tree is a method for determining the probability of a top event based on the failure rates of basic events. All the basic events' failure rates are represented as fuzzy numbers to reduce inaccuracies resulting from ambiguity or uncertainty in the data. Various risk analysis approaches aim to reduce the likelihood of failure and improve the ability to identify and address issues before they cause harmful effects. Using P-AND and P-OR gates in FFT analysis is crucial to consider the sequence of component or system failures and properly incorporate their failure rates based on their order of occurrence.

The results of an FFT analysis can be used to inform the development of a FET. The fuzzy fault tree provides information about the component failures contributing to a particular risk scenario. At the same time, the FET focuses on modelling the sequences of events that contribute to the risk. Combining these two perspectives can provide a more comprehensive and accurate representation of the risk scenario.

3.2.3 Fuzzy Event Tree Analysis (FETA)

Fuzzy event trees have been applied across various domains, including engineering, medicine, and finance. For instance, in engineering, FETs have been used to evaluate the risk of system failures and the probability of specific failure scenarios. In medicine, they have been employed to estimate the risk of medical errors and assess the effectiveness of treatments. In finance, they have been used to analyze investment risks and assess the likelihood of various financial scenarios. Recently, the field of FETs has seen considerable progress, focusing on developing new methods for constructing and analyzing FETs and incorporating additional sources of uncertainty into the analysis. These advancements have led to a more accurate and comprehensive understanding of the risks associated with various systems and scenarios. A comprehensive review of the literature on the FET Approach underscores its value as a tool for managing uncertainty in risk assessments. Its wide range of applications and ongoing developments demonstrate its relevance and importance in risk analysis [105].

As the failure possibility of the system is acquired via an FFT, the TE possibility is then entered into the FET of the given system (Fig. 3.13) as the initiating event for the (for example, SBO accident scenario.

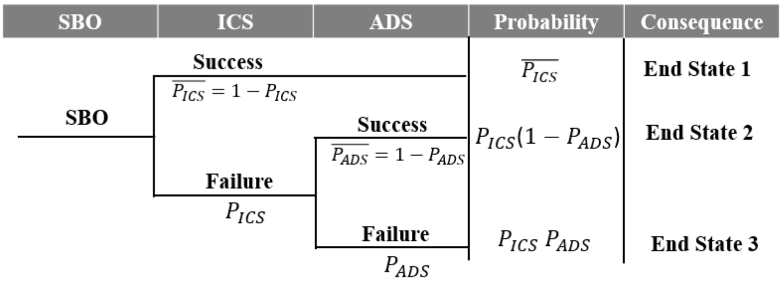


Figure 3.13: Event tree of ICS under SBO accident

The branch possibility shown in Fig. 3.13 denotes the likelihood of a particular sequence of events occurring based on the results of an FFTA. The figure shows the different branches of the ET, each representing a different scenario. Each branch illustrates a sequence of events that leads to a particular outcome. The branch possibility is calculated by multiplying the individual event failure possibilities obtained from the FFTA. This provides an estimate of the overall likelihood of the scenario in different paths. The collection of associated mitigating systems (MS_i) is indicated as follows:

$$\textbf{Mitigating Systems}\,(\mathbf{MS_i}) = \left\{ MS_i \,\middle|\, i = 1, 2, \cdots, n \right\} \tag{3.17}$$

Where MS_i represents the i^{th} mitigating system and n is the total number of mitigating systems engaged in the scenario. The fuzzy possibility of each MS_i can be estimated through FFTA, which uses fuzzy numbers to express the uncertainty of the likelihood of a safety system failure. The resulting fuzzy possibilities can then be incorporated into the FETA to estimate the overall risk of each accident scenario path.

To incorporate the results of an FFTA into the FETA, the success or failure branches in the event tree are used to represent the success or failure of consecutive mitigation systems. In this stage, two sets of fuzzy probabilities are generated based on the probabilities associated with each mitigating system for each pathway. The first set, labelled Mitigating System Failure ($\mathscr{F}$), comprises probabilities that indicate the likelihood of the mitigating systems failing to operate. The second set, labelled Mitigating System Success ($\mathscr{S}$), comprises probabilities that indicate the likelihood of the mitigating systems being effective. The fuzzy possibility failure rates obtained from an FFT of the mitigating systems can be determined by $\mathscr{F}$. Failure and success probabilities for the different mitigating system is formalized in Eqs. 4.1.

$$\begin{cases} \text{Failure Probability} \Longleftrightarrow \bar{P}_{\mathscr{F}}(x) = \left\{ \bar{p}_{\mathscr{F}_i}(x) \,\middle|\, i = 1, 2, \cdots, n \right\} \\ \\ \text{Success Probability} \Longleftrightarrow \bar{P}_{\mathscr{S}}(x) = \left\{ \bar{p}_{\mathscr{S}_i}(x) \,\middle|\, i = 1, 2, \cdots, n \right\} \end{cases} \tag{3.18}$$

Where subscript f and s represent the failure and success of the mitigating system in the fuzzy event tree. $\bar{p}_{\mathscr{S}_i}(x)$ in the Eq. 4.1 indicate the success probability of i^{th} mitigating system and quantified as:

$$\bar{p}_{\mathscr{S}_i} = 1 - \bar{p}_{\mathscr{F}_i}(x) \tag{3.19}$$

The α-cut is a concept in fuzzy set theory that is used to convert a fuzzy set into a crisp set (3.1). Given a triangular fuzzy set $A = (a, b, c)$, the α-cut for a value of α, where $\alpha \in [0, 1]$; the $\alpha - cut$ for a triangular fuzzy set $A = (a_, b, c)$ is as follows:

$$A^{\alpha} = \left[\alpha_1^{(\alpha)},\, \alpha_2^{(\alpha)}\right] = [(b-a)\cdot\alpha + a, c - (c-b)\cdot\alpha] \tag{3.20}$$

The probability of each path consequence is estimated by converting the TFN into the $\alpha - cut$ set. each mitigating system probability fuzzy number mapping into the $\alpha - cut$ set based on Eq. 3.20 and executing mathematical calculations such as $\alpha - cut$ adding and multiplying on fuzzy numbers, $A^{\alpha} = \left[\alpha_1^{(\alpha)},\, \alpha_2^{(\alpha)}\right]$ and $B^{\alpha} = \left[\beta_1^{(\alpha)},\, \beta_2^{(\alpha)}\right]$, is as follow:

$$A^{\alpha} + B^{\alpha} = \left[\alpha_1^{(\alpha)} + \beta_1^{(\alpha)},\, \alpha_2^{(\alpha)} + \beta_2^{(\alpha)}\right] \tag{3.21}$$

$$A^{\alpha} \cdot B^{\alpha} = \left[\alpha_1^{(\alpha)} \cdot \beta_1^{(\alpha)},\, \alpha_2^{(\alpha)} \cdot \beta_2^{(\alpha)}\right] \tag{3.22}$$

The probability of each pathway consequence can be estimated by converting the triangular fuzzy numbers into the $\alpha - cut$ set and performing mathematical operations such as adding and multiplying. This approach allows for a more realistic representation of uncertainty in probability analysis and provides a more robust decision-making process for ensuring the safety of NPPs.

In conclusion, this study presented a fuzzy probabilistic safety assessment method using fuzzy numbers, FTs, and ETs. The proposed method provides a flexible approach to estimating accident probabilities considering the uncertainties associated with the system's success and failure rates. TFN was used to represent the system's success and failure rates, and the $\alpha - cut$ set was utilized to convert the TFN into a crisp value. In this way, the FFTs and FETs were constructed to evaluate the system's safety in a probabilistic manner, considering all possible consequences and the associated probabilities of each path. Moreover, the proposed method allows the incorporation of multiple Pandora gates (PAND and POR) in the analysis, enhancing the assessment's accuracy. To summarize, the proposed method provides a comprehensive approach to the probabilistic safety assessment of complex systems, incorporating uncertainties and addressing the limitations of traditional methods.

In the following section, we will delve into the topic of fuzzy FMEA and explore its application in the assessment of risk. We will examine the use of fuzzy logic in combination with the traditional FMEA methodology to provide a more comprehensive and nuanced approach to risk analysis. Additionally, we will discuss calculating the risk priority number, which is an important aspect of FMEA and provides a measure of the relative risk of different failures. This discussion will provide insight into the application of fuzzy FMEA in practical settings and demonstrate its effectiveness in managing risk in complex systems.

3.3 Fuzzy Failure Modes and Effects Analysis

Fuzzy failure modes and effects analysis is an approach to risk analysis and management that incorporates fuzzy logic into the traditional FMEA method. Fuzzy failure modes and effects analysis is a widely used technique for identifying and evaluating the potential failure modes of a system or process and the consequences of these failures. The traditional FMEA method uses crisp (deterministic) values to assess the risk of each potential failure mode. However, in many real-world applications, the values used in the risk assessment often need to be more precise and precise. Fuzzy failure modes and effects analysis overcome this limitation by using fuzzy logic to represent the uncertainty and imprecision in the data used for the risk assessment. In fuzzy FMEA, fuzzy numbers represent the uncertainty in the risk parameters, such as the probability of occurrence, the severity of consequences, and the detection capability. This enables the analyst to capture the inherent uncertainty and imprecision in the data, leading to a more accurate and comprehensive risk assessment.

The following table presents a compilation of various studies that have explored the application of fuzzy logic in the realm of FMEA. These studies provide insights into utilizing fuzzy techniques to improve the accuracy and reliability of FMEA results. The information presented in this table sheds light on the current state of research in the field of fuzzy FMEA and highlights the potential of fuzzy techniques in enhancing the risk assessment process. This literature review serves as a comprehensive overview of the various applications of fuzzy FMEA and the outcomes that have been reported in the relevant research literature.

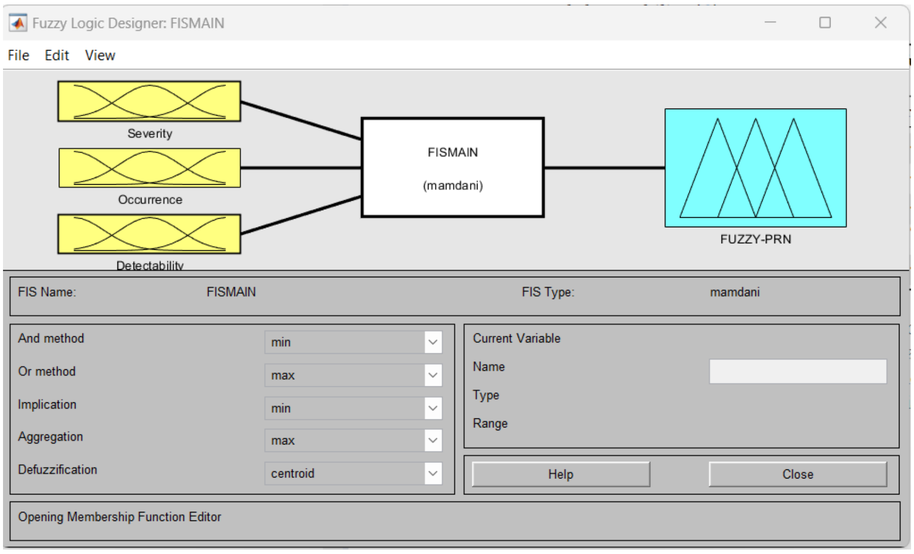
Table 3.4: Risk Analyses methods based on FMEA

References	**Proposed approaches**
Guimaraes et al. [2004]	Fuzzy inference system (FIS) modeling (IF-THEN rules) is applied to investigate the impacts of ageing on a PWR's CVCS. Traditional FMEA RPN is compared to fuzzy RPN (FRPN).
Alizadeh et al. [2022]	Incorporating the expert judgments in the fuzzy FMEA via MATLAB software to prioritize and analyze risks related to the physical operations of the Sahand municipal wastewater treatment facility.
Panchal et al. [2022]	In the coal-fired power systems, an upgraded FMEA was designed where RPN factors have been evaluated as fuzzy variables, and then fuzzy RPN values are subsequently calculated to determine the most critical component.
Reda et al. [2022]	Employing Fuzzy QFD and FMEA, the decision-making process for the choice of lean devices prioritizes the essential sources relevant to the specified wastes and determines the risk associated with failure mode.
Ding et al. [2021]	The FMEA, fault tree analysis, and fuzzy Bayesian network approaches were employed to develop a unique way for assessing the dependability of the RHRS for the Hualong Pressurized Reactor 1000. (HPR1000)
Mutlu et al. [2019]	An FMEA and FTA-based strategy is provided to examine the ring spinning yarn manufacturing operation in textile business, showing that decision-makers may readily reduce threats.
Rafie et al. [2015]	Estimating the threat of ground subsidence due to drilling underground employing a FIS and an ANN in FMEA.
Naamnh et al. [2021]	Integrating MATLAB, FIS, and ANN to create more accurate risk analysis methods to overstep the conventional approach boundaries in Busbars Production.
Abdelgawad et al. [2012]	Incorporating fuzzy ETA and proposing a complete structure relying on a combination of fuzzy-FMEA, FT, and ET, this paper provides a realistic and comprehensive way for evaluating the level of criticality of risk events in the construction industry.
Balaraju et al. [2019]	RPN was computed using the MATLAB fuzzy logic toolbox for several potentially failing components of a Load-Haul-Dumper (LHD) machine. If two or more failure modes have a similar rating, the fuzzy-FMEA approach is used to prioritize the failure modes appropriately.

The above research is in Table. 3.4 on fuzzy FMEA highlights several benefits of this approach compared to traditional FMEA, including improved accuracy and consistency in the assessment, reduced subjectivity, and better handling of uncertainty. Several studies have applied fuzzy FMEA in various industries, including the aerospace, automotive, electrical, and nuclear power industries, demonstrating its effectiveness in identifying and mitigating risks.

Fuzzy Inference System

The Fuzzy inference system in MATLAB® is a tool for building fuzzy models, allowing the modelling of uncertainty and subjectivity in a given problem (as shown in Fig. 3.14). Fuzzy inference system in MATLAB® includes a comprehensive set of functions and graphical interfaces for building, managing, and analyzing fuzzy models. Building a FIS in MATLAB® involves specifying the fuzzy input and output variables, defining the fuzzy rules that connect the inputs to the outputs, and specifying the MFs for each fuzzy set in the system. The fuzzy inference engine in MATLAB® uses these rules and MFs to predict based on the inputs.



FIS Name: FISMAIN

FIS Type: mamdani

And method: min

Or method: max

Implication: min

Aggregation: max

Defuzzification: centroid

Opening Membership Function Editor

Figure 3.14: Fuzzy inference system showing the MF for the linguistic variable (occurrence, sensitivity and detectability) as crisp inputs, are plugged into the model to estimate fuzzy PRN.

The initial step in creating a FIS is determining the system's inputs and outputs and identifying the linguistic variables associated with each input and output. This involves defining the range of values for each variable and dividing the range into a set of fuzzy sets, representing the linguistic terms used to describe the input and output variables. The next phase is to design a fuzzy rule set that captures the expert knowledge or relevant data and the relationship between the inputs and outputs. These rules are then implemented in the FIS, and the system is tested using appropriate input values to ensure the results are consistent with the intended behaviour.

In the following sections, we will systematically proceed through each step in creating a FIS, ensuring a thorough understanding and application of the concepts and procedures involved.

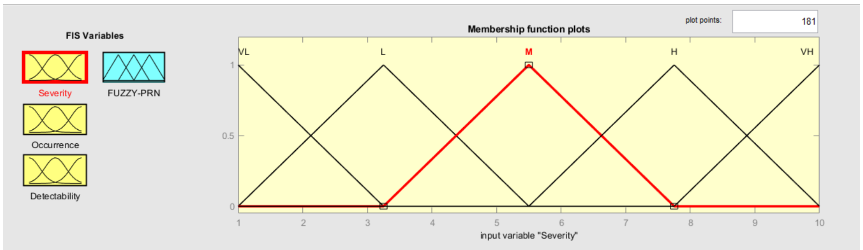
Fuzzification Using MATLAB®

The conversion of linguistic variables such as "Low" and "High" into numerical values for severity, occurrence, and detectability in a fuzzy FMEA evaluation process is achieved through the fuzzification process. This step involves mapping the linguistic terms into MFs, which are represented by fuzzy numbers that quantify the degree of truth for each term. The membership functions are then used to calculate the degree of possibility for each attribute, leading to the determination of the fuzzy RPN. Employing a 1 to 10 scale for severity, occurrence, and detectability (as shown in Table. 3.5) in fuzzy RPN evaluations is a common practice in risk assessment. This scale provides a quantitative representation of the subjective judgments made by experts regarding the potential impact of a failure mode on the system under consideration.

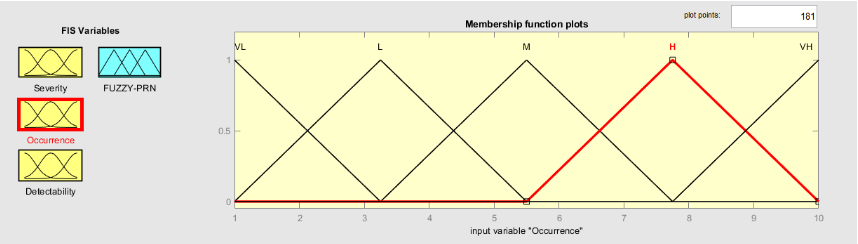
Table 3.5: Linguistic terms and TFN for the input variables' severity, occurrence and detectability [115].

	Triangular fuzzy numbers		
Linguistic terms	Severity (S)	Occurrence (O)	Detectability (D)
Very low (VL)	(1.00, 1.00, 3.25)	(1.00, 1.00, 3.25)	(1.00, 1.00, 3.25)
Low (L)	(1.00, 3.25, 5.50)	(1.00, 3.25, 5.50)	(1.00, 3.25, 5.50)
Moderate (M)	(3.25, 5.50, 7.75)	(3.25, 5.50, 7.75)	(3.25, 5.50, 7.75)
High (H)	(5.50, 7.75, 10.00)	(5.50, 7.75, 10.00)	(5.50, 7.75, 10.00)
Very high (VH)	(7.75, 10.00, 10.00)	(7.75, 10.00, 10.00)	(7.75, 10.00, 10.00)

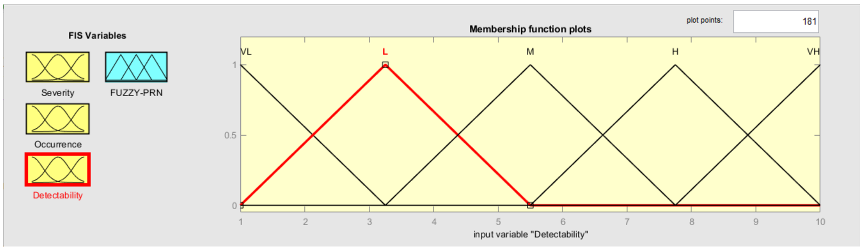
Estimating the fuzzy RPN requires multiplying the crisp values for severity, occurrence, and detectability. The membership functions for each linguistic variable are depicted in Fig. 3.15. These MF are used to convert the linguistic phrases into fuzzy numbers, which are then employed for computation purposes in the fuzzy inference system implemented in MATLAB®.



(a) Input Variable Severity Membership Function Plot



(b) Input Variable Occurrence Membership Function Plot

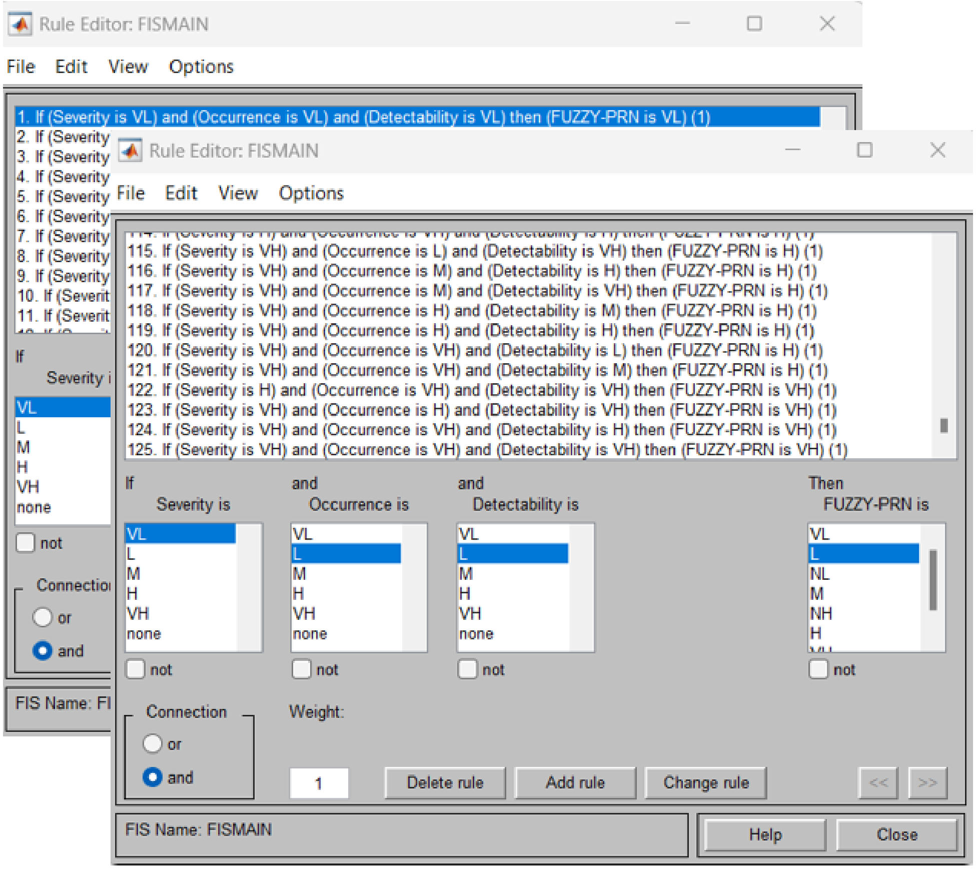


(c) Input Variable Detectability Membership Function Plot

Figure 3.15: Membership function plots of Input variable (Occurrence, Severity, and Detectability) in FIS using MATLAB®

Inference

According to section 3.1.2, the fuzzy inference structure is based on the IF-THEN "rule-based" approach. It usually comprises a series of actions that begin with if a fact is met and end with a conclusion based on professional experience. However, shallow knowledge has a disadvantage because it does not reflect the more profound forms of information often connected with object structure and behaviour [77]. The fuzzy inference system frequently uses this IF-THEN rule (antecedent-consequent linguistic rules), as shown in Expression 3.5, to compute the degree to which the incoming information fulfils the criteria of a rule. Therefore, based on the deductive form of procedure, there is the given fact as a conclusion for the given antecedent 3.5.



1. If (Severity is VL) and (Occurrence is VL) and (Detectability is VL) then (FUZZY-PRN is VL) (1)

115. If (Severity is VH) and (Occurrence is L) and (Detectability is VH) then (FUZZY-PRN is H) (1)
116. If (Severity is VH) and (Occurrence is M) and (Detectability is H) then (FUZZY-PRN is H) (1)
117. If (Severity is VH) and (Occurrence is M) and (Detectability is VH) then (FUZZY-PRN is H) (1)
118. If (Severity is VH) and (Occurrence is H) and (Detectability is M) then (FUZZY-PRN is H) (1)
119. If (Severity is VH) and (Occurrence is H) and (Detectability is H) then (FUZZY-PRN is H) (1)
120. If (Severity is VH) and (Occurrence is VH) and (Detectability is L) then (FUZZY-PRN is H) (1)
121. If (Severity is VH) and (Occurrence is VH) and (Detectability is M) then (FUZZY-PRN is H) (1)
122. If (Severity is H) and (Occurrence is VH) and (Detectability is VH) then (FUZZY-PRN is VH) (1)
123. If (Severity is VH) and (Occurrence is H) and (Detectability is VH) then (FUZZY-PRN is VH) (1)
124. If (Severity is VH) and (Occurrence is VH) and (Detectability is H) then (FUZZY-PRN is VH) (1)
125. If (Severity is VH) and (Occurrence is VH) and (Detectability is VH) then (FUZZY-PRN is VH) (1)

Figure 3.16: Implementation of the FIS for calculating the fuzzy RPN, a total of 125 rules were established to minimize the complexity of the fuzzy rule base, facilitated through the use of MATLAB®.

All possible combinations of linguistic terms and the results are demonstrated in Fig. 3.16 for calculating the fuzzy risk priority RPN. These rules serve as a basis for the computation of the RPN, considering the uncertainty and subjectivity involved in assessing risk in a practical setting. After establishing the rules for calculating the fuzzy RPN, the next step would be using FIS in MATLAB to perform defuzzification.

Defuzzification

The defuzzification process in a FIS involves converting the fuzzy output obtained from the inference process into a crisp value that can be interpreted and understood easily. This process is critical in making the system usable in real-world applications. In MATLAB®, the process of defuzzification is often achieved using various methods such as the centroid method, bisector method, and others. The centroid method calculates the center of mass of the MF, while the bisector method finds the point that divides the MF into two equal areas. Both methods require the computation of definite integrals and can be efficiently performed using MATLAB®'s built-in functions and symbolic computation capabilities. The defuzzification process is an important step in FISs that converts the fuzzy output into a crisp value, allowing for a better understanding and utilization of the system in real-world applications. Using MATLAB® makes this process easy and efficient.

Once defuzzification is complete, the next step in calculating the fuzzy RPN in a fuzzy FMEA would involve aggregating and interpreting the results obtained from the previous step. This can involve mathematical operations such as calculating weighted sums, applying decision-making algorithms, or developing a mathematical model to predict the outcome based on the input data. This step aims to quantify the risk level associated with each potential failure mode and prioritize the corrective actions based on the level of risk. This step requires a clear understanding of the problem and the goals of the analysis and a comprehensive evaluation of the data obtained from the previous step to ensure accurate and meaningful results.

In conclusion, the proposed fuzzy FMEA evaluation process is a viable solution to evaluate and prioritize risks. The process comprises three key phases, fuzzification, inference and defuzzification, that convert the crisp failure probability into a single value representing the RPN. The fuzzy inference system was implemented in MATLAB®, and it utilized a rule-based approach to computing the degree to which incoming information fulfils the criteria of a rule. The fuzzy inference structure rules for computing the fuzzy RPN were generated using software MATLAB®, with a total of 125 rules produced. The proposed process provides a more robust and reliable risk evaluation and prioritization method than traditional FMEA methods.

Due to the limitations of traditional FT outlined in reference 5, the utilization of ANNs has been proposed to improve the performance of FT analysis. Artificial neural networks are inspired by the functioning of the human brain, allowing for algorithm learning through processing information and identifying correlations between inputs and outputs. This approach facilitates estimating and refining the input-output relationship rules through continual learning.

3.4 Artificial Neural Networks Methods in Reliability Assessment

Operating and controlling an NPP are challenging due to the complex and nonlinear dynamics of its Structures, Systems, and Components (SSCs). To ensure proper functioning under normal and abnormal conditions, the SSCs must be continuously monitored, which generates a significant amount of data to be processed. This challenge is further compounded in the case of SMRs, where innovative design and lack of operating experience add to the complexity. Conventional risk assessment techniques, such as FT and ET, face difficulties handling this large amount of information and cannot efficiently process the data related to component failure rates and accident scenarios. This limitation can be addressed by incorporating ANNs into the risk assessment process. Artificial neural networks, inspired by the function of the human brain, can operate information to determine correlations between the independent and dependent variables and, as a result, enable the estimation and updating of the rules governing the input-output relationship. Using ANNs in NPP risk assessment allows quicker and more accurate behaviour forecasting and enhances decision-making based on actual operational information. Data-Driven Models (DDMs) also utilize ANNs to autonomously learn from data trends, providing an alternative to physics-based simulations that often require extensive computational resources and may not accurately reflect the actual operating conditions of an NPP [116]. In conclusion, integrating ANNs into NPP risk assessment is a promising approach that offers improved performance and accuracy compared to traditional methods.

3.4.1 Introduction

Definition 3.4.1 (neural network) *"is a computing system comprising several simple, highly interconnected nodes or processing elements, which process information by its dynamic state response to external inputs".*

Artificial neural networks are used to address complex and ill-defined problems because of their unique approach to problem-solving. This approach is inspired by the functioning of the human brain, allowing for the development of algorithms that can learn from information and establish correlations between dependent and independent variables. The versatility and capacity of ANNs are demonstrated through various applications, including but not limited to facial and speech recognition and classification, function modelling and fitting, image restoration, and language translation. These applications showcase the potential of ANNs in solving complex problems that are challenging to articulate algorithmically.

Artificial neural networks rely on the principle of learning to imitate the behaviour of complex dynamic systems. Unlike conventional programming, where a model is provided with information and rules to produce desired outputs based on computational laws, ANNs work by discovering a relationship between inputs and outputs based on given input-output pairs. This flip in the traditional programming process highlights the unique and innovative approach of ANNs in solving complex problems.

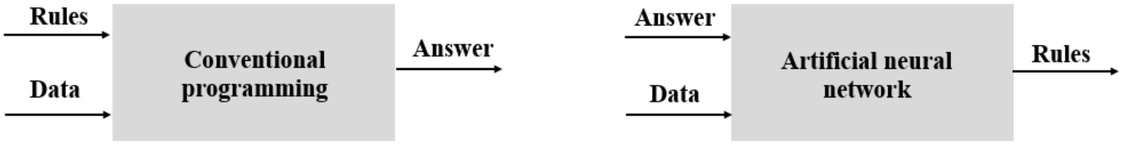


Figure 3.17: Illustrates the conventional approach to programming, where the model is supplied with information and rules to generate outputs, compared with ANN, where the inverse relationship between inputs and outputs can also be studied by reversing this process.

The conventional programming approach is shown in Fig. 3.17, where the model is given rules and data in order to generate the desired outputs in accordance with those rules and guidelines. It is known as an ANN, a model that reveals the association between inputs and outputs if the process depicted in the figure is reversed to uncover the relationship between inputs and outputs[6].

Artificial Neurons

Artificial neurons, also known as artificial nodes, are the basic processing units of artificial neural networks. They are modelled after the biological neurons in the human brain and are responsible for receiving, processing, and transmitting information within the network. Artificial neurons are connected through pathways called synapses and are activated based on a weighted sum of their inputs, then transformed through an activation function. This operation allows artificial neurons to make predictions and decisions and learn from patterns in the data fed into the network.

An Artificial neural network is a network of artificial neurons separated into various layers. Perceptrons and Sigmoid neurons represent two fundamental kinds of neurons. Perceptrons are used for binary classification tasks, while Sigmoid neurons are used for multiclass classification and regression tasks. These neurons receive inputs, process them, and produce an output signal, representing the neural network's output. Combining multiple neurons in an artificial neural network enables it to perform complex computations, such as learning and pattern recognition, making it a powerful tool for various real-world applications. Sigmoid neurons, on the other hand, receive continuous inputs and produce outputs that are continuous values between 0 and 1. In this case, the sigmoid function is used to estimate the output, with the weights serving as multiplicative factors determining the strength of each input's effect on the neuron's output. This allows sigmoid neurons to model non-linear relationships between inputs and outputs, making them a crucial component of deep learning algorithms.

Figure 3.18 depicts the detailed structure of a perceptron, which, similar to human neurons, receives multiple inputs $(x_1, x_2, \ldots, x_n)$ that correspond to the outputs of other neurons. The strength of each input's effect on the perceptron's output is determined by the corresponding weight w_i, which acts as a multiplicative factor for the input. The weighted

---

[6] The outcome (output) is often referred to as the dependent variable or response variable, and the input is the independent variable.

inputs are then transmitted to an activation function to determine the final input value for the neuron, also referred to as a perceptron, unit, or node.

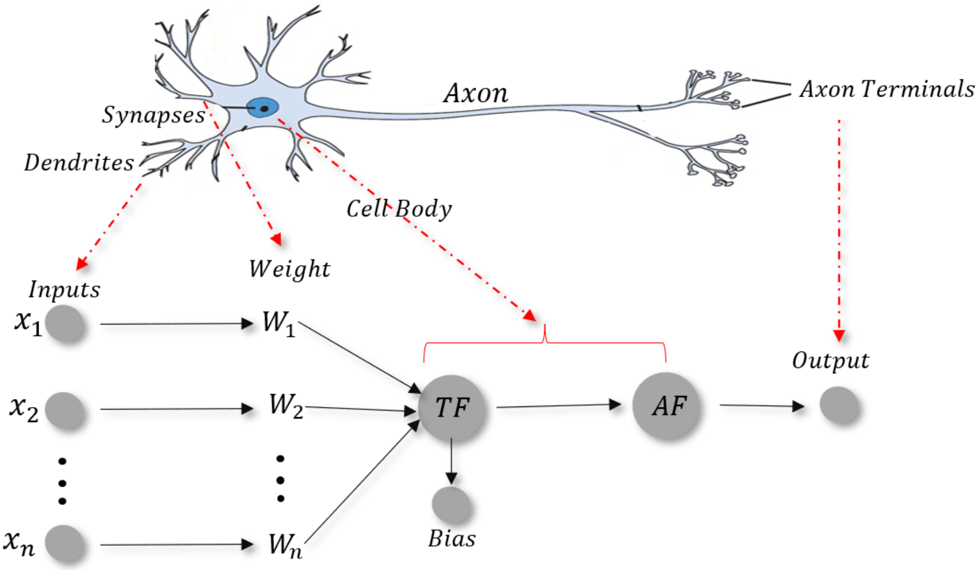


Figure 3.18: Detailed structure of a perceptron that works similarly to human neurons by receiving multiple inputs corresponding to the outputs of other neurons.

The transfer function (z) is a crucial component of the perceptron model, where the inputs are transformed into the neuron's output. The inputs $(x_1, x_2, \ldots, x_n)$ are multiplied by their respective weights w_i, which correspond to the strength of each input's effect on the output. This is a linear combination of the inputs, where each input impacts the output differently based on its weight. The transfer function then computes this linear function to produce the final output of the neuron. This output can be considered the neuron's activation and serves as the input to other neurons in the network. The activation function transforms the weighted inputs into a value to determine the neuron's output. It is important to note that the transfer function is a simple mathematical operation that can be performed efficiently, enabling fast processing of the inputs and production of the output. The transfer function provides the mechanism for the output computation, and the weights provide the mechanism for learning, which is the key aspect of ANNs.

$$z = \sum_{i=1}^{n} w_i \cdot x_i + b_i \tag{3.23}$$

Equation represents the weighted sum of the inputs and is used as the input for the activation function, which computes the output of the artificial neuron.

Inputs $(x_1, x_2, \ldots, x_n)$ receive numeric values and may represent unprocessed signals or the outputs of other neurons. The significance of each input is controlled by numerical weights $(w_1, w_2, \ldots, w_n)$, which indicate that important inputs have a higher value. The numerical value of the **Bias** (b_i) serves to prevent the transfer function (TF) of each perceptron from being zero.

The result, or perceptron's activation, is specified by whether the value of the **weighted sum** $\sum^n x_i \cdot w_i$ is more remarkable than some **Threshold** value or not. This clause explicitly shows as:

$$\text{Output} = \begin{cases} 0 \quad \text{if} \quad \overbrace{\sum_{i=1}^{n} x_i w_i}^{\textbf{Weighted sum}} \leq \text{Threshold} \\ 1 \quad \text{if} \quad \sum_{i=1}^{n} x_i w_i > \text{Threshold} \end{cases} \tag{3.24}$$

Where i represents iterate over input x weight w pairings. To make the notation less cumbersome, let x and w be the vectors of inputs and their related weights, respectively and illustrate a b_i value $b_i = -\text{Threshold}.$; Then:

$$\text{Output} = \begin{cases} 0 \quad \text{if} \quad \sum_{i=1} w \cdot x + b_i \leq 0 \\ 1 \quad \text{if} \quad \sum_{i=1} w \cdot x + b_i > 0 \\ \qquad \Downarrow \\ 0 \quad \text{if} \quad \sum_{i=1} w \cdot x + (-T_i) \leq 0 \\ 1 \quad \text{if} \quad \sum_{i=1} w \cdot x + (-T_i) > 0 \end{cases} \tag{3.25}$$

The activation of a perceptron is determined by the comparison of the weighted sum of inputs ($\sum_{i=1}^{n} xi \cdot w_i$) and a threshold value. This threshold value can be incorporated into the equation as a bias term (b_i), where $b_i = -\text{Threshold}$. The AF calculates the weighted sum of inputs and the bias, effectively determining whether the neuron will fire. If the value of the AF surpasses the Threshold of 0, the neuron outputs a value of 1 ($b_i \simeq 1$), indicating activation. Conversely, if the AF is less than the Threshold, the neuron outputs a value of 0 ($b_i \simeq -1$), indicating inactivity. The activation function, in essence, acts as a decision-making mechanism for the perceptron. An activation function can be written as [117, 118, 119]:

$$AF = f(TF) \tag{3.26}$$

The activation function determines the NN's ability to learn complex functions. It acts as a constraint on the output of a neuron, preventing it from growing arbitrarily large or small. By limiting the outputs to a specific range, the activation function helps control the flow of information through the NN and prevents overfitting. Thus, the choice of activation function is a trade-off between ensuring that the NN can model complex interactions in the data and controlling the model's complexity to prevent overfitting. Different NN models have proposed and implemented various activation functions, including step functions, sigmoid, hyperbolic tangent, rectified linear unit (ReLU), and others. The choice of activation function depends on the specific problem and the requirements of the NN model. The step function is used in perceptrons and simple linear classifiers, while sigmoid is commonly used for logistic regression models. Hyperbolic tangent is used for deep learning models, and ReLU is widely used for computer vision problems and other image-based tasks. As previously noted, the functionality of the perceptron is contingent upon the input weights and the activation function. Sigmoidal functions are widely utilized as activation functions within multi-layer static neural networks. Prominent examples of activation functions used in neural networks are depicted in Fig. 3.19.

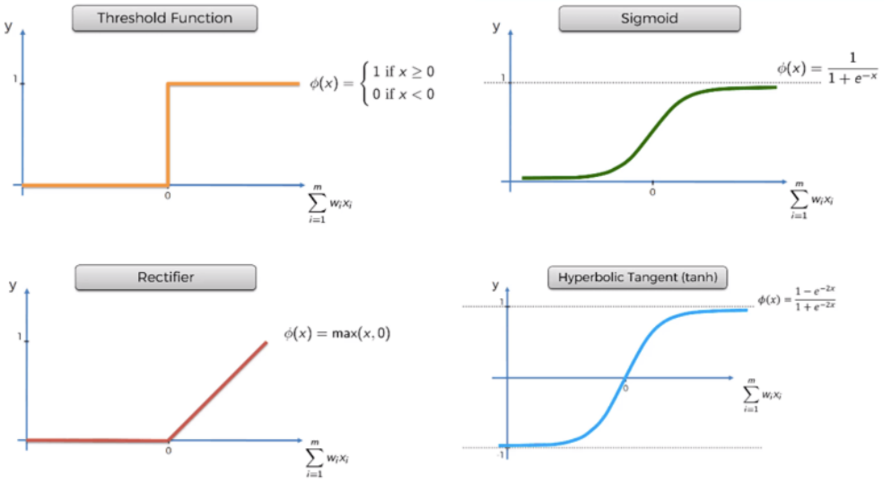


Figure 3.19: Shapes of four commonly used activation functions in a ANN: Sigmoid, Hyperbolic Tangent (Tanh), Rectified Linear Unit (ReLU), and Threshold Function.; each activation function has a unique characteristic.

Single-layer perceptrons, also known as single-layer neural networks, have several limitations, including their inability to solve complex non-linear problems and their tendency to over-fit the data. As a result, single-layer perceptrons are not appropriate for solving many practical machine learning problems. In response to these limitations, alternatives have been proposed, such as multi-layer perceptrons (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and many others, which have been shown to effectively solve complex, non-linear problems in various domains such as image classification, speech recognition, and natural language processing. These models introduce additional layers and sophisticated architectures, enabling them to capture complex, non-linear interactions in the data effectively.

Multi-layer perceptron (MLP)

A multi-layer perceptron, also known as a feed-forward neural network or an ANN, is a type of artificial intelligence model comprised of multiple layers of interconnected nodes or artificial neurons. The layers are organized sequentially, with the output of one layer serving as input to the next. This allows the network to learn complex relationships between inputs and outputs and perform nonlinear computations. The activation function is a critical network component that introduces nonlinearity into the computations. Without an activation function, the network would only be able to reflect linear relationships between inputs and outputs, limiting its overall effectiveness.

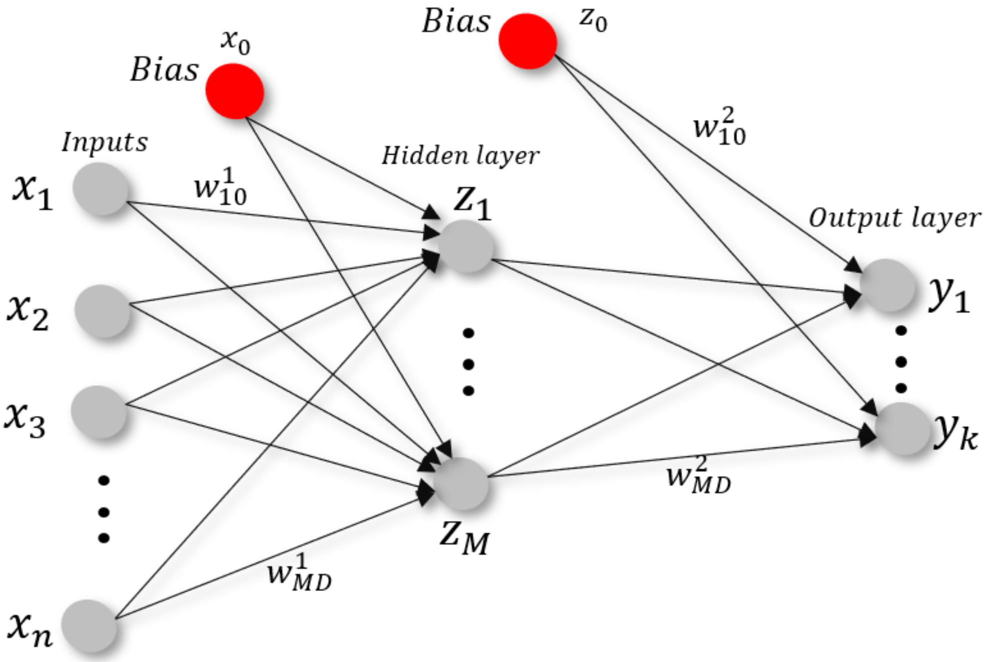


Figure 3.20: Diagram of structure and flow of information through MLP with two layers of weights, illustrating the organization of the neurons and the connections between the input layer, hidden layer, and output layer.

The network diagram of an MLP with two layers of weights can be visualized as follows:

- The input layer is the first layer of the network, which receives the inputs or features of the data. It plays a crucial role in the multi-layer perceptron as it provides the initial input features for the network to process and generate predictions;
- The hidden layer(s) is(are) the intermediate layer(s) of the network, which perform complex computations using the input data. The number of hidden layers and the number of neurons in each layer can be varied to adjust the network's complexity.
- The output layer is the final layer of the network, which provides the output or predictions of the network.

Each neuron in a hidden layer or output layer is connected to all the neurons in the previous layer through weights. The activation function is applied to the weighted sum of inputs to produce the neuron's output. The weights are updated during training. The network diagram of an MLP can be represented graphically (3.20) as a series of nodes connected by weighted edges, where the values of the weights determine the strength of the connections between the nodes.

The first layer represents a collection of M, d-dimensional inputs, which are then processed by a combination of weights w_{ij} to produce a M dimensional output vector (activation for current layer) a_j. This first layer is commonly referred to as the input layer; the weights of the input layer $w_{ij}^{(1)}$ can be interpreted as the importance or significance of each feature in the input vector and can be trained using optimization algorithms to minimize the error between the predicted and actual outputs.

$$a_j = \sum_{\substack{j=0\\i=1}}^{\substack{n\\M}} w_{ij}^{(1)} \cdot x_i + b_i, \qquad i = 0, 1, \cdots, n; \quad j = 1, 2, \cdots, M. \tag{3.27}$$

Where $x_0 = 1$, and superscript "(1)" represent the first layer. If the activation function considers being sigmoid, Each of the activations is equal to:

$$z_j = h\left(a_j\right) = \frac{1}{1 + e^{-a_j}} \tag{3.28}$$

In Eq. 3.28, z_j denotes the outputs of the hidden layer, and its values do not correspond to the inputs or outputs of the networks; it is employed to transmit values for subsequent layers. The function $h(a_j)$ is the activation function, in this case, the sigmoid function, which maps the weighted sum of inputs a_j to a value between 0 and 1. The sigmoid activation function is commonly used in multi-layer perceptrons because it produces a smooth transition from 0 to 1, allowing the network to model non-linear relationships in the input data.

Therefore, for the second layer, the outputs of the first layer are allocated as inputs, and they are linearly combined to produce the activations shown below:

$$a_k = \sum_{\substack{j=0\\k=1}}^{\substack{K\\M}} w_{kj}^{(2)} \cdot z_j + b_j, \qquad k = 1, 2, \cdots, K; \quad j = 1, 2, \cdots, M. \tag{3.29}$$

Where $z_0 = 1$, and $w_{kj}^{(1)}$, a_k, and z_j represent the weights, activations and inputs respectively. and The superscript "(2)" represent the second layer. If the activation function is considered to be Sigmund, each activation is equal to:

$$y_k = g\left(a_k\right) = \frac{1}{1 + e^{-a_k}} \tag{3.30}$$

Combining Eqs. 3.27 and 3.29 provide the final solution that defines the feed-forward propagation show, transferring the input vectors into the output vector given the weight matrices as shown in Fig. 3.20.

$$y_k = g\left(\sum_{j=0}^{M} w_{kj}^{(2)} z_j h \cdot \left(\sum_{j=0}^{n} w_{ji}^{(1)} x_i\right)\right) \tag{3.31}$$

To conclude, single-layer and multi-layer perceptrons are fundamental concepts in the field of artificial neural networks and play a crucial role in deep learning and machine learning. Understanding these concepts provides a solid foundation for exploring more complex neural network architectures.

Artificial intelligence, machine learning, and deep learning are interrelated fields that work together to enable computers to perform tasks that typically require human intelligence. Deep learning is a specific subset of machine learning, a subset of AI (Fig. 3.21). The key difference between deep learning and traditional machine learning is that deep learning algorithms are designed to self-learn and improve their performance over time, much like the human brain. This ability to self-learn and adapt has made deep learning particularly useful for tasks such as object classification, pattern recognition, and predictive analysis, among others [120].

The selection of deep learning as a method for artificial intelligence is due to its ability to mimic the structure and function of the human brain. Compared to traditional machine learning techniques, this improves performance in object classification, pattern recognition, and predictive analysis tasks. Additionally, deep learning algorithms can self-learn, further enhancing their potential for creating human-like artificial intelligence.

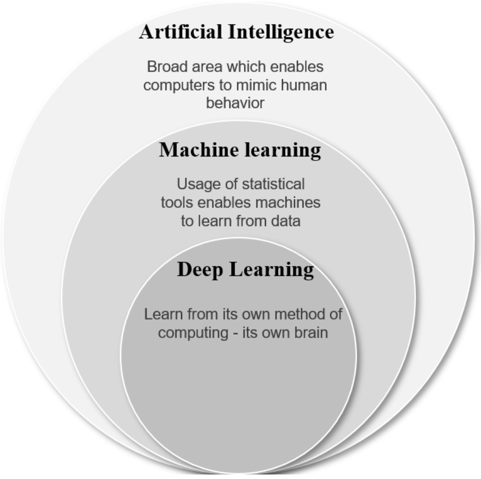


Figure 3.21: Artificial Intelligence subsets

Deep learning development flow

Deep learning focuses on machine learning through the use of neural networks. The deep learning development flow typically involves several key steps, including [121]:

(i) Selection of a framework for development and Gathering data:

Data collection is reliant on the kind of presented issue desired; in the event of a real-time data project, it is recommended to employ various sensor information. The data set may be gathered from various inputs, including documents, databases, and devices. Nevertheless, since there may be a lot of missing data, enormous quantities, disorganized text data, or noisy data, the acquired data can be utilized immediately for executing the data analysis. As a result, Data Preparation is required to overcome this issue.

(ii) Data pre-processing

In the field of deep learning, data pre-processing is a crucial step in the development flow. This step aims to convert raw and unstructured information into a clean and organized dataset that can be effectively utilized for training the deep learning model. This process is crucial for obtaining accurate results from the deep learning algorithm, as the presence of missing data, noisy data, and inconsistent data can negatively impact the model's performance. Data pre-processing helps overcome these challenges and ensures that the data used for training is high quality [122].

Table 3.6: Data pre-processing challenges and solutions

Problems	**Solving Methods**
Missing Data	Ignore the tuple Fill in the missing value manually or automatically
Noisy Data	Binning Regression Clustering Combined computer and human inspection
Inconsistent Data	Remove duplicate or irrelevant observations

(iii) Exploring the suitable algorithm for data format:

In the training phase of deep learning, the objective is to develop the optimal model using the pre-processed data described in the previous stage. Selecting the appropriate algorithm for the task requires a thorough understanding of the problem's nature. The primary techniques used for addressing different problems in deep learning are Supervised Learning, Classification, Regression, Unsupervised Learning, and Clustering.

(iv) Model's training and testing:

During the training phase, the objective is to determine the optimal network parameters that can consistently address the problem. For this purpose, the model is divided into three sets: training, validation, and testing data. The classifier is trained using the training data set, the validation set is used to tune the parameters, and the accuracy is verified using the test data set. It is important to note that only the training and/or validation sets are accessible during classifier training, while the test set should not be used for training. The test set is only available during the final testing phase of the classifier.

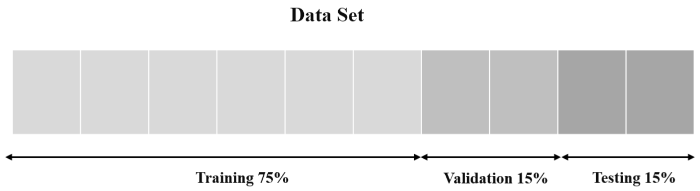


Figure 3.22: Splitting and balancing the data-set between the training, validation, and testing

The process of dividing and balancing the data-set, as illustrated in Fig. 3.22, plays a crucial role in the deep learning flow 4.13. It is essential to emphasize that the training data must never be utilized for testing the algorithm. This approach ensures that the results obtained during testing are unbiased and accurate, providing a robust evaluation of the algorithm's performance.

$$S_{Train} \cap S_{Test} \equiv \varnothing \tag{3.32}$$

Evaluating the model's performance on the validation set during the training phase is crucial in avoiding overfitting. The provision of a validation set enables automatic assessment of the model's effectiveness by utilizing tools such as Keras. The model's performance on the validation set indicates its ability to generalize and handle novel, unseen data [123, 124].

(v) Inference and Evaluation:

Applying a trained deep learning model to new data to generate predictions or inferences is called deep learning inference. The evaluation of the performance of a neural network (NN) on this new data set is crucial in determining the model's validity. A standard method for evaluating the accuracy of the predictions generated by a NN is the calculation of Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) values.

Due to the data preparation challenges outlined in Table 3.6 (such as missing data and noisy data), assessing the model's performance is essential. Mean squared error is a commonly used metric for measuring predicted and actual values. It calculates the average of the squares of the differences between the predicted and actual values and represents the difference between the estimated and actual values. The value of MSE indicates the prediction's accuracy, reflecting any deviation from the expected outcome.

$$MSE = \underbrace{\frac{1}{n}\sum_{i=1}^{n}}_{\textbf{test set}} (y_i - x_i)^2 \tag{3.33}$$

Where y_i and x_i are anticipated (Actual) value predicted value, respectively, MSE values are not associated with a specific unit [125]. As an example, a line graph in Fig. 3.23 depicts the mean squared error loss for the train (Red), and test (Dashed Blue) sets across the training epochs[7]. Undoubtedly, the algorithm merged very rapidly, and the efficiency of the train and the test stayed equal. The model's effectiveness and convergent behaviour indicate that Mean Square Error (MSE) is a suitable metric for a NN learning this task.

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[7] The overall quantity of training data iterations in a single loop for training the algorithm

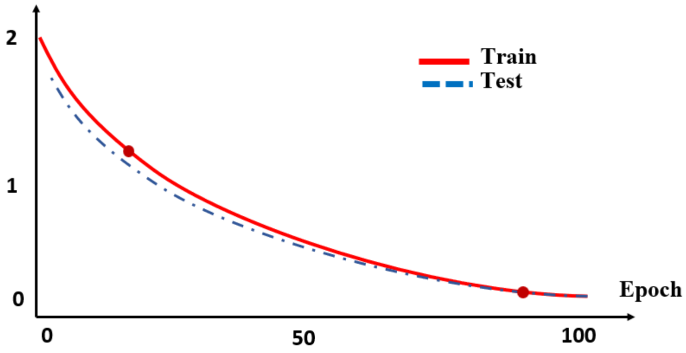

Figure 3.23: Mean squared error loss

The Root Mean Square Error (RMSE) is equal to the square root of MSE [125];

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{Predicted_i - Actual_i}{\sigma_i}\right)^2} \tag{3.34}$$

Deep learning is a rapidly growing area of artificial intelligence that has become increasingly relevant in recent years. It involves using neural networks to analyze data and make predictions based on the learned relationships. The process of deep learning involves several key steps, including data collection, pre-processing, training, and inference. During the training phase, the model is evaluated using techniques such as mean squared error to assess its accuracy. Overall, deep learning has the potential to revolutionize many industries by providing innovative solutions to complex problems.

3.4.2 Application of ANN in Risk Assessment

In risk assessment, ANNs are used to model the relationship between different variables that impact risk and to predict the potential for hazards and risk levels. ANNs can be trained on large data sets and learn and adapt to new data, making them useful for real-time risk analysis. The use of ANNs in risk assessment can provide many benefits. For example, ANNs can handle non-linear relationships between variables, identify patterns and relationships in large and complex data sets, make predictions, and perform extrapolations beyond the data used in training. Despite these benefits, applying ANNs in risk assessment also poses some challenges. One of these challenges is the need for accurate and comprehensive data to train the model. Another challenge is the need for effective model validation and testing to ensure the model's predictions are reliable and trustworthy. As listed in Table. 3.7 ANNs can play an increasingly important role in enhancing safety in various engineering fields, and industries [126].

Table 3.7: Risk Analyses methods based on Fuzzy Fault Tree

References	Proposed approaches
In [127]	Employing the FMEA and FTA integrated with the Ann, a generic model is developed to determine the ship's mechanical system's most vital modules and elements. ANN employs physical characteristics (temperature, pressure) of essential elements of the FTA as input in NN for time series analysis and possible trend prediction.
In [128]	Combining PRA and ANN was employed to detect potentially risky situations in a polymer storage facility for bulk styrene. The Ann algorithm forecasts BEs probabilities. Accordingly, a sensitivity analysis of the implicated basic events was conducted to determine their influence on the accident's cause and effect.
In [129]	ANN is trained using the vertical jet fire forms of propane. A Bayesian neural network was utilised as the three-layer backpropagation training with the sigmoid transfer function. Furthermore, to predict the outcome variables of jet flame lengths and jet flame diameters, it was contrasted with a Radial based functions method based on a single hidden layer.
In [130]	A system breakdown risk analysis is conducted using ANN in the Tesoro Anacortes Refinery disaster and is supported by a technique for projecting FT into ANN. The outcomes demonstrate the utility of the ANN framework translated from the fault tree as a method for risk evaluation.
In [131]	Coupling ANN and FTA applied to estimate the frequency of coal and gas outburst occurrences. This pairing provides a solid option prediction technique.
In [132]	They established a neural network algorithm to signify the hazard of CO_2 leakage in Texas oil fields. This proposal improves the storage procedures' implementation by identifying the possibility of CO_2 leakage.
In [133]	To develop an effective ANN model, it is required to modify algorithms such as identifying the number of hidden layer neurons, choosing the right transfer function of neurons, and the training process.
In [134]	ANNs are independent in understanding the link between input and output variables; hence, reliance on expert opinion is less about system structure and complicated connection patterns among system elements.

Fault tree analysis is a comprehensive information base for developing an ANN model. Using FTA provides valuable insights into the interactions between system components and the relationships between the various events that can lead to a system failure. This information can be used to train the ANN to make predictions about the likelihood of a failure event, as well as the impact of the event on the system. By incorporating the knowledge obtained from FTA into the ANN model, the accuracy and reliability of the predictions can be improved. Additionally, using ANNs provides a more flexible and adaptable approach to modelling complex systems compared to traditional FTA, addressing some limitations, such as limitations of probabilistic analysis and incomplete data. Combining FTA and ANN provides a powerful tool for predicting system failures and mitigating their consequences.

3.4.3 Fault tree Mapping into Deep Neural Network

The aim behind mapping an FT into deep learning is to utilize the capabilities of ANNs to address traditional FT analysis's limitations and provide a more effective tool for fault prediction and consequence analysis. These challenges include:

- Complexity and Time-consuming Nature: The complexity and comprehensibility of traditional FTA are often challenging when dealing with large-scale systems, particularly Nuclear NPPs, which consist of hundreds of components that operate independently or interdependently. This complexity can result in significant inaccuracies and inconsistencies in the analysis due to the difficulty in comprehending the numerous BEs and intermediate events involved.
- Limitations of Probabilistic Analysis: Fault tree analysis relies on probabilistic analysis, which is limited in its ability to capture complex interactions between BEs and intermediate events to estimate the failure probability of the top event.
- Incomplete and Missing Data: The scarcity of complete data presents a challenge in conventional FTA as it can hinder the estimation of event probabilities with accuracy. This absence or incompleteness of data can result in significant inaccuracies and inconsistencies within the analysis.

  Rigidity: Probabilistic analysis can be limited in its ability to adapt to changing conditions or new data, as it is based on fixed assumptions and models.

The fault tree will be utilized as an informational basis for creating a DL model. The proposed methods for mapping the FT into the ANN are shown in Fig. 3.24.

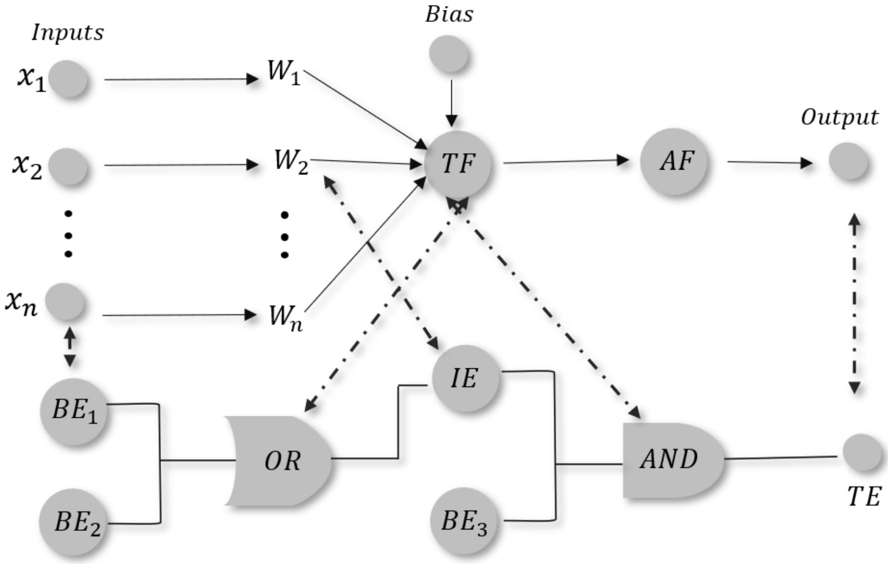

Figure 3.24: Depicts the mapping of fault tree components into an ANN, the BEs serve as inputs, intermediate events are mapped to hidden layers, logical gates are transformed into transfer functions (weights), and the top event is represented as the output of the ANN.

Mapping the components of an FT into the parts of an ANN is an important step in incorporating FT analysis into the framework of ANNs. The main components of an FT are BEs, intermediate events, TE, and logical gates, which are used to model the relationship between the BEs and the TE, representing the system's failure. According to the diagram (Fig. 3.24), each element of FT is converted into a deep learning algorithm. Based on the proposed model, the mapping methods are:

- **Basic Events** serve as **Inputs**; the inputs to the ANN are the states of the BEs, which can be binary (e.g. active or inactive) or continuous. The hidden layer neurons then process the inputs, which capture the complex interactions between the BEs and the TE. Finally, the outputs from the hidden layer are used to estimate the probability of the TE.
- **Intermediate Events** serve as **Hidden layers**; the intermediate events in the FT can be transformed into hidden layer neurons in the ANN, which will capture the complex relationships between the BEs and the TE. The hidden layer neurons in the ANN are crucial in providing a more comprehensive representation of the FT, which can be used to predict potential faults and their consequences. The hidden layer neurons in the ANN can also be trained to improve their representations of the FT, allowing for better predictions over time.
- **Logic Gates (OR and AND)** are mapped into a **Weights and transfer function**; the logic gates present in an FTA are mapped into an ANN by implementing the transfer function and assigning weights to the neurons in the network. The transfer function, which defines the activation or output of a neuron in the ANN, can be utilized to model the operations of the logic gates. For instance, the AND gate in an FT can be represented by a transfer function that only activates and outputs a value of 1 if all inputs to the neuron are active. On the other hand, an OR gate is represented by a transfer function that activates and outputs a value of 1 if any of its inputs are active. It is worth noting that the specific form of the transfer function will vary based on the chosen implementation of the ANN.
- **Top Event (TE)** is transformed into the **Output**; the top event in an FT can be mapped into the output layer of the ANN. This output layer can be depicted by a single neuron representing the probability of the top event (e.g., system failure) occurring. The activation of this output neuron is determined by the activations of the neurons in the hidden layer, which represents the intermediate events in the FT. The activations of these intermediate events are influenced by the weights of the connections between the neurons, which represent the relationships between the events in the FT.

After mapping the components of FT into the ANN, the next step is to train the ANN using historical data. This involves providing the ANN with input data and adjusting the weights of the connections between the neurons to minimize the difference between the actual output and the expected output. Once the ANN is trained, it can be used to predict the likelihood of the top event occurring, given the status of the BEs. The accuracy of these predictions can be evaluated, and the ANN can be further refined as necessary to improve performance.

Configuration of NN Elements

A deep learning algorithm is an ANN subset for complex pattern recognition and prediction tasks. It is based on a regression algorithm, a technique used to determine the relationship between inputs and outputs. The purpose of this relationship is to make predictions about new data based on previously observed patterns. By mapping the components of an FT, such as BEs and logic gates, into the weights and transfer functions of an ANN, the deep learning algorithm can be used to make accurate predictions about the likelihood of the TE in the FT. The specific configuration of the deep learning algorithm will depend on the problem's requirements and the desired accuracy level. The objective is to identify hidden layers density, the transfer function of each layer, and the learning procedure to avoid the over-fitting[8] and under-fitting[9] problems. In order to address the over-fitting and under-fitting, the following rules are considered:

1. The hidden layers' neuron number should amount to less than those in the input and output layers combined.
2. Two-thirds of the input and the output layer neurons should make up the number of hidden neurons.
3. In the FT, the amount of the first hidden layer neuron and intermediate events connected to the BEs might be equal.

Approximating certain boundaries with absolute precision utilizing linear and non-linear transfer functions in a neural network with two hidden layers is possible. It can provide a close approximation of any smooth projection. Due to high network complexity and lengthy overall training time, ANNs with three or more hidden layers are rarely deployed [135]. Furthermore, the last layer correlates to the output of deep learning, also known as the TE.

In the next chapter, we will utilize the earlier mapping to convert FT into an ANN to obtain the failure probability of TE (PRHRS) in CAREM-25. This will involve assigning weights and transfer functions to the neurons in the ANN to accurately capture the interactions and relationships between the BEs and the TE in the FT. This process aims to use the ANN to simulate the behaviour of the passive safety system and estimate its failure probability, thereby providing valuable information for risk analysis and design optimization.

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[9] Network over-fitting denotes a network's well performance on training data and poor performance on testing data due to learning many details and noises in training data.

[9] Under-fitting, while, meaning that the model performs poorly on both datasets

3.5 Conclusion of Chapter 3

In conclusion, fuzzy logic and ANN integration have been widely explored to support risk assessment processes in various engineering fields. Using fuzzy logic allows for the representation of uncertainty in risk analysis, while ANN can be employed for complex and non-linear risk analysis. Meanwhile, the integration of fuzzy PSA and fuzzy FMEA leverages the advantages of both fuzzy logic and conventional risk analysis methods, resulting in improved efficiency and accuracy of the risk analysis process.

In the subsequent chapter, we will examine the application of these techniques to a specific passive safety system in a small modular reactor. By combining the strengths of fuzzy logic, ANN, fuzzy PSA, and fuzzy FMEA, we aim to provide a comprehensive and robust risk assessment framework to ensure the safe and reliable operation of the small modular reactor. The mapping of ANN into the FTA further enhances the risk analysis process by enabling the efficient and accurate identification and evaluation of potential hazards in complex systems.

Chapter 4

Fuzzy risk analysis methods and ANN-based safety Analysis

The previous chapters have conducted a comprehensive analysis and discussed the limitations of conventional safety analysis methods, specifically PSA and FMEA. It has been established that these methods have constraints regarding their ability to handle uncertainty in input data and imprecise information. The fuzzy logic and ANNs approach was proposed and implemented to address these limitations. The isolation condenser system in a CAREM-25 small modular reactor has been selected as the benchmark system for the present analysis due to its simplified design, which primarily aims to remove decay heat from the RPV. The simplicity of the ICS design provides an ideal environment for evaluating the performance of fuzzy and ANN-based methods in the analysis of ICS.

This chapter comprises three primary sections: fuzzy PSA, fuzzy-FMEA, and ANN-based FTA. Each section discusses a distinct analytical approach to evaluating the safety of ICS systems. The first approach proposes a fuzzy PSA method for evaluating the failure probability of the PRHRS during severe beyond design basis (SBO) accident scenarios. The fuzzy fault tree analysis approach is adopted to model the system behaviour and quantify the failure probability of the PRHRS components. A Simulink/Matlab-based model is developed to replace Pandora and fuzzy operators with classical Boolean gates. This captures the interactions between various BEs and intermediate events, considers the time and event order sequence, and calculates the failure probability of TE. The Fuzzy Fault Tree Analysis (FFTA) results are then incorporated into the Fuzzy Event Tree Analysis (FETA) to estimate the consequence and its probability of core damage frequency under SBO.

The next step proposes a fuzzy-FMEA for the PRHRS under consideration. This analysis aims to integrate the results obtained from the FFTA into the fuzzy-FMEA framework by incorporating dynamic failure occurrence. This requires the identification of the potential failure modes within the PRHRS, evaluating their associated effects, and multiplying occurrence, severity, and detectability to calculate the fuzzy RPN.

In the final step of this study, the FTA will be mapped into an ANN to perform an ANN-based FTA. This mapping process aims to convert the FT components (BEs, logic gates, intermediate events, and TE) into the ANN ones. The ANN-based FT analysis results will then be compared to those obtained from the traditional FTA to evaluate the ANN's performance accurately representing the system's FT. Comparing the two methods will provide valuable insights into the ability of ANNs to perform PSA and highlight each approach's strengths and limitations.

4.1 CAREM-25's PRHRS

CAREM-25, being an SMR project, places a significant emphasis on PSSs to ensure the plant's safe operation and minimize the consequences of an accident. One critical PSSs in CAREM-25 is the Passive Residual Heat Removal System (PRHRS), designed to extract decay heat from the core during a heat sink failure. The Passive residual heat removal system is responsible for removing the residual heat generated by the reactor in the event of an accident scenario, such as a LOCA or a Small Break Loss of Coolant Accident (SBLOCA). The isolation condenser system is designed to remove decay heat and provide secondary depressurization for the Reactor Pressure Vessel (RPV) in emergency scenarios. The system consists of two HXs immersed in a cooling pool connected to the RPV. The isolation condenser system uses natural circulation to transfer heat from the RPV to the pool, where the high-temperature steam is condensed and pumped back into the RPV.

The heat exchangers are responsible for absorbing heat from one fluid stream, and they are submerged in an Isolation Condenser (IC) pool, which helps to dissipate the heat absorbed by the HXs into the surrounding environment. The pipelines connecting the HXs to the RPV serve as the medium through which the fluid streams flow in and out of the HXs. These pipelines ensure that the fluid streams are adequately transported to and from the HXs and that the heat transfer process is efficient. The pressure vessel serves as the containment for the fluid streams in the system. It is designed to withstand the fluid streams' internal pressure and prevent any leakage or release of the fluids into the surrounding environment. Overall, the passive system with the layout described in Fig. 4.1 is designed to efficiently transfer heat between the two fluid streams using the HXs, while ensuring the safe containment of the fluids within the RPV.

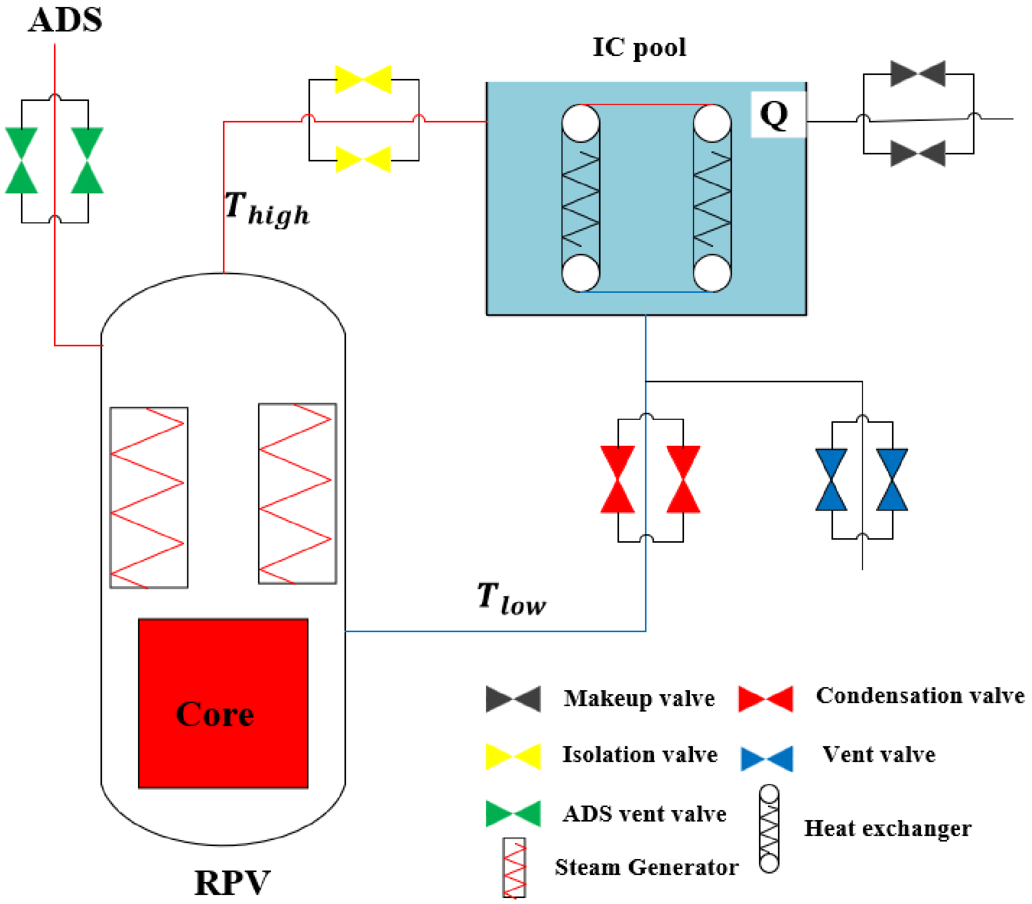


Figure 4.1: PRHRS and ADS in CAREM-25

According to Fig. 4.1, PRHRS is operated by releasing specific valves that are designed to fail to open in the event of a power failure or a signal failure, allowing vapour to reach the submerged HXs and be condensed (removing heat (Q) into the cooling tank) through heat transfer. The isolation condenser system comprises a cooling pool and two immersed HXs. It is placed above the RPV, and HXs condense the arriving steam with high temperature (T_{high}) in the pool, and after taking the heat, the low-temperature flow (T_{low}) pumps into the reactor vessel.

In CAREM-25, the PRHRS uses NC to transfer heat from the RPV to the cooling system. Two shared headers link two submerged HXs to the RPV. The upper (hot leg) and lower (cold leg) headers lead to the RPV's steam dome, and the lower head is tied below the reactor water level. The inlet valve on the steam line is generally open, and two redundant condensation valves on the outlet line are usually closed. The heat exchanger tubes are thus filled with condensate (cold water). The condensation valves regulate the Counter-Current Flow (CCF) to enable water to drain into the RPV without recirculating to the ICS through the cold leg. The condensation valves are coupled to two vent valves that evacuate the non-condensable gas during condensation. Two redundant makeup valves are installed in the IC pool to regulate the condensate level. The isolation condenser system is triggered when the high reactor pressure, MSIV closure, or RPV water level signal is detected. Steam enters the HXs from the RPV via the hot leg isolation valves and is cooled on the cold shell of the tubes, transmitting heat to the IC pool. The cold leg is then carried to the lower head of the reactor pressure vessel, inducing a natural circulation loop caused by the variation in water density. Heat is extracted, created steam travels to the IC, then steam condenses on the HXs tube side and returns to the core; heat is transferred to the pool on the shell side of the IC; after pool water vaporizes, heat is vented out to the atmosphere above the IC pool. The heat source and sink guarantee the NC's faultless operation. Nevertheless, the ICS fails if the IC or the NC fails. Therefore, when the pressure reaches the predetermined target, the ADS depresses the containment vessel. In the near term, the activation of ADS results in the loss of water inventory but simultaneously eliminates decay heat. The loss of inventory due to long-term cooling is eventually detrimental. In addition, the ADS valves are often requested after they have been activated, resulting in pressure oscillations. Meanwhile, the ADS valves are more prone to break as their use increases. In this case, ICS is also used to reduce the activation of ADS [42].

Conducting a fuzzy PSA for PRHRS described above involves incorporating uncertainty and imprecision into the assessment process by using fuzzy sets to represent probabilities of failure or consequences. The steps involved defining the scope of the assessment, developing an FFT and assigning fuzzy MFs, estimating the TE failure probability, then developing a FETA based on data obtained from FFTA.

4.2 Fuzzy PSA model for PRHRS failure

The primary objective of the proposed fuzzy PSA is to evaluate the reliability of PRHRS in the CAREM-25. To accomplish this objective, a combination of FFTA and FETA methodologies is suggested to identify potential weaknesses in the system, assess its operational efficiency, and determine the overall risk to the reactor core in the event of ICS failure. The concept of fuzzy PSA has been introduced and explained in detail in the previous chapter (sections 3.2). In this work, conducting a fuzzy PSA for the PRHRS involves the following two main steps:

- Fuzzy Fault Tree:
  1. Define the scope of the assessment: Clearly define the system and component boundaries of the PRHRS that will be included in the assessment. This should include the heat exchangers, pumps, and piping.
  2. Develop FFT: Constructing an FT diagram for ICS failure based on BEs, intermediate events and undesired TE.
  3. Assign fuzzy MFs and implement Pandora gates: In this stage, assign fuzzy MFs to the FT components based on triangular failure probabilities and connect BEs to intermediate events using Pandora gates and fuzzy operators.
- Fuzzy Event Tree:
  1. Develop the FET: In a FET, each mitigating system's probability of failure or success is represented by TFN.
  2. Conduct the FETA: Using Simulink/Matlab, the FETA is conducted to estimate the path consequence probabilities.

Following FFTA and FETA, the fuzzy PSA results are interpreted by analyzing the top event's probabilities and the events' consequences. This information can inform decisions about the safety of the PRHRS and identify areas for improvement.

4.2.1 Fuzzy Fault Tree Analysis for ICS and ADS

Understanding the potential failure modes and their underlying causes is crucial for ensuring a reliable passive means of removing residual heat in case of an accident. These potential failure modes illustrate in Fig. 4.2, where three main contributors to the failure of PRHRS are outlined. It is important to note that these failures are not isolated incidents but result from a composite of three distinct events. Firstly, NC failure occurs when the system's flow is disrupted and no longer functions as intended. Secondly, failure of the ICS refers to a breakdown or malfunction of specific parts within the system (HXs and valves). Finally, pipe rupture can occur in the inlet or outlet pipelines, resulting in a breach in the flow, losing heat sink and potentially causing system failure.

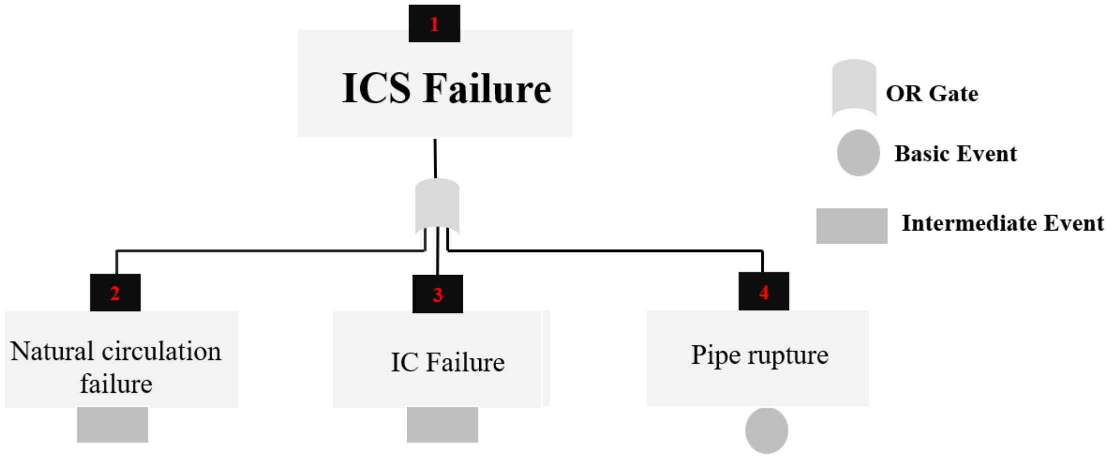


Figure 4.2: Different failure modes of the ICS, including NC, pipe rupture, and IC failure.

The natural circulation failure in the ICS can be attributed to several underlying causes, including envelope failure, cracking, thermal stratification, and components failure. The probability of NC failure can be assessed through FFTA, as demonstrated in Fig. 4.3. This analysis highlights possible failures, including insufficient heat transfer to external sources and a high concentration of non-condensable (resulting from a failure of the vent valve to purge uncondensables), which contribute to NC failure.

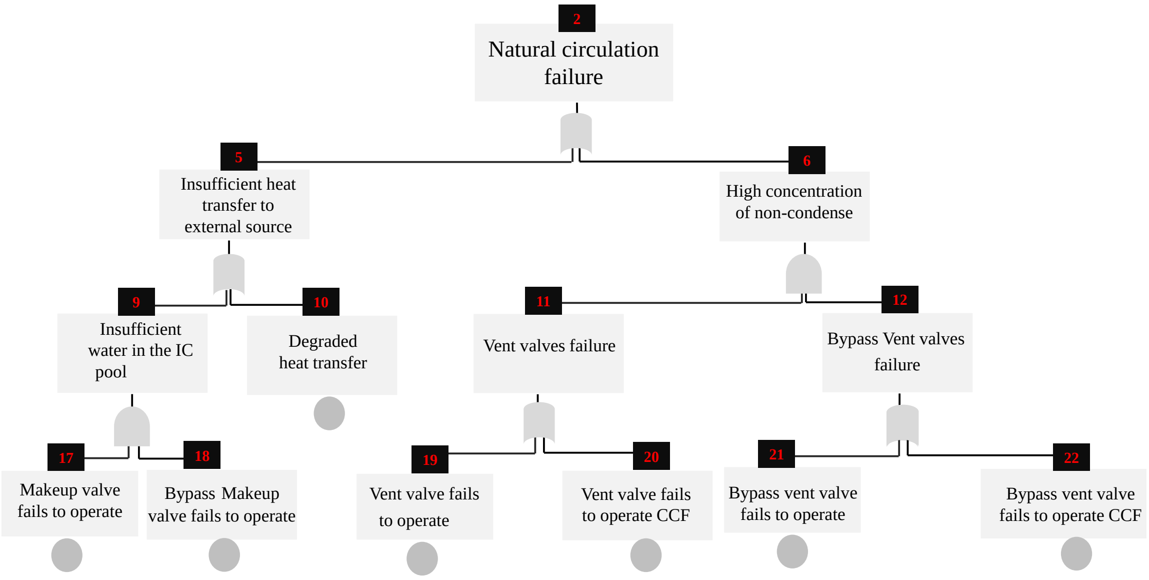


Figure 4.3: Causes of NC failure, including insufficient heat transfer and high non-condensable concentration and their BEs

In the ICS's FT (as shown in Fig. 4.4), the failure of the two main components, the HXs and the condensation valves are the leading causes of ICS failure. Each component has its failure modes; for example, the HXs could fail if there is a multiple pipe rupture or multiple pipes plugging during operation.

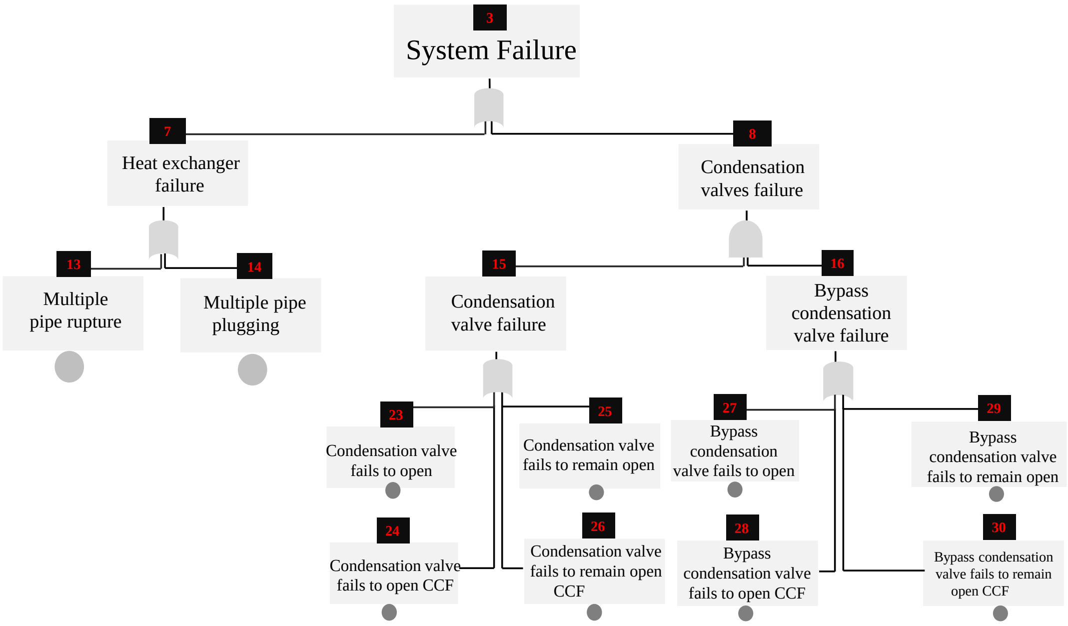


Figure 4.4: The ICS failure contributions, HXs and condensation valves, each component has its causes of failure.

Figure 4.5 depicts the FT for the ADS system, which reveals that the system will fail if either the safety relief valve or the bypass valve fails to operate. The combination of these two failures is modelled using AND gates, which require all input events (BEs) to occur for the output event to be positive. From a system reliability perspective, it is essential that both valves operate correctly for the ADS system to function properly.

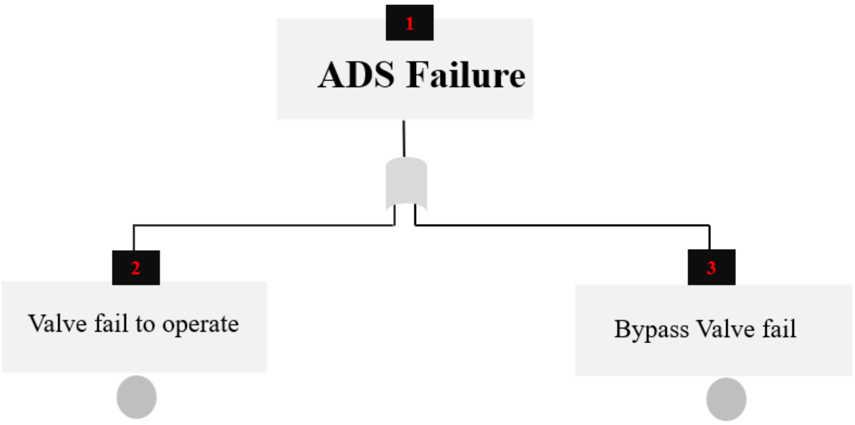


Figure 4.5: Fault tree of ADS

In Table. 4.1 listed failure rates (for all BEs, intermediate events) adopted from [42, 136]. There are 18 BEs and 11 intermediate events contributing to the failure of the ICS, including component failures and failure of natural processes that serve as PSSs.

Table 4.1: List of events with probability from the fault tree [42, 136]

Failure Number	**Event**	**Failure Rate**
1	PRHRS failure	1.95×10^{-06}
2	Natural circulation failure	2.17×10^{-07}
3	System failure	6.42×10^{-06}
4	Pipe rupture	2.4×10^{-06}
5	Insufficient heat transfer to external source	3.35×10^{-09}
6	High concentration of non-condense (Vent valve fails to purge uncondensables)	2.13×10^{-07}
7	Heat exchanger failure	4.32×10^{-09}
8	Condensation valves failure	2.12×10^{-09}
9	Insufficient water in the IC pool (makeup valve fails to operate)	1.19×10^{-09}
10	Degraded heat transfer (excessive pipe fouling)	2.19×10^{-09}
11	Vent valves failure	4.62×10^{-04}
12	Bypass Vent valves failure	4.62×10^{-04}
13	Multiple pipe rupture	2.16×10^{-09}
14	Multiple pipe plugging	2.16×10^{-09}
15	Condensation valve failure	4.59×10^{-05}
16	Bypass condensation valve failure	4.59×10^{-05}
17	Makeup valve fails to operate	3.45×10^{-05}
18	Bypass makeup valve fails to operate	4.20×10^{-05}
19	Vent valve fails to operate	4.20×10^{-04}
20	Vent valve fails to operate CCF	4.20×10^{-05}
21	Bypass vent valve fails to operate	4.20×10^{-04}
22	Bypass vent valve fails to operate CCF	4.20×10^{-05}
23	Condensation valve fails to open	3.45×10^{-05}
24	Condensation valve fails to open CCF	3.45×10^{-06}
25	Condensation valve fails to remain open	7.20×10^{-06}
26	Condensation valve fails to remain open CCF	7.20×10^{-07}
27	Bypass condensation valve fails to open	3.45×10^{-05}
28	Bypass condensation valve fails to open CCF	3.45×10^{-06}
29	Bypass condensation valve fails to remain open	7.20×10^{-06}
30	Bypass condensation valve fails to remain open CCF	7.20×10^{-07}

To implement FFTA, first, the failure rates in Table 4.1 are converted from crisp values to TFN to reflect the uncertainty in the data. Each crisp failure rate is represented by ξ, and the lower and upper boundaries of the fuzzy number can be calculated using a range of uncertainty (ϱ) and a specified percentage of the lower and upper bounds (e.g. 15%). This approach provides a more accurate representation of the uncertainty in the failure rates and allows for a more comprehensive analysis.

The TFN method's use for converting crisp values into fuzzy numbers has been discussed in the preceding chapter 3.2. This method is based on the mathematical expression:

$$\begin{cases} \tilde{A} = (\xi - \varrho \times \xi, \xi, \xi + \varrho \times \xi) \\ \\ \text{Lower bound} \Longleftrightarrow \xi - \varrho \times \xi \\ \\ \text{Upper bound} \Longleftrightarrow \xi + \varrho \times \xi \end{cases} \tag{4.1}$$

In this work, the uncertainty around failure rates is considered $\varrho = 15\%$, encompassing both aleatory and epistemic uncertainty. For example, if the crisp failure rate of a pipe rupture is reported as $\xi = 2.4 \times 10^{-06}$, this value can be plugged into equation (4.1) to convert it into a fuzzy number, taking into account the uncertainty ϱ:

$$\begin{aligned} &\tilde{A} = (2.4 \times 10^{-06} - 15 \times 2.4 \times 10^{-06}, 2.4 \times 10^{-06}, 2.4 \times 10^{-06} + 15 \times 2.4 \times 10^{-06}) \\ &= (2.0 \times 10^{-06}; 2.4 \times 10^{-06}; 2.8 \times 10^{-06}) \end{aligned} \tag{4.2}$$

The TFN representation of the pipe rupture failure rate can be denoted by $\tilde{A}$, and the corresponding shape of this fuzzy number is illustrated in Fig. 4.6. The TFN method converts crisp failure rates for all basic events listed in Table 4.1 into fuzzy numbers, enabling uncertainty incorporation in the failure rates.

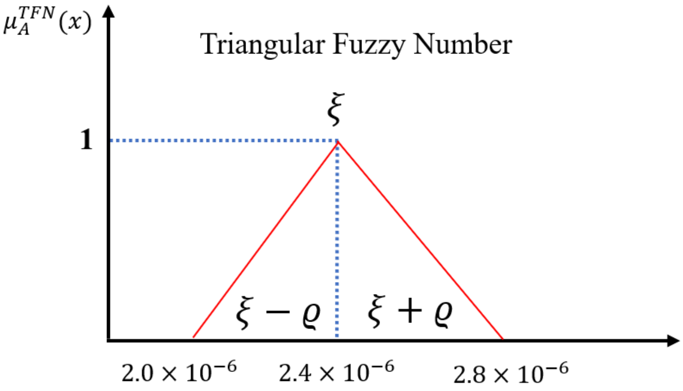


Figure 4.6: The TFN for pipe rupture, including lower bound, best estimate, and upper bound

Converting failure rates into fuzzy numbers using the TFN method allows for a more comprehensive system safety analysis by capturing the uncertainty and imprecision associated with failure rate estimates. Table 4.2 and 4.15 show the fuzzy numbers generated by applying the TFN method to the failure rates of other BEs. As the intermediate event probabilities are generated using FFTA, they are not required in this work.

Table 4.2: Triangular fuzzy number for BEs in ICS

#	Basic Events	**Triangular Fuzzy number**
4	Pipe rupture	$\tilde{A}_1$=$(2.0{\times}10^{-06}; 2.4 \times 10^{-06}; 2.8 \times 10^{-06})$
10	Degraded heat transfer	$\tilde{A}_1$=$(2.5{\times}10^{-11}; 3.0 \times 10^{-11}; 3.4 \times 10^{-11})$
15	Condensation valve failure	$\tilde{A}_1$=$(2.9{\times}10^{-05}; 3.4 \times 10^{-05}; 3.9 \times 10^{-05})$
13	Multiple pipe rupture	$\tilde{A}_1$=$(1.8{\times}10^{-09}; 2.1 \times 10^{-09}; 2.9 \times 10^{-09})$
24	Condensation valve failure to open (CCF)	$\tilde{A}_1$=$(2.5{\times}10^{-06}; 3.4 \times 10^{-06}; 3.9 \times 10^{-06})$
14	Multiple pipe plugging	$\tilde{A}_1$=$(1.8{\times}10^{-09}; 2.1 \times 10^{-09}; 2.9 \times 10^{-09})$
25	Condensation valve fails to remain open	$\tilde{A}_1$=$(6.1{\times}10^{-06}; 7.2 \times 10^{-06}; 8.2 \times 10^{-06})$
17	Makeup valve failure	$\tilde{A}_1$=$(2.9{\times}10^{-05}; 3.4 \times 10^{-05}; 3.9 \times 10^{-05})$
26	Condensation valve fails to remain open CCF	$\tilde{A}_1$=$(6.1{\times}10^{-07}; 7.2 \times 10^{-07}; 8.2 \times 10^{-07})$
18	Bypass makeup valve failure	$\tilde{A}_1$=$(2.9{\times}10^{-05}; 3.4 \times 10^{-05}; 3.9 \times 10^{-05})$
27	Bypass condensation valve fails to open	$\tilde{A}_1$=$(2.9{\times}10^{-05}; 3.4 \times 10^{-05}; 3.9 \times 10^{-05})$
11	Vent valve failure to operate	$\tilde{A}_1$=$(3.6{\times}10^{-04}; 4.2 \times 10^{-04}; 4.8 \times 10^{-04})$
28	Bypass condensation valve fails to open CCF	$\tilde{A}_1$=$(2.5{\times}10^{-06}; 3.4 \times 10^{-06}; 3.9 \times 10^{-06})$
20	Vent valve failure to operate (CCF)	$\tilde{A}_1$=$(3.6{\times}10^{-05}; 4.2 \times 10^{-05}; 4.8 \times 10^{-05})$
29	Bypass condensation valve fails to remain open	$\tilde{A}_1$=$(6.1{\times}10^{-06}; 7.2 \times 10^{-06}; 8.2 \times 10^{-06})$
21	Bypass vent valve failure to operate	$\tilde{A}_1$=$(3.6{\times}10^{-04}; 4.2 \times 10^{-04}; 4.8 \times 10^{-04})$
30	Bypass condensation valve fails to remain open CCF	$\tilde{A}_1$=$(6.1{\times}10^{-07}; 7.2 \times 10^{-07}; 8.2 \times 10^{-07})$

Note*: The number behind the BEs indicates the positions in FT diagrams in 4.2 - 4.4
CCF Stands for Counter-Current Flow.

Table 4.3: Triangular fuzzy number for BEs in ADS

Basic Events	**Failure Probability** [42]	**Fuzzy Failure Possibility**
Valve Fail to Operate	1.0×10^{-06}	$\tilde{A}_1$=$(0.8{\times}10^{-06}; 1.0 \times 10^{-06}; 1.2 \times 10^{-06})$
Bypass Valve Fail	1.0×10^{-06}	$\tilde{A}_1$=$(0.8{\times}10^{-06}; 1.0 \times 10^{-06}; 1.2 \times 10^{-06})$

Implementing fuzzy operators and Pandora gates in an FT involves the incorporation of the corresponding logic gates to represent complex dependencies and interactions between events. Specifically, the Pandora gate can combine several BEs that lead to a particular consequence or failure. This incorporation represents a shift from classical gates to dynamics and is predicated on the priority of failure, which asserts that components with higher failure rates will fail sooner. In this thesis, based on the relationship between different BEs and intermediate events, the fuzzy operator and Pandora gate can be expressed as follows:

The failure possibilities $P_i(t) = (a_i(t), b_i(t), c_i(t))$ associated with the input events of a dynamic fuzzy operator AND gate at time t can be represented as:

$$P_{AND^F}(t) = AND^F\left\{P_1(t), P_2(t), \ldots, P_N(t)\right\}$$
$$=\left\{\prod_{i=1}^{N} a_i(t), \prod_{i=1}^{N} b_i(t), \prod_{i=1}^{N} c_i(t)\right\} \quad (i = 1, 2, \ldots, N) \tag{4.3}$$

Considering there is triangular fuzzy failure rates $\lambda_i = (a_i, b_i, c_i)$

Suppose the failure possibilities of the event BE_i are provided as a fuzzy triangular number λ_i and let $P_i(t) = (a_i(t), b_i(t), c_i(t))$ represent a triangular illustration of the failure possibilities associated with an OR gate's input events at time t. Then, the fuzzy OR operator can be applied to λ_i and $P_i(t)$ to determine the output fuzzy number associated with the OR gate's failure possibilities.

$$P_{OR^F}(t) = OR^F\left\{P_1(t), P_2(t), \ldots, P_N(t)\right\} = 1 - \prod_{i=1}^{N}(1 - P_i(t))$$
$$= \left\{1 - \prod_{i=1}^{N}(1 - a_i(t)), 1 - \prod_{i=1}^{N}(1 - b_i(t)), 1 - \prod_{i=1}^{N}(1 - c_i(t))\right\} \quad (i = 1, 2, \ldots, N) \tag{4.4}$$

When the MF is modelled as trapezoidal, an element must be added to Eqs. 4.3 and 4.4 to incorporate this shape into calculating failure possibilities associated with PAND and POR gates.

Specifically, for a set of N statistically independent BEs, each characterized by a triangular fuzzy number $\lambda_i = (a_i, b_i, c_i)$, the failure possibilities associated with a PAND gate can be represented via an algebraic model denoted by the symbol $\lhd$, which can be calculated as follows:

$$P\left\{BE_1 \lhd BE_2 \lhd BE_3 \lhd \cdots \lhd BE_{n-1} \lhd BE_n\right\}(t) = \prod_{i=1}^{N} \lambda_i \sum_{k=0}^{N} \left[\frac{e^{u_k t}}{\prod_{\substack{j=0 \\ j \neq k}}^{N}(u_k - u_j)}\right] \tag{4.5}$$

Where the $\lambda_i(t) = (a_i(t), b_i(t), c_i(t)) = (1 - e^{-\lambda_{i1} t}, 1 - e^{-\lambda_{i2} t}, 1 - e^{-\lambda_{i3} t})$ and t represent the fuzzy failure rate for i^{th} component and mission time, respectively. N is the total number of BEs, $\lambda_i(t)$ is the fuzzy failure rate of the i^{th} basic event λ_{i1}, λ_{i2}, and λ_{i3} are the elements of that fuzzy failure rate. There are some criteria $\begin{cases} \mathrm{u}_0 = 0 \\ \mathrm{u}_m = -\sum_{j=1}^{m(m>0)} \lambda_i \end{cases}$.

$$P^{PAND}(t) = \left[\prod_{i=1}^{N} a_i \sum_{k=0}^{N} \left[\frac{e^{u_k t}}{\prod_{\substack{j=0 \\ j \neq k}}^{N}(u_k - u_j)}\right], \prod_{i=1}^{N} b_i \sum_{k=0}^{N} \left[\frac{e^{u_k t}}{\prod_{\substack{j=0 \\ j \neq k}}^{N}(u_k - u_j)}\right],\right.$$
$$\left.\prod_{i=1}^{N} c_i \sum_{k=0}^{N} \left[\frac{e^{u_k t}}{\prod_{\substack{j=0 \\ j \neq k}}^{N}(u_k - u_j)}\right]\right. \tag{4.6}$$

As FT proposed (Fig. 4.2-4.4), the ICS has some intermediate events with 2, 3, and 4 facets BEs as inputs (with failure rate $\lambda_i(t) = (a_i(t), b_i(t))$) in the PAND gate, Eq. 4.5 rewriting as:

PAND for 2 BEs Input:

$$P_{N=2}^{PAND}(t) = \frac{\lambda_2}{(\lambda_1 + \lambda_2)} - e^{(-\lambda_1 t)} + \frac{\lambda_1}{(\lambda_1 + \lambda_2)} e^{[-(\lambda_1+\lambda_2)t]} \tag{4.7}$$

For 3 BEs Input:

$$\begin{aligned} P_{N=3}^{PAND}(t) = {} & \frac{\lambda_2 \cdot \lambda_3}{(\lambda_1 + \lambda_2) \cdot (\lambda_1 + \lambda_2 + \lambda_3)} - \frac{\lambda_3}{(\lambda_2 + \lambda_3)} e^{(-\lambda_1)t} \\ & + \frac{\lambda_1}{(\lambda_1 + \lambda_2)} e^{-(\lambda_1+\lambda_2)t} - \frac{\lambda_1 \cdot \lambda_2}{(\lambda_2 + \lambda_3) \cdot (\lambda_1 + \lambda_2 + \lambda_3)} e^{-(\lambda_1+\lambda_2+\lambda_3)t} \end{aligned} \tag{4.8}$$

For 4 BEs Input:

$$\begin{aligned} P_{N=4}^{PAND}(t) = {} & \frac{\lambda_2 \cdot \lambda_3 \cdot \lambda_4}{(\lambda_1 + \lambda_2) \cdot (\lambda_1 + \lambda_2 + \lambda_3) \cdot (\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4)} \\ & - \frac{\lambda_3 \cdot \lambda_4}{(\lambda_2 + \lambda_3) \cdot (\lambda_2 + \lambda_3 + \lambda_4)} e^{-(\lambda_1)t} + \frac{\lambda_1 \cdot \lambda_4}{(\lambda_1 + \lambda_2) \cdot (\lambda_3 + \lambda_4)} e^{-(\lambda_1+\lambda_2)t} \\ & - \frac{\lambda_1 \cdot \lambda_2}{(\lambda_2 + \lambda_3) \cdot (\lambda_1 + \lambda_2 + \lambda_3)} e^{-(\lambda_1+\lambda_2+\lambda_3)t} \\ & + \frac{\lambda_1 \cdot \lambda_2 \cdot \lambda_3}{(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4) \cdot (\lambda_2 + \lambda_3 + \lambda_4) \cdot (\lambda_3 + \lambda_4)} e^{-(\lambda_1+\lambda_2+\lambda_3+\lambda_4)t} \end{aligned} \tag{4.9}$$

Similar to PAND gate, for N statistically independent BEs with a TFN $\lambda_i(t) = (a_i(t), b_i(t), c_i(t))$, an algebraic model represent a POR gate with the notation $\wr$, can be calculated as follows:

$$P\Big\{BE_1 \wr BE_2 \wr BE_3 \wr \cdots \wr BE_{n-1} \wr BE_n\Big\}(t) = \lambda_1 \cdot \left[\frac{1 - e^{-(\sum_{i=1}^{N} \lambda_i t)}}{\sum_{i=1}^{N} \lambda_i}\right] \tag{4.10}$$

Where λ_1 represents the failure rate of BE_1, meaning that, despite the conventional gates utilized in Fault Tree Analysis (FTA) in POR and PAND, it is crucial to consider which components or systems fail first, then plug in their failure rates depending on occurrence order. The probabilities of being in states 2, 3 and 4 are similarly given as:

POR for 2 BEs Input:

$$P_{N=2}^{POR}(t) = \frac{\lambda_1}{(\lambda_1+\lambda_2)} \cdot [1 - e^{-(\lambda_1+\lambda_2)t}] \tag{4.11}$$

For 3 BEs Input:

$$P_{N=3}^{POR}(t) = \frac{\lambda_1}{(\lambda_1+\lambda_2+\lambda_3)} \cdot [1 - e^{-(\lambda_1+\lambda_2+\lambda_3)t}] \tag{4.12}$$

For 4 BEs Input:

$$P_{N=4}^{POR}(t) = \frac{\lambda_1}{(\lambda_1+\lambda_2+\lambda_3+\lambda_4)} \cdot [1 - e^{-(\lambda_1+\lambda_2+\lambda_3+\lambda_4)t}] \tag{4.13}$$

The quantitative analysis of Pandora and fuzzy operators provide a means of estimating the probability of a TE occurring based on the failure rates of a system's BEs and intermediate events. To quantify TE accurately, it is necessary to quantify the gates within the FT. The analytical solutions for the fuzzy and Pandora gates equations are obtained by implementing Simulink blocks, which connect different BEs into intermediate events and TE.

For instance, Fig. 4.15 indicates that vent valve failure is caused by the sequential failure of the vent valve and the bypass vent valve CCF. By incorporating POR gate, mission time and order of events can be considered, allowing for prioritization, meaning that the valve with the higher failure rate is more likely to fail first. The probability of that POR gate for vent and bypass valves can be evaluated as:

$$P_{N=2}^{POR}(t) = \frac{\lambda_1}{(\lambda_1+\lambda_2)} \cdot [1 - e^{-(\lambda_1+\lambda_2)t}] \tag{4.14}$$

The fuzzy failure rates for the vent valve and bypass vent valve are represented by $\lambda_1 = (3.6 \times 10^{-04}; 4.2 \times 10^{-04}; 4.8 \times 10^{-04})$ and $\lambda_2 = (3.6 \times 10^{-05}; 4.2 \times 10^{-05}; 4.8 \times 10^{-05})$, respectively. In Pandora gates, the occurrence sequence of events is crucial, with the failure of the vent valve first, followed by the failure of the bypass valve. This sequence order is considered in the FFT's calculation, as shown in 4.14. The POR gate for vent and bypass valves is implemented in the Simulink environment, with the code presented in the corresponding block of the model as follows:

MATLAB®-Simulink Code For Priority-OR

```matlab
  function [y1,y2,y3] = fcn(l1,m1,n1,l2,m2,n2, t)
%POR
y1= (l1*(1-exp(-(l1+l2)*t)))/(l1+l2);
y2= (m1*(1-exp(-(m1+m2)*t)))/(m1+m2);
y3= (n1*(1-exp(-(n1+n2)*t)))/(n1+n2);
```

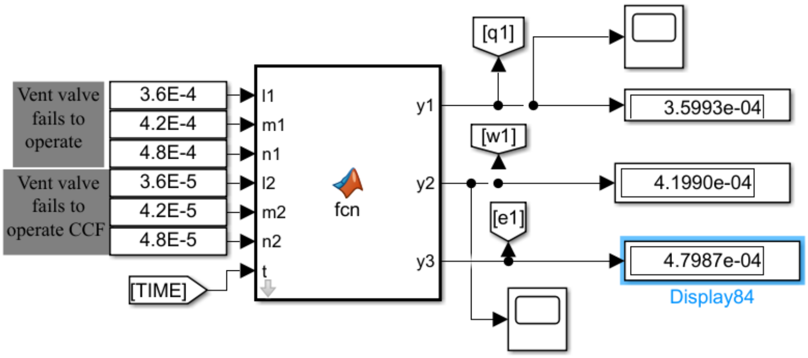


Figure 4.7: Priority-OR gate for vent valve failure in Simulink

During the running model, The intermediate events and the top event's failure possibilities are expressed as TFN upon incorporating the fuzzy operators and Pandora gates in the FFT. Then, defuzzification techniques must be applied to convert these fuzzy values into failure probability. Top event failure possibility (ICS failure) is estimated during mission time 100 hours under SBO scenario. The fuzzy failure possibility using fuzzy operators and Pandora gates is estimated using the defuzzification technique (see Eq. 4.15) to convert the failure possibilities into the failure probability.

$$\text{ADT} = \frac{1}{18}(4a + b + d) \tag{4.15}$$

For comparison purposes, FFTA results can be contrasted against those from various established approaches using statistical failure data. The fuzzy fault tree is validated by determining the failure probability of intermediate events for the specified BEs. This approach is similar to traditional statistical FT analysis but considers priority gates and fuzzy operators. The timing and sequence of BEs are embedded in FFT model, making it more comprehensive and dynamic than traditional FT. The results obtained from the FFTA (listed in Table. 4.15) are compared to those reported in previous studies ([42]) to validate this model's effectiveness in analyzing the ICS's reliability.

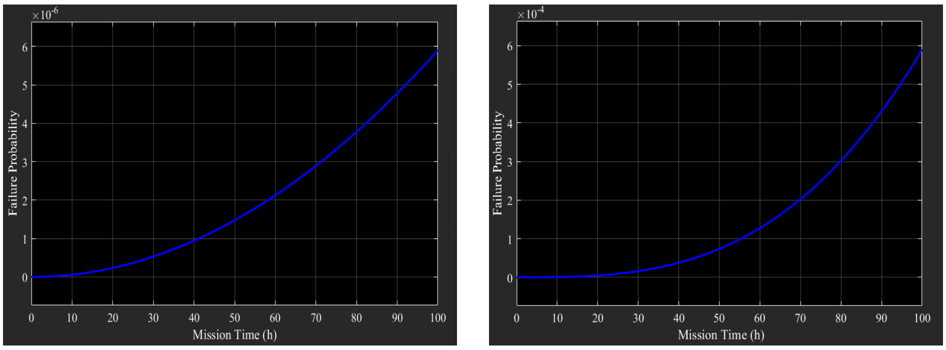
Table 4.4: Comparison between classical and fuzzy intermediate events' failure rates

Intermediate Events	**Failure Probability**	**Fuzzy Failure Probability**
Insufficient heat transfer to external source	3.35×10^{-09}	1.11×10^{-10}
Heat exchanger failure	4.32×10^{-09}	1.53×10^{-09}
Condensation valve failure	2.12×10^{-09}	1.69×10^{-10}
Insufficient water in the IC pool	1.19×10^{-09}	1.70×10^{-10}
Vent valves failure	4.62×10^{-04}	1.29×10^{-04}
Bypass Vent valves failure	1.32×10^{-04}	4.62×10^{-04}
High concentration of non-condense	2.13×10^{-07}	9.20×10^{-08}
Natural circulation failure	2.17×10^{-07}	1.11×10^{-7}
System Failure	4.42×10^{-06}	8.2×10^{-07}
Condensation valve failure	3.45×10^{-05}	1.05×10^{-05}
Bypass condensation valve failure	4.59×10^{-05}	1.05×10^{-05}

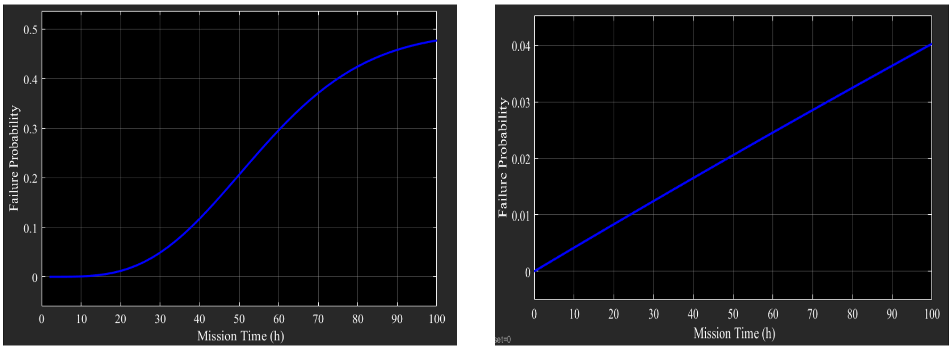
According to Table 4.4, the results obtained from calculating intermediate events in both the FFTA and conventional FT showed a good fit, indicating the model's efficacy and precision. This demonstration validates the FFT approach proposed for assessing the reliability of ICS.

The present study aims to apply FFTA to evaluate the reliability of ICS in CAREM-25 small modular reactor. To this end, the failure possibility of BEs is represented using TFN. Given the inherent uncertainty of failure rate data for BEs, the study employs TFN to quantify their failure possibilities. The analysis considers a mission time of 100 hours, and the resulting output includes the fuzzy possibility and overall probability of ICS failure at the end of this time frame. The results indicated a successful implementation of the FFTA model. The results showed that the intermediate events' failure probabilities were accurately calculated for the specified basic events. The comparison between the FFT and the conventional FT demonstrated a good fit. The implementation of the PAND(POR) and fuzzy operators, derived from the equations outlined in 4.7 to 4.13, has demonstrated an exponential increase in the failure probability. This highlights the importance of considering mission time, ageing, multiple demands, physical changes, and other variables in conducting thorough system reliability evaluations, particularly in PSSs dependent on natural laws, such as gravity and convection. Figures 4.8 present the failure probabilities for various components and systems contributing to the NC failure.

a) Insufficient water in the IC pool **b)** Insufficient heat transfer to external source



c) High concentration of non-condense **d)** Vent valve fails to operate



f) Natural circulation failure

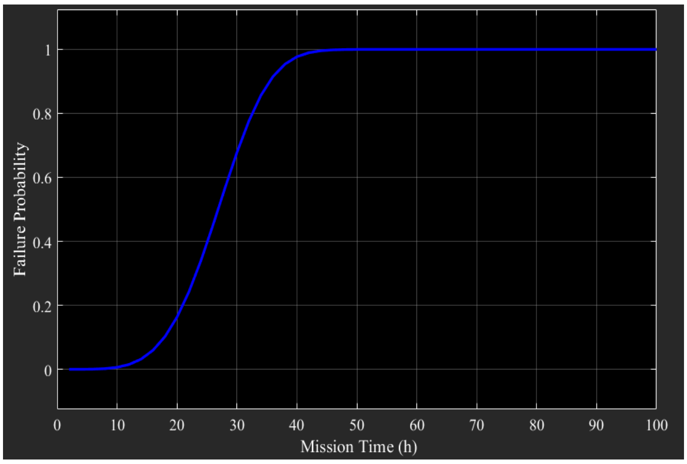


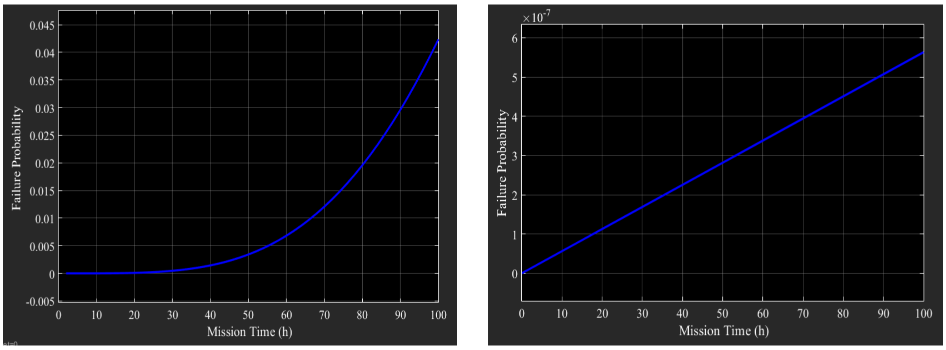
Figure 4.8: The probability of various failure modes that contribute to NC failure over the mission time ($t = 100\,h$).

The failure probabilities of various components and systems that contribute to the overall failure of the NC system are depicted in Fig. 4.8, which displays a line graph of the failure probabilities for each contributing factor over a mission time of 100 hours.

As shown in graph 4.8a, the insufficient heat transfer's failure probability was initially recorded at (3.35×10^{-9}), and it remained constant until 20 hours before gradually increasing to reach (5.59×10^{-4}) at the end of the mission. Conversely, the failure probability of insufficient water in the IC pool started at (1.19×10^{-9}) before experiencing a sudden drop to reach (5.9×10^{-6}). In graph 4.8f, the failure probability of NC remained stable until 10 hours, after which it began to increase, reaching 1 at approximately 50 hours into the mission, meaning that the NC would fail with certainty.

The trend of increasing failure probability was observed in all failure modes over the mission time and is likely to continue. These results demonstrate the importance of monitoring and mitigating the contributing factors to the failure of the NC system.

a) Condensation valves failure **b)** Heat exchanger failure



c) System failure

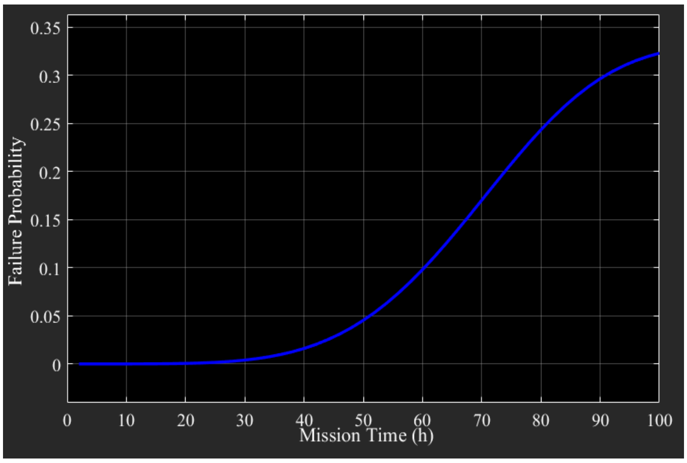


Figure 4.9: Failure probability evaluation for the ICS, condensation valves and HXs.

The diagram in 4.9 illustrates the evolution of failure probabilities for the IC system, condensation valves, and HXs over a 100, h mission time under the SBO accident scenario. In particular, from 4.9a, it can be observed that the failure probability of the condensation valves remained stable during the first 30, h of the mission before gradually increasing to almost 0.043 at the end of the given time. Conversely, the HXs failure probability began to increase rapidly without any delay after the start of the accident. The system failure probability started at a low level of (6.42×10^{-6}) and remained relatively stable until 30, h before undergoing a sharp increase, eventually reaching nearly 0.33 by the end of the mission time.

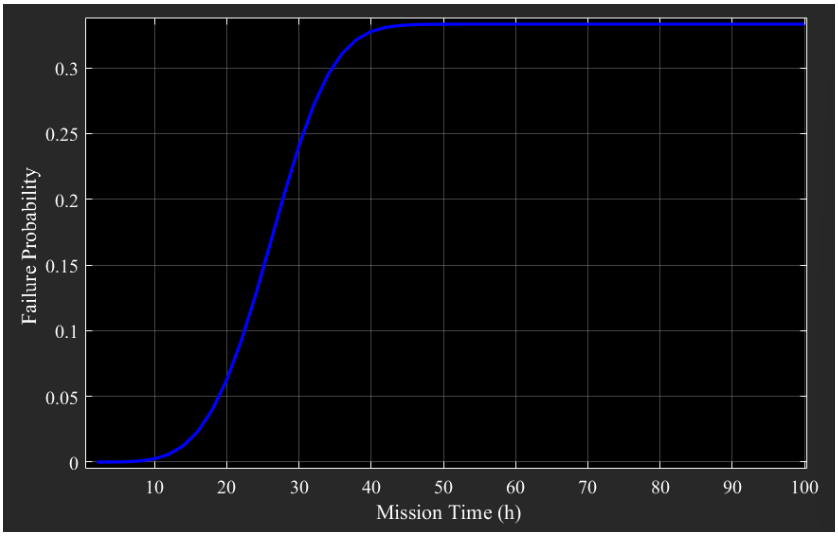


Figure 4.10: PRHRS failure probability

The graph in 4.10 displays the failure probability of the TE, which is the passive ICS in the fault tree diagrammed in 4.2, under the SBO scenario. Figures 4.9 and 4.8 demonstrate that the failure probability of various systems and components increases at different rates and trends during the postulated accident scenario. The top event failure probability remains constant in the first $10, h$ and then sharply rises to reach a plateau of almost 0.33

During the accident scenario, if the isolating condenser system fails to operate, the ADS will take responsibility for reducing the pressure of the RPV in order to activate the emergency cooling injection.

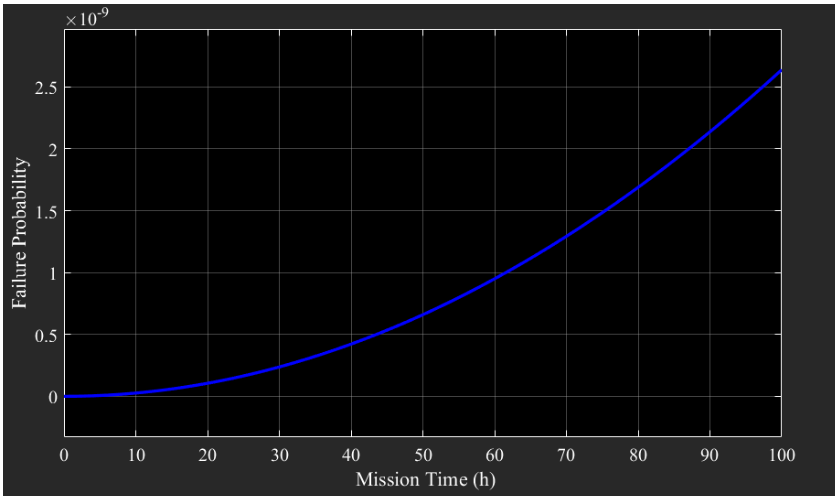


Figure 4.11: ADS Failure Probability

The 4.11 graph shows changes in the failure probability for ASD when the ICS is unavailable to eliminate the residual decay heat. the failure probability rising from about 1.0×10^{-12} at begin of time to almost 1.0×10^{-9} in $100\,h$.

4.2.2 Fuzzy Event Tree Analysis

Fuzzy fault trees and fuzzy event trees are useful for assessing the risk of core damage during SBO-initiating events and evaluating the effectiveness of mitigating systems. In this context, fuzzy fault tree analysis can estimate the fuzzy failure probabilities of the primary and backup mitigating systems, such as the ICS and ADS. As illustrated in Figure 4.12, the ICS serves as the first line of defence against core damage by removing residual heat from the core via NC. If the ICS fails, the ADS is designed to depressurize the RPV's excess steam by transferring it to the pressure suppression pool.

On the other hand, FETA can estimate the probability of CDF, considering the possible failure probability of both the ICS and the ADS. The combination of ICS and ADS failure and success probabilities can be incorporated into FETA to assess the CDF.

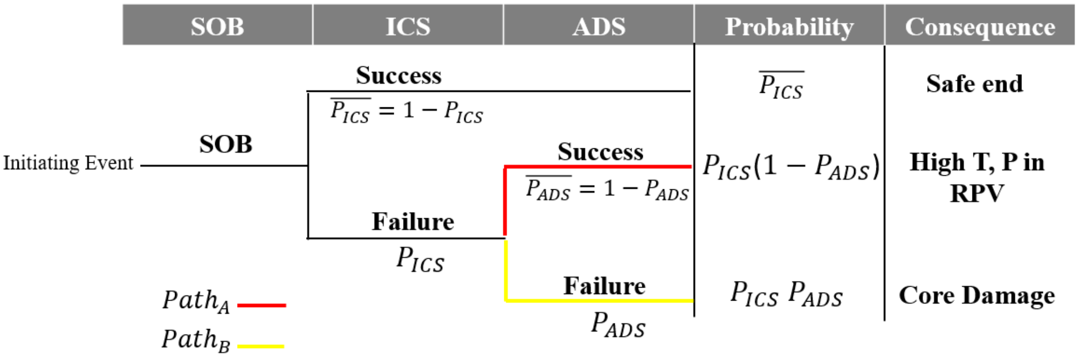


Figure 4.12: Fuzzy event tree of ICS and ADS under SBO initiating event

The branch possibility (failure and success) shown in Fig. 4.12 is calculated from each event failure possibility obtained from FFTA. The collection of associated MS is indicated as follows:

$$\textbf{Mitigating Systems} = \left\{ICS, ADS\right\} \tag{4.16}$$

The fuzzy event tree is constructed, and the probabilities are assigned to each ICS and ADS; the overall probability of success or failure for the system can be estimated by:

$$\bar{p}_{ICS_{Sucsess}} = 1 - \bar{p}_{ICS_{Fail}} \tag{4.17}$$

$$\bar{p}_{ADS_{Sucsess}} = 1 - \bar{p}_{ADS_{Fail}} \tag{4.18}$$

For instance, if the failure possibility of the ICS at $t = 1$ is $\bar{p}_{ICS_{Fail}} = (1.86 \times 10^{-6}, 3.09 \times 10^{-6}, 4.12 \times 10^{-6})$; the triangular fuzzy number for success possibility is:

$$\begin{aligned}\bar{p}_{ICS_{Sucsess}} &= 1 - (1.86 \times 10^{-6}, 3.09 \times 10^{-6}, 4.12 \times 10^{-6}) \\ &= (1 - 1.86 \times 10^{-6}, 1 - 3.09 \times 10^{-6}, 1 - 4.12 \times 10^{-6})\end{aligned} \tag{4.19}$$

After obtaining all failures and successes of ICS and ADS, the possibility of each path $(Path_A, Path_B)$ is estimated using Eq. 3.22 to multiply each element of the TFN to gather.

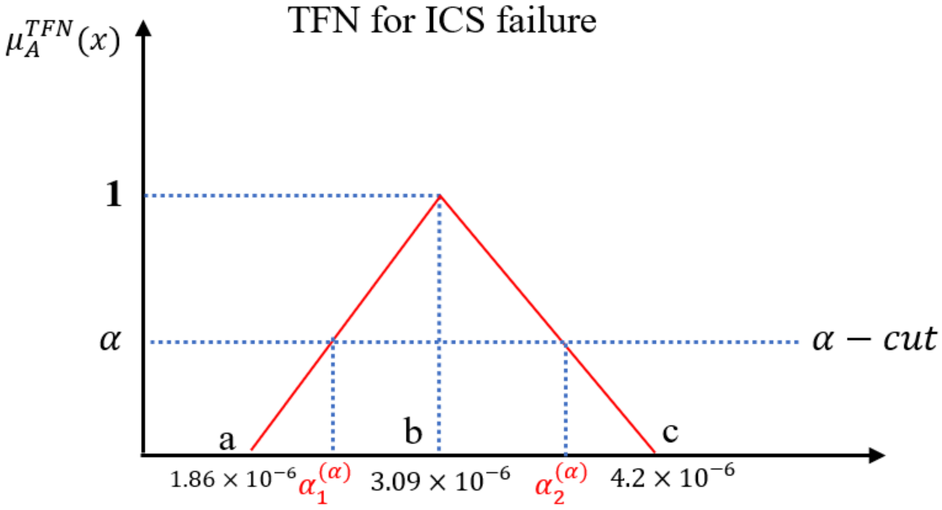


Figure 4.13: The $\alpha - cut$ of normal TFN for ICS failure

To transform the TFN representing the failure and success probabilities of ICS and ADS into their corresponding $\alpha - cut$ sets (as detailed in Table 3.1 and Fig. 4.13), the following methodology is employed; for $\bar{p}_{ICS_{Fial}} = (1.86\times10^{-6}, 3.09\times10^{-6}, 4.12\times10^{-6})$ and $\bar{p}_{ADS_{Fial}} = (1.24 \times 10^{-13}, 1.12 \times 10^{-12}, 3.12 \times 10^{-12})$ we have:

$$\begin{aligned}\bar{p}_{ICS_{Fial}} = \left[\alpha_1^{(\alpha)},\, \alpha_2^{(\alpha)}\right] &= [(3.09 \times 10^{-6} - 1.86 \times 10^{-6}) \cdot \alpha \\ &+1.86 \times 10^{-6}, 4.12 \times 10^{-6} - (4.12 \times 10^{-6} - 3.09 \times 10^{-6}) \cdot \alpha\end{aligned} \tag{4.20}$$

$$\begin{aligned}\bar{p}_{ADS_{Fial}} = \left[\beta_1^{(\alpha)},\, \beta_2^{(\alpha)}\right] &= [(1.2 \times 10^{-12} - 1.24 \times 10^{-13}) \cdot \alpha \\ &+1.24 \times 10^{-13}, 3.12 \times 10^{-12} - (3.12 \times 10^{-12} - 1.12 \times 10^{-12}) \cdot \alpha\end{aligned} \tag{4.21}$$

Using an $\alpha - cut$ method for performing arithmetic operations on fuzzy numbers, such as an $\alpha - cut$ addition and a multiplication to calculate the α in 4.29:

$$a = \alpha_1^{(\alpha)}(\alpha = 0) \tag{4.22}$$

$$b = \alpha_1^{(\alpha)}(\alpha = 1) \quad \textbf{or} \quad b = \alpha_2^{(\alpha)}(\alpha = 1) \tag{4.23}$$

$$c = \alpha_2^{(\alpha)}(\alpha = 0) \tag{4.24}$$

Where a, b, c represent TFN's lower bound, best estimate, and upper bound. If $\alpha = 0$ in 4.22 and 4.24, the line of the $\alpha - cut$ is in $y = 0$ of the Cartesian coordinate system as shown in Fig. 4.13. On the other hand, $\alpha = 1$ in 4.23 means that the line of the $\alpha - cut$ is in $y = 0$ of the Cartesian coordinate system.

$$\bar{p}_{ICS_{Fial}} = \left[(2.01 \times 10^{-6}) \cdot \alpha + 1.86 \times 10^{-6}, 4.12 \times 10^{-6} - (1.04 \times 10^{-6}) \cdot \alpha\right] \tag{4.25}$$

$$\bar{p}_{ICS_{Fial}} = \left[(1.076 \times 10^{-12}) \cdot \alpha + 1.24 \times 10^{-13}, 3.12 \times 10^{-12} - (2.00 \times 10^{-12}) \cdot \alpha\right] \tag{4.26}$$

After obtaining the $\alpha - cut$ set for ICS and ADS failure possibility, the equations 4.22, 4.23, and 4.24 is applied to calculate following:

$$A^{\alpha} \cdot B^{\alpha} = \left[\alpha_1^{(\alpha)} \cdot \beta_1^{(\alpha)},\ \alpha_2^{(\alpha)} \cdot \beta_2^{(\alpha)}\right] = \bar{p}_{ICS_{Fial}} \cdot \bar{p}_{ADS_{Fial}} \tag{4.27}$$

To obtain the α-cut sets for ICS and ADS failure probabilities, each element of the TFN representing ICS failure is multiplied by the corresponding element in the TFN representing ADS failure. Subsequently, equations 4.22, 4.23, and 4.24 are utilized to assign a value to the α variable, thereby enabling us to establish the α-cut sets for both ICS and ADS failure probabilities (all mathematical calculation is don in Simulink block).

The triangular fuzzy numbers were converted into the $\alpha - cut$ set to estimate the CDF in the event all mitigating systems fail in the FET. The failure fuzzy numbers for the ICS and ADS were obtained using the methods described in the previous section, while the success possibility was estimated to identify the various paths in the FET. The $\alpha - cut$ set was then used to calculate the fuzzy set and defuzzify the failure possibility into the failure probability. The resulting CDF in the event of failure of all mitigating systems under SBO was estimated as $CDF = (2.3 \times 10^{-19}, 3.48 \times 10^{-18}, 1.2 \times 10^{-18})$.

$$\begin{aligned} \text{CDF (Path B)} &= \frac{1}{18}(4a + b + d) = \frac{1}{18}((4 \times (1.86 \times 10^{-6}, 3.09 \times 10^{-6}, 4.12 \times 10^{-6}))) \\ &= 3.02 \times 10^{-6} \end{aligned} \tag{4.28}$$

$$\begin{aligned}\text{CDF (Path A)} &= \frac{1}{18}(4a+b+d) = \frac{1}{18}((4\times(2.3\times10^{-19}), 3.48\times10^{-18}, 1.2\times10^{-18})) \\ &= 9.96\times10^{-18}\end{aligned} \tag{4.29}$$

The core damage frequency was estimated by applying the ADT method to the fuzzy numbers obtained from the FFTA. The Fuzzy Event Tree was used to determine the different paths ($Path_A$ and $Path_B$) leading to CDF. Success and failure probabilities were calculated for each path, and the resulting CDF for $Path_A$ and $Path_B$ were found to be 3.02×10^{-6} and 9.96×10^{-18}, respectively. These results demonstrate that activating the ADS system reduces the probability of core damage and the release of radioactive material.

The event tree, including ICS and ADS as mitigating systems triggered by an initiating event of station blackout, is constructed by considering the failure of ICS and ADS as an event (Table 4.5). The branch probability is calculated for each event failure, estimated through fuzzy FFT, and the classical CDF consequences are obtained from the simulation results presented in [42]. The PAND and POR gates in the simulation model enable us to consider the time-dependent evaluation of failure probabilities during the modelling process. The table below shows the failure and success frequency of ICS and ADS at different times after SBO accident.

Table 4.5: Fuzzy event tree with ICS and ADS failure

Path	**Time1**	**Time40**	**Time80**	**Time100**
ICS Success	1.00	1.00	1.00	1.00
ICS fail ⟶ **ADS Success**	3.09×10^{-6}	3.27×10^{-1}	3.33×10^{-1}	1.00
ICS fail ⟶ **ADS Fail**	2.23×10^{-18}	4.19×10^{-10}	1.67×10^{-9}	1.4×10^{-8}

Table. 4.5 shows the FFTA results with ICS and ADS failures under the initiating station blackout event for different time points. The ICS is successful in mitigating the CDF. The values in this path are equal to 1, indicating that the core damage frequency is fully mitigated and no damage is expected.

The table's $Path_A$ represents the case where the ICS system fails, but the ADS system successfully mitigates the CDF. The values in this path show the fuzzy probabilities of CDF, ranging from 3.09×10^{-6} at Time 1 to 1.00 at Time 100, which means that considering the mission times and time evaluation of failure rates are essential in the system analysis. These probabilities indicate the likelihood of CDF, given the ICS system's failure and the ADS system's success. The $Path_B$ represents the case where both the ICS and ADS systems fail. The values in this path also show the fuzzy probabilities of CDF, ranging from 2.23×10^{-18} at Time 1 to 1.4×10^{-8} at Time 100. These probabilities indicate the likelihood of CDF, given the failure of both the ICS and ADS systems.

The use of fuzzy set theory and related techniques has played a critical role in this research, particularly in assessing the ICS failure and risk of CDF under SBO. Fuzzy fault tree analysis was used to model the ICS and ADS failure with uncertain or vague failure data, while the use of fuzzy operators and Pandora gates in the FFTA allowed for the consideration of time-dependent failure probabilities and even order sequence, leading to more accurate failure probabilities for using in the FETA. Fuzzy event tree analysis was used to model complex event sequences with uncertain or vague probabilities, allowing for the modelling of uncertainty and vagueness in estimating event probabilities, which led to a more accurate and realistic estimation of the CDF. Integrating FFTA and FETA has provided a comprehensive methodology for assessing the ICS failure and CDF, with a more accurate and realistic estimation of failure probabilities and consequences.

The next section proposes fuzzy-FMEA to evaluate the different failure modes and effects for ICS systems and components. Using Fuzzy Logic in FMEA allows for considering uncertainty and vagueness in the analysis, which can lead to a more accurate and comprehensive risk assessment.

4.3 Coupling Fuzzy Fault tree and Fuzzy-FMEA

Fuzzy FMEA is a technique that employs fuzzy if-then rules and expert judgments to prioritize risks associated with failure modes. The core concept of fuzzy FMEA is to utilize linguistic variables to represent the parameters of severity, occurrence, and detectability and rank them using fuzzy numbers, such as TFN, rather than crisp numerical values. This approach is designed to accommodate the imprecision and uncertainty in the assessments and evaluations made by experts and data, thereby improving the quality of risk prioritization. The application of fuzzy FMEA has been shown to enhance the accuracy of risk assessments and facilitate better decision-making.

As discussed in the previous section, the combination of fuzzy logic and PSA provides a more reliable model for evaluating the failure of the ICS. Integrating FFTA and fuzzy FMEA offers a more comprehensive approach to analyzing risks associated with complex systems' failures. In this thesis, FFTA is an informative tool for obtaining the occurrence of events, which can then be multiplied by the severity and detectability of different failure modes to calculate the fuzzy RPN. The fuzzy risk priority number provides a more comprehensive and accurate measure of the failure mode's risk by considering the uncertainties and imprecision's associated with the ICS system's parameters. Through integrating the results from both FFTA and FMEA, the critical failure modes can be identified, and mitigation actions can be prioritized more effectively, ultimately leading to optimal resource allocation and mitigation measures.

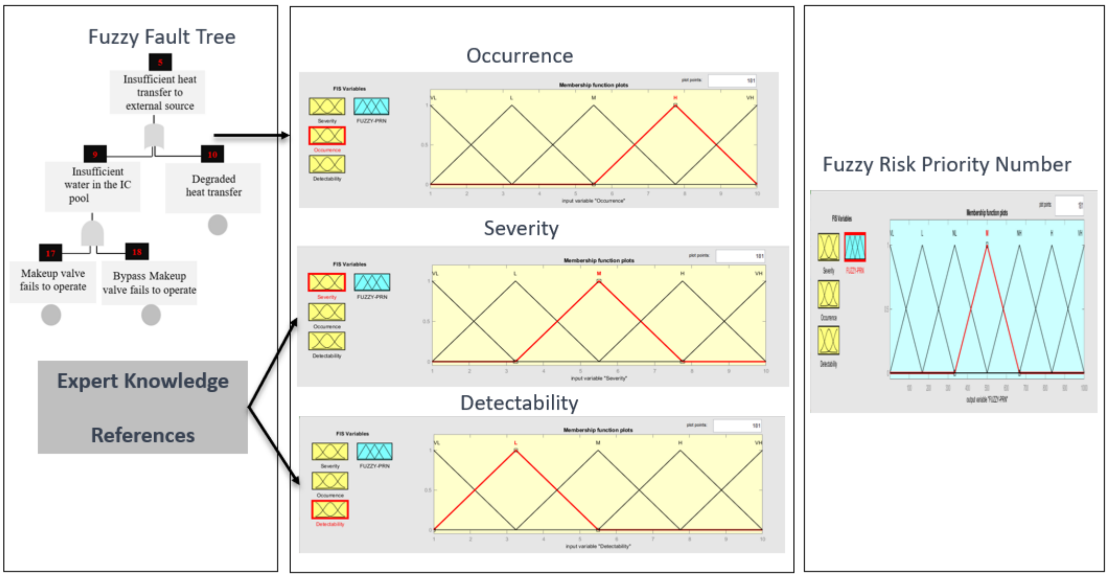


Figure 4.14: Proposed fuzzy-FMEA model

The diagram in Figure 4.14 outlines the proposed method for fuzzy FMEA. Data for severity, occurrence, and detectability is gathered in the first stage. The fuzzy fault tree, described in the previous section, is then used as an informative tool to provide the fuzzy FMEA occurrence for each BEs, which are the components and events that can lead to different failure modes of the PRHRS. In cases where there is no data available for severity and detectability, expert judgment should be considered. However, this thesis uses data from different references and papers to feed the model. A TFN is applied for severity and detectability to address the uncertainty around the data.

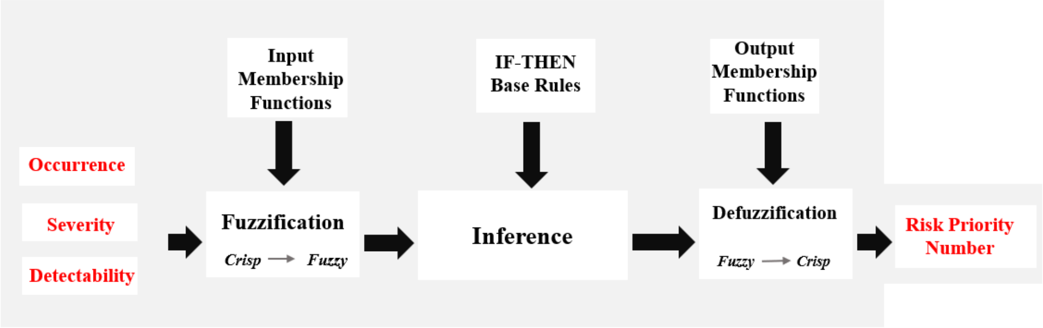


Figure 4.15: Proposed method for calculating fuzzy PRN, the occurrence, sensitivity and detectability as crisp inputs, are plugged into the model to estimate fuzzy PRN.

The proposed fuzzy FMEA evaluation process is visualized in Fig. 4.15. This process consists of three crucial phases: Fuzzification, Inference, and Defuzzification, which can be implemented in FIS in MATLAB®. The crisp inputs (S, O, D) are transformed into the fuzzy number in the fuzzification phase. Then, the inference phase involves the application of IF-Then Rules. Finally, the defuzzification phase converts the fuzzy numbers into a single value using the ADS method. The fuzzy inference structure used in MATLAB® is illustrated in Fig. 3.14.

The first step in conducting a fuzzy-FMEA is to comprehensively understand the system under examination, in this case, the PRHRS. Understanding the different failure modes and their causes can be achieved through the FT diagrams presented in Figs. 4.2, 4.3, and 4.4. The next step is identifying system components and attributing failure modes to each component or subsystem (Table 4.6 is an example of organizing this information). This step is crucial in identifying potential points of failure and assessing their impact on the overall system.

Table 4.6: Systems and Components related Failure Modes

Failure Mode	**Cause**
Insufficient heat transfer to external source	Degraded heat transfer (excessive pipe fouling)
Heat exchanger failure	Multiple pipe rupture Multiple pipe plugging
Insufficient water in the IC pool	Makeup valve fails to operate Bypass makeup valve fails to operate
Vent valves failure	Vent valve fails to operate Vent valve fails to operate CCF
Bypass vent valves failure	Bypass vent valve fails to operate Bypass vent valve fails to operate CCF
Condensation valve failure	Condensation valve fails to open Condensation valve fails to open CCF Condensation valve fails to remain open Condensation valve fails to remain open CCF
Bypass condensation valve failure	Bypass condensation valve fails to open Bypass condensation valve fails to open CCF Bypass condensation valve fails to remain open Bypass condensation valve fails to remain open CCF

The table shows the different systems and components related to failure modes identified during the fuzzy-FMEA analysis of PRHRS. BEs related to the failure modes have also been listed.

The Table. 4.7 shows the severity of BEs, categorized into five levels of severity from very low to very high, and the corresponding frequency of events per year for each severity level. For example, the range for very low is $10^{-6}/y$, which means that the event associated with this rank is expected to occur at a frequency of once in a million years.

Table 4.7: Severity ranking of different BEs, with corresponding annual frequencies in units of events per year.

Basic Events Severity Rank	**Very Low**, $10^{-6}/y$	**Low**, $10^{-4} - 10^{-6}/y$	**Moderate**, $10^{-2} - 10^{-4}/y$	**High**,$10^{-2}/y$	**Very High, more than** $10^{-2}/y$
Pipe rupture	✓				
Degraded heat transfer (excessive pipe fouling)				✓	
Multiple pipe rupture	✓				
Multiple pipe plugging			✓		
Makeup valve fails to operate			✓		
Bypass makeup valve fails to operate			✓		
Vent valve fails to operate			✓		
Vent valve fails to operate CCF		✓			
Bypass vent valve fails to operate			✓		
Bypass vent valve fails to operate CCF		✓			
Condensation valve fails to open			✓		
Condensation valve fails to open CCF	✓				
Condensation valve fails to remain open		✓			
Condensation valve fails to remain open CCF	✓				
Bypass condensation valve fails to open			✓		
Bypass condensation valve fails to open CCF	✓				
Bypass condensation valve fails to remain open		✓			
Bypass condensation valve fails to remain open CCF	✓				

The purpose of associating linguistic variables with these reported frequencies ranges in Table. 4.8 and 4.9 is to represent the event's severity, occurrence and detectability and RPN level more intuitively and understandably. The uncertainty around data is considered by assigning linguistic values such as very low or high to these frequency ranges. Triangular fuzzy numbers convert the crisp values into linguistic values. For example, the range of very low ($10^{-6}/y$) can be represented as a TFN with a peak at $10^{-6}/y$ and slopes that decrease to zero as the frequency moves away from this value.

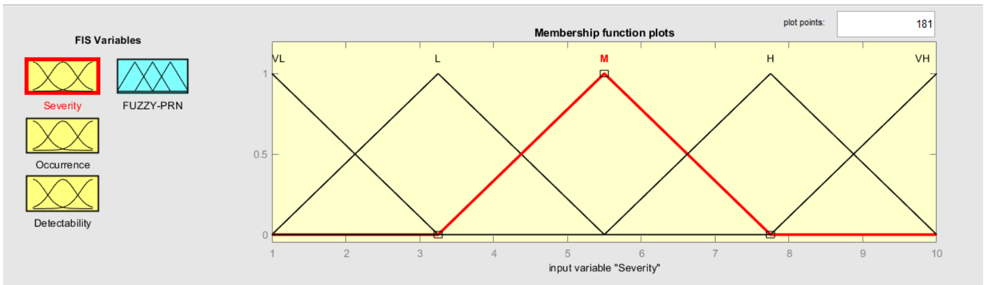
Table 4.8: Linguistic terms and TFN for the input variables' severity, occurrence and detectability

	Triangular fuzzy numbers		
Linguistic terms	Severity (S)	Occurrence(O)	Detectability (D)
Very low (VL)	(1.00, 1.00, 3.25)	(1.00, 1.00, 3.25)	(1.00, 1.00, 3.25)
Low (L)	(1.00, 3.25, 5.50)	(1.00, 3.25, 5.50)	(1.00, 3.25, 5.50)
Moderate (M)	(3.25, 5.50, 7.75)	(3.25, 5.50, 7.75)	(3.25, 5.50, 7.75)
High (H)	(5.50, 7.75, 10.00)	(5.50, 7.75, 10.00)	(5.50, 7.75, 10.00)
Very high (VH)	(7.75, 10.00, 10.00)	(7.75, 10.00, 10.00)	(7.75, 10.00, 10.00)

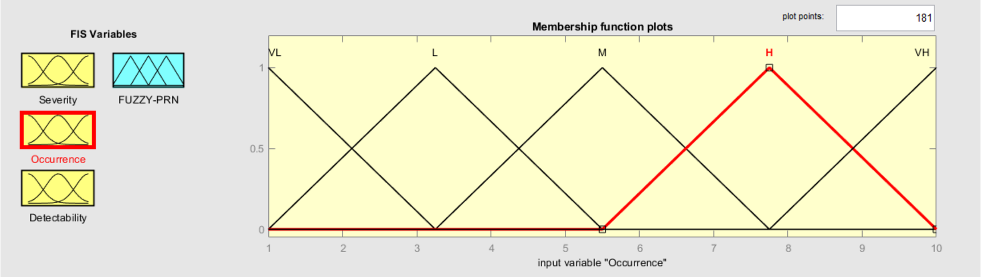
Table 4.9: Linguistic terms and TFN for the output variable fuzzy RPN.

Linguistic terms	**Triangular fuzzy numbers**
Very low (VL)	(1.00, 1.00, 167.5)
Low (L)	(1.00, 167.5, 334.0)
Nearly low (NL)	(167.5, 334.0, 500.5)
Moderate (M)	(334.0, 500.5, 667.0)
Nearly high (NH)	(500.5, 667.0, 833.5)
High (H)	(667.0, 833.5, 1000)
Very high (VH)	(833.5, 1000, 1000)

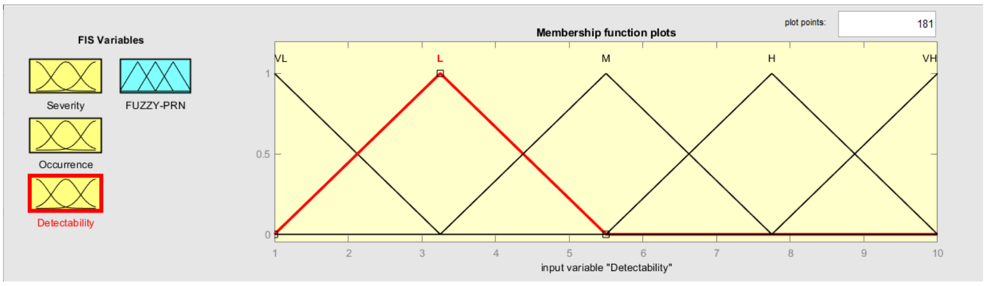
The next step is to implement the fuzzy FMEA into MATLAB software. MATLAB has a built-in fuzzy logic toolbox that provides functions and tools for implementing fuzzy inference systems. This thesis uses the toolbox to define membership functions, define fuzzy rules, and perform fuzzy inference. The membership function shape and ranges are shown in Fig. 4.16 for severity, occurrence, and detectability.



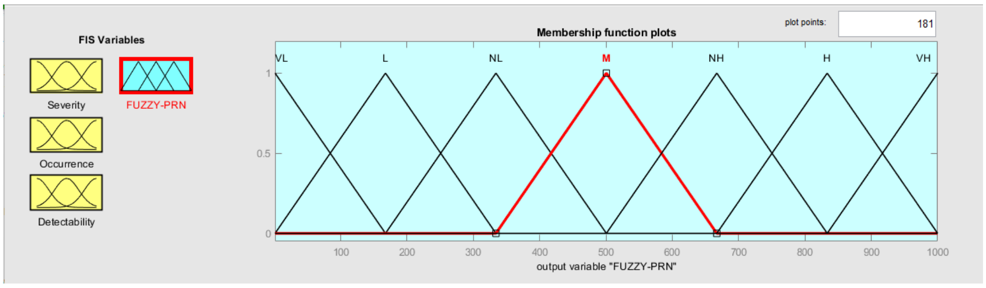
(a) Membership function plot for severity



(b) Membership function plot for Occurrence



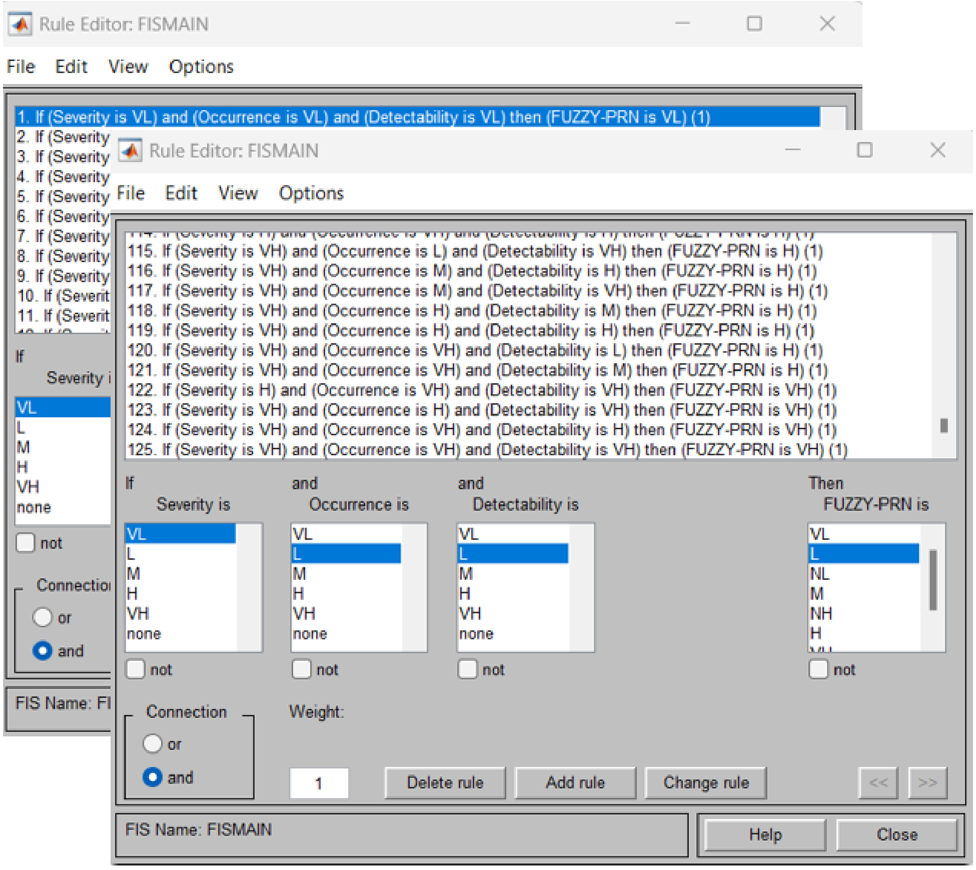
(c) Membership function plot for Detectability



(d) Membership Function Plot for RPN

Figure 4.16: Four MF plots for S, O, D, and RPN from FIS in MATLAB®.

After defining MF plots in FIS, the next step is to define the rules of the fuzzy inference system using "if-then" statements, as shown in Fig. 4.17. These rules establish the relationship between the input and output variables and the system's response to the inputs. Each rule consists of conditions (antecedents) and a resulting action (consequent). The antecedents comprise one or more fuzzy propositions that use the input variables, while the consequent is a fuzzy proposition that describes the output variable.



1. If (Severity is VL) and (Occurrence is VL) and (Detectability is VL) then (FUZZY-PRN is VL) (1)

115. If (Severity is VH) and (Occurrence is L) and (Detectability is VH) then (FUZZY-PRN is H) (1)
116. If (Severity is VH) and (Occurrence is M) and (Detectability is H) then (FUZZY-PRN is H) (1)
117. If (Severity is VH) and (Occurrence is M) and (Detectability is VH) then (FUZZY-PRN is H) (1)
118. If (Severity is VH) and (Occurrence is H) and (Detectability is M) then (FUZZY-PRN is H) (1)
119. If (Severity is VH) and (Occurrence is H) and (Detectability is H) then (FUZZY-PRN is H) (1)
120. If (Severity is VH) and (Occurrence is VH) and (Detectability is L) then (FUZZY-PRN is H) (1)
121. If (Severity is VH) and (Occurrence is VH) and (Detectability is M) then (FUZZY-PRN is H) (1)
122. If (Severity is H) and (Occurrence is VH) and (Detectability is VH) then (FUZZY-PRN is VH) (1)
123. If (Severity is VH) and (Occurrence is H) and (Detectability is VH) then (FUZZY-PRN is VH) (1)
124. If (Severity is VH) and (Occurrence is VH) and (Detectability is H) then (FUZZY-PRN is VH) (1)
125. If (Severity is VH) and (Occurrence is VH) and (Detectability is VH) then (FUZZY-PRN is VH) (1)

Figure 4.17: Fuzzy inference structure rules in MATLAB®

Some of these rules can be merged to reduce the number of rules in the fuzzy rule base. Nevertheless, 125 rules in all are produced. Software MATLAB® was used to generate the rules, for instance:

Rule Number 1: if (severity is VL) and (occurrence is VL) and (detectability is VL) then (RPN is VL)

⋮

Rule Number 90: if (severity is M) and (occurrence is H) and (detectability is M) then (RPN is NH)

⋮

Rule Number 125: if (severity is VH) and (occurrence is VH) and (detectability is VH) then (RPN is VH)

After defining the FIS and creating the rules in MATLAB, the next step is implementing the system in Simulink. This involves using Simulink's Fuzzy Logic Controller block to link the system's inputs and outputs and simulate the system's behaviour. Once the block is added to the Simulink model, as shown in Fig. 4.18, the input signals are connected to the block's input ports, and the block's output is connected to the desired output of the system.

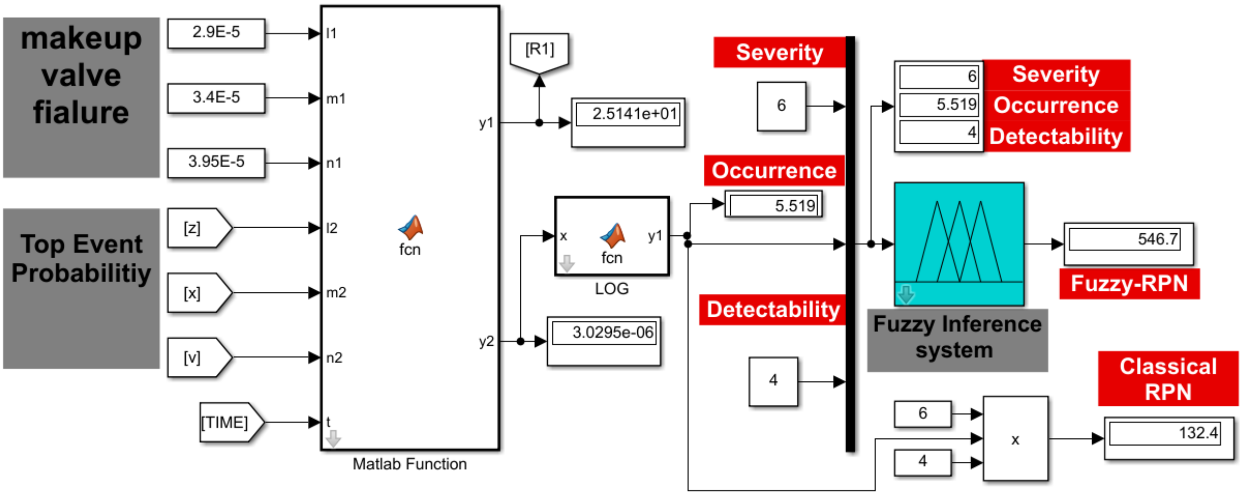


Figure 4.18: MATLAB®/Simulink block, including FIS, demonstrates linking FFT and fuzzy FMEA to calculate the Fuzzy RPN.

The block diagram in Simulink for the Fuzzy-FMEA process, shown in Fig. 4.18, involves several blocks and connections. The failure rates of the FFT serve as input for the occurrence variable. The occurrence variable is then converted into linguistic variables multiplied by the severity and detectability variables to calculate the fuzzy RPN. The Simulink model utilizes a FIS block, where the occurrence, severity, and detectability variables serve as inputs and the fuzzy RPN as the output. The block diagram also includes additional blocks for calculating conventional RPN to compare the result with fuzzy RPN. in addition, calculating the vesely–Fussell Importance Measure (V–FIM) to rank the BEs based on their importance on TE.

In this study, a risk assessment of the ICS was performed using FFT and fuzzy-FMEA approach. The resulting Table. 4.10 and 4.11 present the failure modes of the IC system, their causes and effects, severity, occurrence, detection, classical RPN, and fuzzy RPN values. The classical RPN values were calculated by multiplying the severity, occurrence, and detection values, and the fuzzy RPN values were calculated by applying fuzzy logic to the RPN values. The results show that the pipe rupture and degraded heat transfer failure modes pose the highest risk, with fuzzy RPN values of 576.4 and 581.0, respectively, while the multiple pipe rupture and vent valve and bypass vent valve failure modes have the lowest risk with fuzzy RPN values of 241.5 and 513.0, respectively. These findings can help improve the safety and reliability of the IC system and inform decision-making related to risk management.

Table 4.10: Risk assessment of isolation condenser system using linking fuzzy-fault tree and fuzzy-FMEA

		Risk Estimation				
Failure Mode	**Cause and Effect**	Severity	Occurrence	Detection	RPN	Fuzzy-RPN
Pipe Rupture	**Causes:** Material defects, abnormal operation **Effects:** LOCA, Loss of NC, Loss of heat removal capacity	10	5.5	2.00	110.1	576.4
Degraded heat transfer	**Causes:** Thermal insulation, Inaccurate material assembly **Effects:** Heat convection Limitation, NC impairment	8.00	3.95	6.00	185.1	581.0
Multiple pipe plugging	**Causes:** curd detachment from destructive pressure ad vibration **Effects:** NC Stop	6.00	3.85	3.00	69.3	360.1
Multiple pipe rupture	**Causes:** deterioration caused by corrosion, stress, and pressure fluctuations **Effects:** Decreased capacity to dissipate heat, Primary coolant discharge to the pool, Loss of coolant inventory NC impairment	2.00	3.85	3.00	23.1	241.5
Makeup valve fails to operate	**Causes:** Valve malfunction, **Effects:** Insufficient water in the IC pool	6.00	6.163	4.00	147.9	556.6
Bypass Makeup valve fails to operate	**Causes:** Valve malfunction, **Effects:** Insufficient water in the IC pool	6.00	6.163	4.00	147.9	556.6
Vent valve fails to operate	**Causes:** Valve malfunction, **Effects:** Increasing pressure and temperature in RPV, Loss of heat removal system	6.00	7.00	4.00	166.5	562.0
Vent valve fails to operate CCF	**Causes:** Valve malfunction, **Effects:** Increasing pressure and temperature in RPV, Loss of heat removal system	5.00	6.19	4.00	124.0	513.0
Bypass Vent valve fails to operate	**Causes:** Valve malfunction, **Effects:** Increasing pressure and temperature in RPV, Loss of heat removal system	6.00	7.00	4.00	166.5	562.0
Bypass Vent valve fails to operate CCF	**Causes:** Valve malfunction, **Effects:** Increasing pressure and temperature in RPV, Loss of heat removal system	5.00	6.19	4.00	124.0	513.0

Table 4.11: CONTINUE. Risk assessment of isolation condenser system using linking fuzzy-fault tree and fuzzy-FMEA

		Risk Estimation				
Failure Mode	**Cause and Effect**	Severity	Occurrence	Detection	RPN	Fuzzy-RPN
Condensation valve fails to open	**Causes:** Valve malfunction, Control circuit failure **Effects:** Non-triggering of IC if bypass valve does not operate, Loss of heat removal capability, Reactor pressure and temperature increase	6.00	6.16	5.00	184.9	555.5
Condensation valve fails to open CCF	**Causes:** Valve malfunction, Control circuit failure **Effects:** Non-triggering of IC, Loss of heat removal capability, Reactor pressure and temperature increase	2.00	5.54	5.00	55.45	363.5
Condensation valve fails to remain open	**Causes:** Valve malfunction, Control circuit failure **Effects:** Natural circulation stop in case bypass valve does not operate	4.00	5.69	5.00	114	475.5
Condensation valve fails to remain open CCF	**Causes:** Valve malfunction, Control circuit failure **Effects:** Non-triggering of IC, Loss of heat removal capability, Reactor pressure and temperature increase	2.00	5.53	5.00	55.35	363.5
Bypass condensation valve fails to open	**Causes:** Valve malfunction, Control circuit failure **Effects:** Natural circulation stop in case bypass valve does not operate	2.00	5.54	5.00	55.45	363.5
Bypass condensation valve fails to open CCF	**Causes:** Valve malfunction, Control circuit failure **Effects:** Natural circulation stop in case bypass valve does not operate	2.00	5.53	5.00	55.35	363.5
Bypass condensation valve fails to remain open	**Causes:** Valve malfunction, Control circuit failure **Effects:** Natural circulation stop in case bypass valve does not operate	4.00	5.69	5.00	114	475.5
Bypass condensation valve fails to remain open CCF	**Causes:** Valve malfunction, Control circuit failure **Effects:** Natural circulation stop, High pressure and Temperature in core	2.00	5.53	5.00	55.35	363.5

As reported in Table. 4.10, 4.11 and bar chart in 4.19, the Fuzzy-RPN is expected to be higher than the traditional RPN value; this was because the classical method assumes that the values assigned to the severity, occurrence, and detection scales are precise and accurate, which is not always the case. On the other hand, the fuzzy method considers the imprecision and uncertainty (applying linguistic variables) in these values, resulting in a more realistic and accurate risk estimate. However, in some cases, the Fuzzy-RPN value may be lower than the RPN value due to how the fuzzy logic is applied to the RPN calculation. This could happen if the membership functions used in the fuzzy logic calculation result in a lower overall score than the traditional RPN calculation. Additionally, it's also possible that the RPN and Fuzzy-RPN values have been calculated using different scales, which also explains the difference in the values.

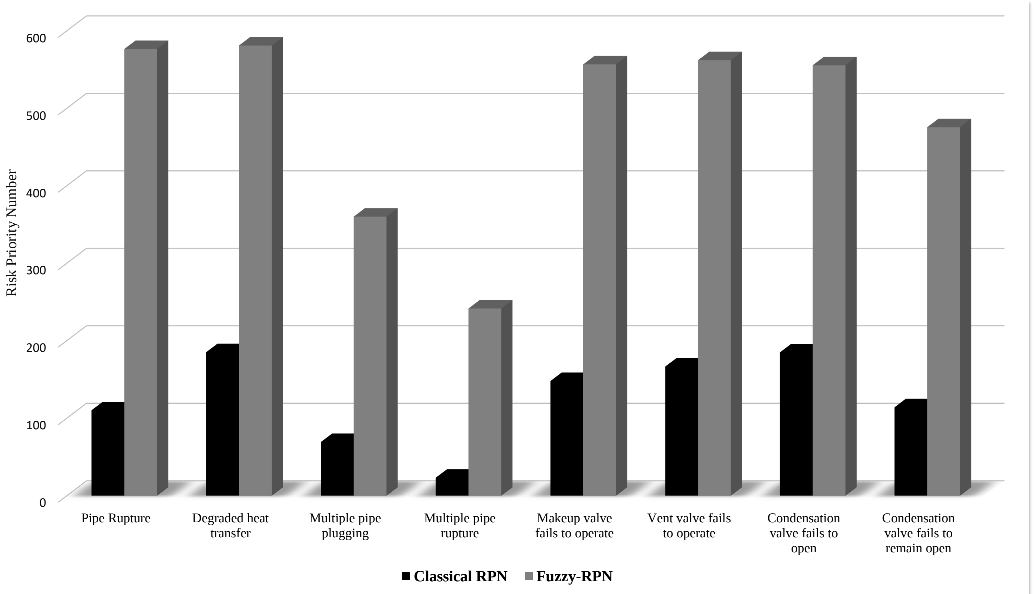


Figure 4.19: RPN values for classical and fuzzy method

The Surface Viewer Simulink block in MATLAB is used to visualize the output of a FIS in Simulink. The block provides a 3D view of the FIS output surface, which helps to understand how the FIS behaves in response to changes in the input variables. The block can identify and diagnose FIS problems and optimize its performance.

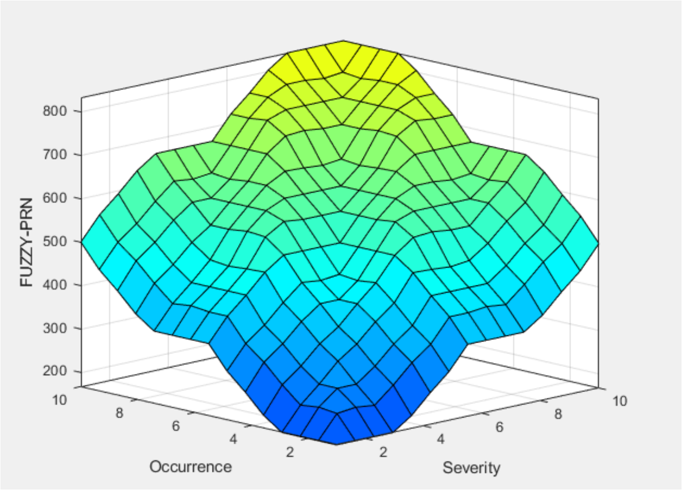


Figure 4.20: Surface viewer in MATLAB®/Simulink Blocks

Figure 4.20 depicts the Surface Viewer Simulink block in MATLAB, which is a three-dimensional graphic that maps two inputs (occurrence, severity, or detection) to one output (fuzzy RPN). The surface viewer can illustrate the correlation between O, S, and D and the fuzzy RPN. The surface viewer allows visualization of the outcome's (fuzzy RPN) dependence on inputs (S, O). In the case of the fuzzy logic approach versus the classical RPN technique, it is evident that the fuzzy logic methodology gives a broader spectrum of risk evaluation and narrower intervals between various degrees of risk, allowing for greater precision.

This section introduces a fuzzy FMEA technique and a fuzzy FMEA analysis of PRHRS failure modes to demonstrate the model. The study outlines that the fuzzy interference system offers several advantages, including representing failure information in FMEA as TFN, resulting in a more realistic and flexible reflection of situations. Additionally, the probability of occurrence is directly taken from the FFTA, connecting the two models. Finally, using a fuzzy RPN is more effective in situations where input uncertainty is considered in the severity and detectability fuzzy variables.

Mapping fault trees into ANNs is a promising approach to improving fault diagnosis and prediction. By converting the logical structure of a fault tree into a neural network architecture, the network can be trained to predict the likelihood of different failure modes and their consequences. In the following section, we will discuss the methodology of mapping fault trees into ANNs in more detail.

4.4 ANN-based Fault tree

Mapping an FT into an ANN involves translating the logical relationships between events and failures into a network of nodes and connections in the ANN. This allows the ANN to predict system reliability and failure probability based on input variables, which can be useful for system design and optimization. Mapping FT into an ANN involves identifying the BEs, intermediate events, and TE in the FT and then assigning corresponding input, hidden, and output layers in the ANN. The connections and weights between the ANN nodes represent the logical relationships between events and failures (see section 3.4.3).

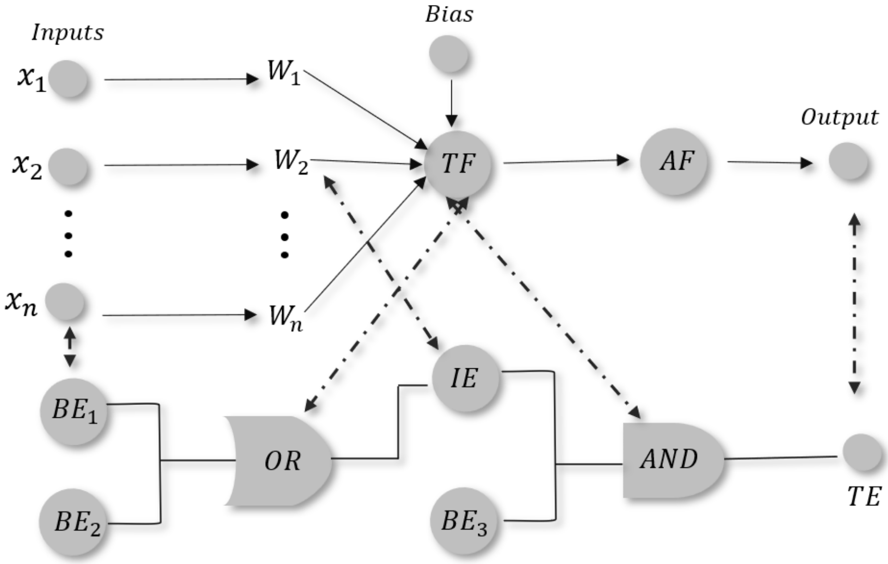


Figure 4.21: Diagrams for mapping FT into ANN

Mapping FT into ANNs has several advantages over traditional FTA methods, particularly for dealing with complex systems, time-consuming analysis, and incomplete or missing data. Artificial neural networks can handle large datasets and extract patterns, making them suitable for modelling and predicting system behaviour. Through training the ANN model on relevant data, it can learn the relationships between the system components and their failure modes, allowing for more accurate predictions of system behaviour and improved risk assessment. Furthermore, ANNs can be used to identify critical components of a system and potential failure modes, aiding in the development of targeted maintenance and safety strategies. Applying ANNs in FTA provides a promising alternative to traditional FTA approaches and can offer valuable insights for decision-making in complex systems.

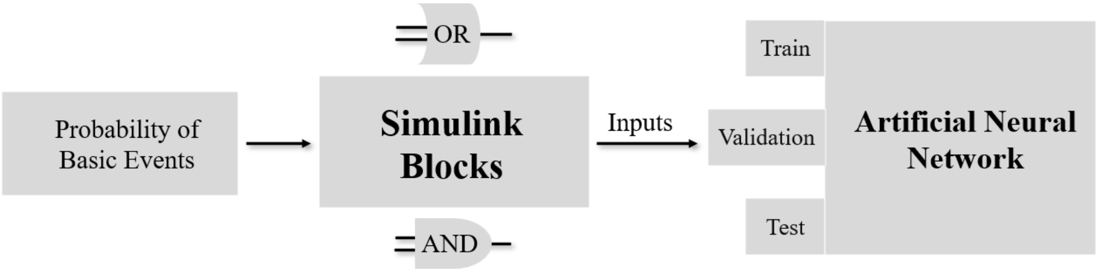


Figure 4.22: Mapping FT into the ANN. (1) obtaining the probabilities of the BEs, (2) constructing the FT gates, (3) training ANN.

Figure 4.22 depicts the proposed model for mapping the fFT into the ANN. The model consists of three main stages. In the first stage, the probabilities of basic and intermediate events are obtained from different references. In the second stage, the FT gates and components are transformed into Simulink blocks, where the gate analytical equations are applied to calculate the outputs of the logic gates. In the final stage, inputs for the ANN models are generated, and the ANN models are trained based on these inputs to predict the model outputs.

This study proposes an innovative approach for creating an ICS failure FT using Simulink as a first step toward mapping the FT to the NN. A fault tree is constructed in Simulink with enough inputs for the NN algorithm, based on the accident scenarios (SBO) Simulink model, which is provided with BEs probabilities from Table 4.1. The probability of the TE is then calculated using probability equations and AND/OR gate linkages. Simulink's ability to depict a system's topology is highly valuable in modelling technical processes.

The failure probabilities for the intermediate events and the TE are based on the proposed FT framework, which utilizes the Boolean logic gates AND and OR gates. The AND gate outputs a signal only when all inputs are active, while the OR gate outputs a signal when at least one input is active. The AND and OR gates equations are shown in Eq. 4.30 and Eq. 4.31, respectively. The probability values for the intermediate events and the TE are obtained using the information in Table 4.12. [41].

$$P^{AND} = \begin{cases} \prod_{i=1}^{m} P_i, \quad 0 \leq P_i \leq 1 \\ P(Impossible_{event}) = P(\phi) = 0, \\ P(Certain_{event}) = P(\varsigma) = 1, \end{cases} \tag{4.30}$$

$$P^{OR} = \prod_{i=1}^{m} (1 - P_i) \tag{4.31}$$

Table 4.12: "OR" and "AND" gates probabilities equations

Gate	Inputs	**Probability**
OR	2	$P(A) + P(B) - P(A)P(B)$
OR	3	$(P(A) + P(B) + P(C)) - (P(AB) + P(AC) + P(BC) + P(ABC))$
OR	4	*(P(A)+P(B)+P(C)+P(D))-(P(AB)+P(AC)+P(AD)+P(BC)+P(BD)+P(CD))+ (P(ABC)+P(ABD)+P(BCD)+P(ACD)+P(ABCD))*
AND	2	$P(A).P(B) = P(A)P(B)$
AND	3	$P(A).P(B).P(C) = P(A)P(B)P(C)$

It is important to consider the FTA's assumptions to obtain accurate results. In this section, we describe several key assumptions typically made when using FTA to analyze the reliability of a system. For appropriate outcomes, the essential factors must be taken into account:

---

[0] AND gate, the output event occurs if all input events occur.

[0] OR gate, the output event occurs if at least one of the input events occurs.

- The failure rates follow an exponential distribution: This is an assumption often made in reliability analyses. The exponential distribution is commonly used to model random events that occur independently over time, with a constant failure rate. While this assumption simplifies the analysis, it may not be appropriate for all systems, and more complex distributions may be necessary in some cases.
- The simultaneous occurrence of multiple faults is prohibited, and Common Cause Failures (CCFs) are disregarded: In some situations, multiple faults can occur simultaneously, or the occurrence of one fault can increase the probability of another fault occurring. This common cause of failure is an important consideration in some systems. However, for this analysis, common-cause failures are assumed to be absent.
- Unrepairable component: Some components in a system may be unrepairable, meaning they cannot be fixed or replaced once they fail. This is an important consideration when analyzing the reliability of a system, as it may significantly impact the system's availability.
- The model does not include dynamic aspects such as operational dependence, element prioritization, and the utilization of spares: While the fault tree analysis provides a useful framework for analyzing the reliability of a system, it has some limitations. For example, the analysis is typically static and does not consider the effects of changes in the system state or the impact of maintenance or repair activities. Additionally, the analysis does not typically consider the impact of spare components or backup systems that can be used to mitigate the effects of failures.

Considering these factors, the FTA results can be more accurate and reliable. After considering the assumptions mentioned above, probability equations for the logic gates were derived and incorporated into Simulink blocks to construct the FT structure and connection gates. The resulting Simulink model for the ICS's FT is shown in Fig. 4.23.

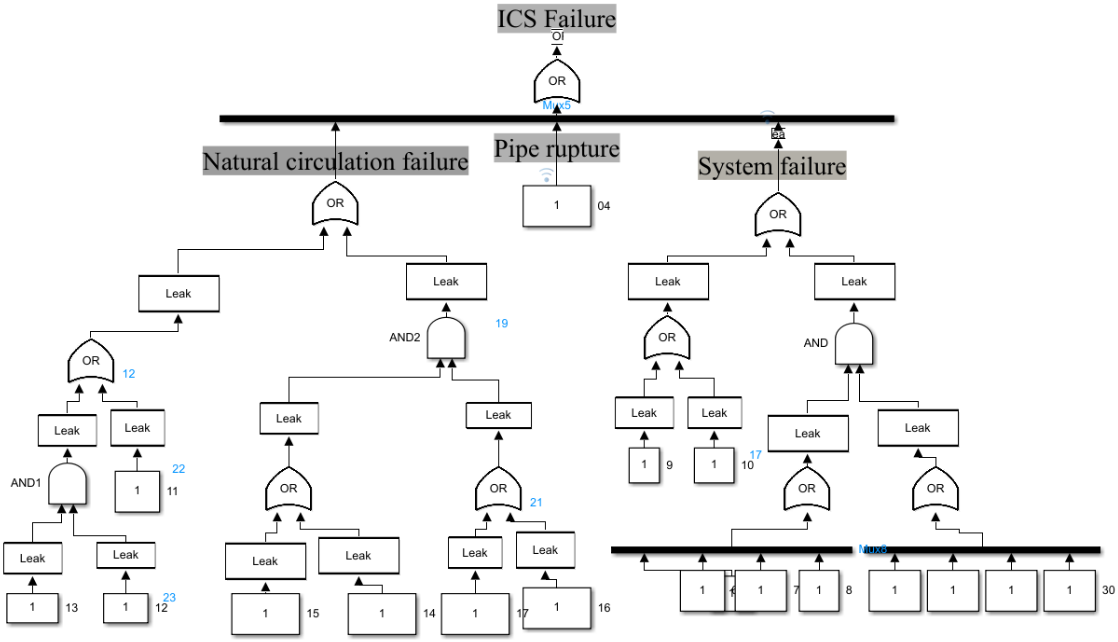


Figure 4.23: Simulink model for the ICS's FT structure and logic gates.

The Simulink FT framework shown in Fig. 4.23 obtains the probabilities of intermediate events and TE failure, the ICS failure for the SBO accident scenario. To validate the proposed Simulink-based FTA, the probabilities of BEs are fed into the model, and the probabilities of intermediate events are estimated using results from [42] where the probabilities of intermediate events are obtained using Computer Aided Fault Tree Analysis System (CAFTA).

Table 4.13: Comparison between the CAFTA and Simulink results for various intermediate events

Intermediate Event	**CAFTA Results**	**Simulink Results**
Insufficient water in the IC pool	1.19×10^{-9}	1.16×10^{-9}
Vent valves failure	4.62×10^{-4}	4.02×10^{-4}
Bypass vent valves failure	4.62×10^{-4}	4.62×10^{-4}
Heat exchanger failure	4.32×10^{-8}	3.12×10^{-8}
Condensation valve failure	4.59×10^{-5}	5.66×10^{-5}
Bypass condensation valve failure	4.59×10^{-5}	4.59×10^{-5}

The comparison table (Table 4.13) presents the results obtained using two methods, CAFTA and Simulink, for various intermediate events. The probabilities for all events are similar between the two methods, with the probabilities for insufficient water in the IC pool and bypass vent valve failure being identical. However, the failure probabilities for PRHRS differ between the two methods, with CAFTA predicting a higher failure probability than Simulink. This difference could be due to each method's different assumptions and simplifications. These results suggest that the modelling approach employed in Simulink is accurate and valid in predicting the probabilities of the considered events. Moreover, the Simulink model can serve as a basis for feeding the NN algorithm, indicating that the model is a suitable input for further analysis and prediction.

In Section 3.4.3, a detailed description of the proposed methods for mapping FT into ANN is provided. The subsequent sections will delve into the configuration of the ANN, the model algorithm, and the data acquisition methods used. Once these steps are covered, the results of this mapping will be presented.

This work uses a deep neural network to map the FT into the ANN. A fundamental aspect of deep learning algorithms is their configuration, which is critical for achieving high accuracy in predicting new data. This involves determining the appropriate density of hidden layers, the transfer function for each layer, and learning procedures to mitigate potential over-fitting and under-fitting issues. To address the over-fitting and under-fitting, the following rules are considered:

1. The hidden layers' neuron number should amount to less than those in the input and output layers combined.

2. Two-thirds of the input and the output layer neurons should make up the number of hidden neurons.
3. In a fault tree, the amount of the first hidden layer neuron and intermediate events connected to the basic events might be equal.

A neural network with two hidden layers can accurately approximate certain boundaries using linear and non-linear transfer functions, providing a close approximation of any smooth projection. However, due to the high complexity and lengthy training time, neural networks with three or more hidden layers are rarely used. Instead, this work proposes a mapping technique using several FT layers between the BEs and the TE. In Figs. 4.2, 4.3, and 4.4, there are 18 BEs in the input level, and the intermediate event is connected to the first input BEs and successive layers of intermediate events.

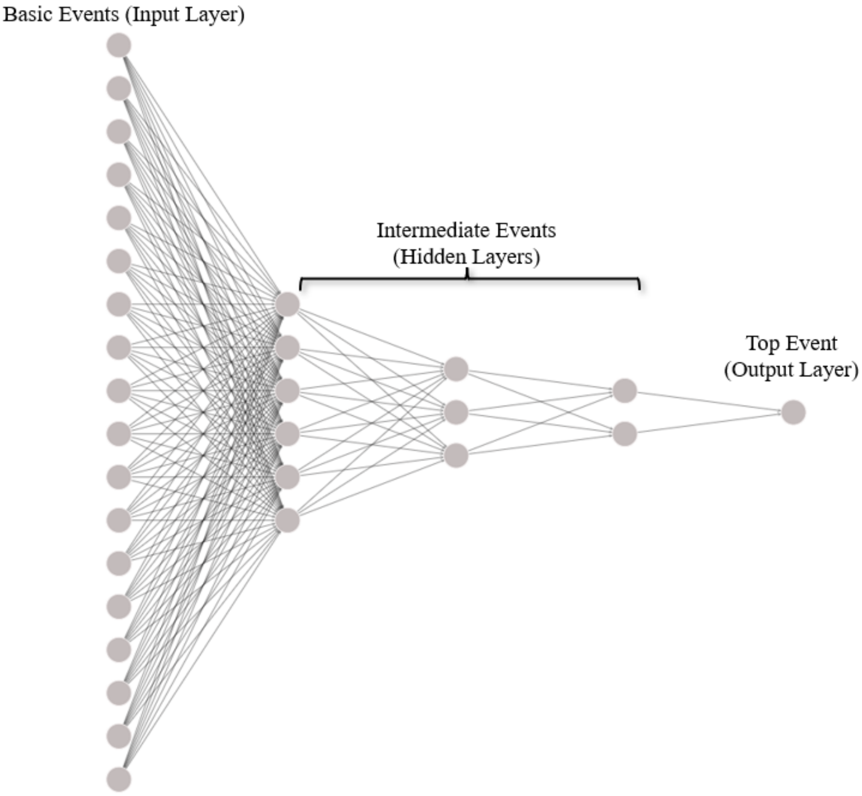


Figure 4.24: Mapping FT into ANN, the network has one input layer (BEs), three hidden layers (Intermediate events), and one output layer (TE).

As depicted in Fig. 4.24, each layer's hidden nodes equals the intermediate events (6, 3, and 2 in the first, second, and third hidden layers, respectively). In this work, the number of hidden layers is set to match the number of intermediate event layers in the FT structure, resulting in three hidden layers in the proposed model. Notably, the last layer of the proposed model corresponds to the output of the deep learning algorithm, which is the top event in the FT analysis.

The present description outlines a modelling procedure to evaluate the likelihood of failure of ICS in CAREM-25 under SBO accident scenario. Specifically, the process generates 500 randomized failure probabilities for each of the 18 BEs, resulting in 9,000 probabilities.

Following this, the failure probabilities of both TE and intermediate events are calculated for each of the 18 BEs. However, it is essential to emphasize that the accuracy of these calculations depends on the quality of the underlying data that informed the generation of the failure probabilities and the assumptions made in the modelling process. As such, the results of this type of analysis should be interpreted with caution, and further validation against empirical data is necessary once such data become available.

Table 4.14: The random probability of BEs and their corresponding TE

	BE$_1$	**BE$_2$**	**BE$_3$**	$\cdots$	**BE$_{499}$**	**BE$_{500}$**	**TE**
1	7.23×10^{-07}	2.38×10^{-09}	3.79×10^{-05}	$\cdots$	6.69×10^{-06}	7.79×10^{-07}	1.011×10^{-3}
2	7.95×10^{-07}	2.02×10^{-09}	3.18×10^{-05}	$\cdots$	6.88×10^{-06}	7.23×10^{-07}	1.57×10^{-4}
3	2.25×10^{-07}	2.86×10^{-09}	3.13×10^{-05}	$\cdots$	7.19×10^{-06}	7.13×10^{-07}	1.51×10^{-4}
$\vdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
499	1.63×10^{-06}	2.66×10^{-09}	3.23×10^{-05}	$\cdots$	7.18×10^{-06}	7.22×10^{-07}	1.48×10^{-4}
500	2.03×10^{-07}	2.03×10^{-09}	3.43×10^{-05}	$\cdots$	7.93×10^{-06}	7.88×10^{-07}	1.15×10^{-4}

After selecting the appropriate training and testing data for the deep learning algorithm and collecting data from the Simulink FT, the next step is to train the deep neural network model to predict the TE based on the BEs. This involves dividing the failure dataset into three parts: training, validation, and test

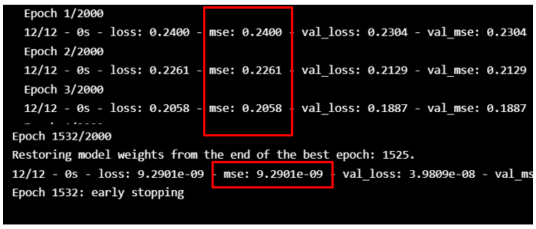
- Training 80%; is used to train the DL model
- Validation 10%; to evaluate the model's performance during training and to tune the hyperparameters
- Test 10%. Assessing the final performance of the trained model

This partitioning of the dataset is a common approach in deep learning modelling and is necessary to prevent overfitting and to ensure that the trained model can generalize well to new data.

After constructing and programming a deep learning model using Python 3.4, it must be trained to establish the mathematical relationship between the input variables (BEs) and the output variable (TE). This is achieved by training the model with a large dataset comprising several hundred data sets for each of the 18 BEs datasets in this instance. The training process involves adjusting the model's parameters until it can accurately predict the output variable for a given set of input variables. This training process enables the model to memorize the mathematical connection between the independent variables (BEs) and the dependent variable (TE). This is accomplished by optimizing the model's parameters to minimize the difference between the predicted and actual output values. Subsequently, once the model has undergone training, it can be evaluated to assess its performance on new and previously unseen data. Before deploying the model in real-world scenarios or utilizing it for scientific investigations, this step is critical. The model's efficacy can be determined by analyzing its predictive accuracy and other relevant performance metrics, essential in evaluating its suitability for specific applications.

The Mean Square Error (MSE) is a widely adopted evaluation metric in the context of machine learning models. The mean square error measures the average error between the predicted and actual values. It is calculated as the sum of squared discrepancies between the predicted value y_i and the corresponding actual value x_i. It is important to note that the MSE values are dimensionless and, thus, not associated with any specific unit of measurement. In the analysis of Fig. 4.25, it can be observed that the MSE of a model decreased from an initial value of 0.2 to nearly 9.2×10^{-9} after 1532 epochs. This reduction in MSE indicates an improvement in the model's performance, suggesting that the model's predictions have become more accurate. Low MSE values are preferred, as they imply the better performance of the machine learning model. The MSE is a valuable metric for evaluating the accuracy of models in various contexts, especially in regression problems, where the objective is to predict continuous target variables.

$$MSE = \underbrace{\frac{1}{n}\sum_{i=1}^{n}}_{test\,set}(Predicted_i - Actual_i)^2 \tag{4.32}$$

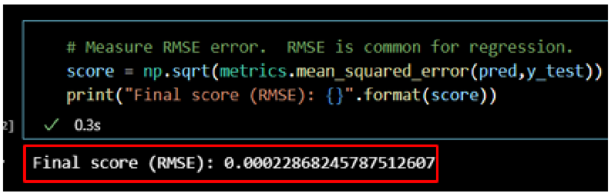


```
  Epoch 1/2000
  12/12 - 0s - loss: 0.2400 - mse: 0.2400 - val_loss: 0.2304 - val_mse: 0.2304
  Epoch 2/2000
  12/12 - 0s - loss: 0.2261 - mse: 0.2261 - val_loss: 0.2129 - val_mse: 0.2129
  Epoch 3/2000
  12/12 - 0s - loss: 0.2058 - mse: 0.2058 - val_loss: 0.1887 - val_mse: 0.1887
Epoch 1532/2000
Restoring model weights from the end of the best epoch: 1525.
12/12 - 0s - loss: 9.2901e-09 - mse: 9.2901e-09 - val_loss: 3.9809e-08 - val_ms
Epoch 1532: early stopping
```

Figure 4.25: Evolution of mean square error during model training

The Root Mean Square Error (RMSE) is a commonly used performance metric in machine learning models, calculated as the square root of the MSE. The root mean square error measures the average magnitude of the errors between the predicted and actual values, expressed in the same units as the target variable. In the analysis of Fig. 4.26, it can be observed that the RMSE error is plotted against the number of epochs, and it gradually decreases as the model is trained. A low RMSE value is typically preferred, indicating that the model's predictions are more accurate.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{Predicted_i - Actual_i}{\sigma_i}\right)^2} \tag{4.33}$$



```
# Measure RMSE error.  RMSE is common for regression.
score = np.sqrt(metrics.mean_squared_error(pred,y_test))
print("Final score (RMSE): {}".format(score))
```

```
Final score (RMSE): 0.00022868245787512607
```

Figure 4.26: Evolution of root mean square error during model training

The loss function is an important component of machine learning models and is used to determine the accuracy of the model's predictions. The loss is calculated for both the training (80%) and validation sets (10%), and its interpretation is dependent on how well the model performs in each of these sets (Fig. 4.27). The loss can be viewed as the total of the mistakes produced by the model for each example in the training or validation sets. During the optimization process, each iteration results in a loss value that reflects how well or poorly the model performs. Optimization aims to minimize the loss function, leading to better performance and greater model accuracy.

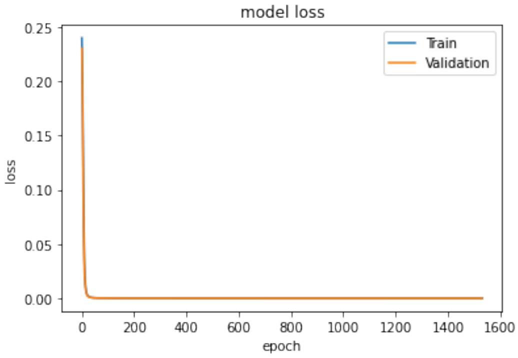


Figure 4.27: Loss function

The loss function plot in Fig. 4.27 offers valuable insights into the model's performance over time. It shows the loss function's evolution for the training and validation datasets over 1532 epochs. The plot demonstrates that the model's performance is almost identical on both datasets, with the training and validation loss decreasing at a comparable rate. This suggests the model is not overfitting the training data and can generalize well to new data. However, if the fitted plots of the training and validation losses begin to diverge regularly, it could indicate that the model is overfitting the training data. In such cases, it may be necessary to halt the model's training at an earlier epoch to prevent it from becoming too specialized to the training data, which can cause it to lose its ability to generalize to new data.

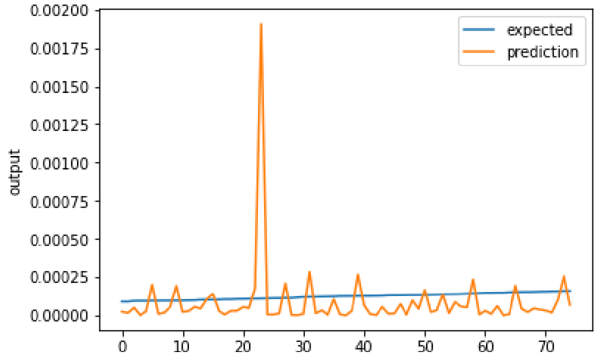


Figure 4.28: Expected values and predicted values

Figure 4.28 provides a visual representation of the comparison between the series of expected values and the predicted values generated by the model. The plot shows that the forecast is a good fit based on the given data, with the model demonstrating the skill to make sensible predictions around the expected values. While some fluctuations are observed in the plot, the chosen deep-learning algorithm is a suitable model for the given data. The model accurately depicts trends and fluctuations, despite failing to capture some of the individual data points.

Table 4.15: Comparison between results of ANN-based FT and conventional FT

	Fault Tree Results [42]	**Deep learning Results**
BEs Data-Set 1	0.00010	0.000734
BEs Data-Set 16	0.00009	0.0007342
BEs Data-Set 422	0.00010	0.0007341

A comparative analysis of the results obtained from both the deep learning and fault tree models was conducted, and the findings are presented in Table 4.15. The results indicate that the two models produced output values near one another regarding accuracy and precision. The negligible disparity between the top events obtained from the BEs and the values of the top events acquired from the BEs further highlights the similarity between the models.

The table shown in 4.15 compares the results obtained using conventional FTA and those obtained using a deep neural network approach for three different data sets (BEs Data-Set 1, BEs Data-Set 16, and BEs Data-Set 422). The table shows that the deep learning approach produces slightly higher results for each of the three data sets, with an average value of 0.000734 compared to the conventional FT approach, which has an average value of 0.000096. It is important to note that the results presented in the table are only for the specific data sets used in the study and may not necessarily represent the performance of the deep learning approach or the conventional FT approach in other contexts or with different data sets. Additionally, the table provides only limited information on the methods used to generate the results or the specific assumptions and limitations of the approaches. Further analysis and discussion of the results and methods used would be necessary for a more complete understanding of the comparison between the two approaches.

4.5 Conclusion of Chapter 4

In this chapter, fuzzy logic and ANN have been employed to improve traditional risk assessment methods. Fuzzy PSA and fuzzy FMEA have been developed and utilized to evaluate the safety of ICS in the CAREM-25 type concept. Unavailability and inaccuracy in failure rates are modelled using fuzzy logic; to do this, upper-bound and lower-bound are considered to model uncertainty around each failure rate in the shape of TFN. The fuzzy fault tree analysis was conducted to calculate the fuzzy failure probability of an ICS during an SBO after 100 hours. Then FFT was constructed using fuzzy failure rates, dynamic fuzzy operators and Priority-AND and Priority-OR gates in Simulink. The top event failure probability at time=0 was found to be consistent with other research results, indicating that the model is valid. However, the results at other times during SBO accidents showed that dynamic gates are essential for modelling the degradation and aging effects of systems and components over time. This suggests dynamic gates and implementing fuzzy failure rates in the fuzzy fault tree can provide more accurate results.

The results obtained from FFTA were then used to develop fuzzy FMEA and FETA. A fuzzy event tree analysis was conducted under an SBO-initiating event. The fuzzy failure and success probability of mitigating systems, namely the ICS and ADS, were evaluated for two paths of accident scenarios to estimate the CDF of the system's performance. The results showed that the probability of CDF under SBO scenarios increased as time passed if layers of safety systems failed to mitigate the accident. This indicates that the longer the SBO event lasts, the greater the likelihood of a failure occurring in the ICS and ADS systems. The proposed FETA is feasible and applicable for quantifying CDF based on fuzzy probability obtained from FFTA to complement the one based on probability distributions.

A fuzzy FMEA is linked to the FFTA to analyze ICS failure modes and estimate the fuzzy RPN for each component using the FIS toolbox in MATLAB. The probability of occurrence is directly obtained from the FFTA, which connects the two models to calculate fuzzy RPN based on the fuzzy representation of occurrence, severity, and detectability. Fuzzy RPN is compared with conventional RPN, showing that the Fuzzy RPN value may be lower than the RPN value due to how the fuzzy logic is applied to the RPN calculation. This could happen if the membership functions used in the fuzzy logic calculation result in a lower overall score than the traditional RPN calculation. The proposed fuzzy FMEA technique provides a more accurate and realistic representation of PRHRS failures where uncertainties and input variability are prevalent.

Alternatively, by mapping FT into ANNs, the proposed approach overcomes the limitations of traditional FT analysis. Specifically, the study maps the FT into a deep neural network with three hidden layers to predict the probabilities of TEs associated with the failure of the PRHRS. The proposed technique addresses traditional FT analysis's complexity and time-consuming nature, especially when dealing with incomplete or missing data. Using 500 sets of BEs as inputs, the model can effectively predict and recognize the relationship between inputs and outputs, regardless of the number of BEs, logical gates, or system complexity. The results demonstrate that the proposed approach is accurate and fast enough to meet the needs of practical applications.

Despite their advantages, challenges still need to be addressed in these approaches, including improving the methods for incorporating expert judgment, handling imprecise data, and addressing uncertainties in the overall risk assessment process. Future research should address these challenges to improve the effectiveness and accuracy of risk assessments for safety-critical systems.

Chapter 5

Conclusions

5.1 Conclusions

In recent years, the development of SMRs has gained significant attention due to their potential benefits, such as flexibility, cost-effectiveness, and enhanced safety features. However, the unique design and new technologies of SMRs present challenges for traditional risk and safety analysis methods. This thesis aims to evaluate various risk analysis methods, including PSA and FMEA, and compare them with innovative approaches, such as fuzzy logic and ANN, in the context of SMRs, more specifically, the passive safety system of the CAREM-25 reactor. The interactions between different systems and components in SMRs may be more complex and harder to model than in traditional NPPs due to their smaller size of them. Therefore, advanced modelling and simulation techniques may be required to evaluate the safety of SMRs effectively.

Moreover, the limited OPEX with SMRs can be seen as a source of challenges in terms of accurately estimating the likelihood of different accident scenarios, lack of operating data and failure rates of systems and components. This uncertainty in input data can lead to high variability in the results of traditional PSA and FMEA. Thus, there is a need for innovative methods that can handle uncertainty and improve the accuracy of risk analysis for SMRs. This thesis explores using fuzzy logic and ANN concepts in innovative risk and safety analysis methods, such as fuzzy PSA and ANN-based fault trees, to address the limitations of traditional risk analysis methods. Fuzzy logic provides a flexible framework for dealing with uncertainties in input data and can be used to model complex relationships between input and output parameters. ANN, on the other hand, can be trained to recognize patterns in data and make accurate predictions.

Probabilistic safety assessment is a widely used methodology for evaluating the safety of nuclear power plants. However, traditional PSA is limited by the assumption of crisp values for the failure rates of components and systems. In reality, the failure rates are associated with uncertainties and imprecisions due to manufacturing defects, aging, and human error. These Uncertainties in failure rates can significantly affect the accuracy of traditional PSA results and cause the rates not to remain constant over time. To overcome these limitations, we proposed a fuzzy Probabilistic Safety Assessment (Fuzzy PSA) technique that considers fuzzy numbers instead of crisp values for failure rates. The proposed technique combines fuzzy set theory and probability theory to represent and propagate uncertainties and imprecisions in the failure rates of components and systems. Using triangular fuzzy numbers in FPSA enables a more accurate representation of the uncertainties and imprecisions associated with failure rates.

We conducted a case study of the proposed technique on the PRHRS of the CAREM-25 type reactor. The case study results demonstrated that using fuzzy numbers in PSA improved the accuracy of the analysis by providing a more nuanced understanding of the system's overall failure risk. The results also showed that FPSA captures uncertainties and imprecisions in failure rates more effectively than traditional PSA. To further elaborate, using FFTA in combination with FETA is a novel risk analysis approach that can significantly consider the uncertainty and vagueness in input data to improve the accuracy of safety assessments. The fuzzy fault tree analysis methodology is designed to consider the inherent fuzziness in failure rates of both BEs and intermediate events in ICS failure. These BEs and intermediate events fuzzy failure rates are connected to calculate the ICS failure as TE using fuzzy operators and Pandora gates (priority-AND and priority-OR gates). This allows for a more nuanced understanding of the overall fuzzy failure risk of the system, as it enables the estimation of the TE failure probability with greater accuracy than traditional methods.

The coupling of FFTA with FETA requires the propagation of uncertainties modelled in FTA into the quantification of CDF under an SBO accident scenario. The primary motivation behind this coupling is to account for uncertainties that arise in FTA when considering the lines of mitigating systems such as the ICS and the ADS. Fuzzy event tree analysis is developed to address this issue, and fuzzy CDF is calculated based on the failure or success of the ICS and ADS for different paths. This approach enables a more comprehensive assessment of the risks associated with an SBO accident scenario and provides a more accurate understanding of the overall failure risk of the system.

In order to identify the weaknesses of the PRHRS system and different failure modes and effects of ICS failure, The linkage between an FFTA and a fuzzy-logic-based FMEA is proposed in this work. In a fuzzy FMEA, the imprecise or uncertain information about severity, occurrence, and detectability is represented using fuzzy sets, which are then used to calculate the fuzzy RPN for each failure mode. In this thesis, the fuzzy probability of occurrence is taken from the FTA into the fuzzy FMEA; instead of using crisp values for severity and detectability, we convert the crisp values into linguistic values to consider uncertainty around certain numbers. Using fuzzy severity, occurrence, and detectability in analyzing ICS' failure risks offers several benefits. Firstly, ICS systems' behaviour and failure modes are inherently uncertain and imprecise, making obtaining precise estimates of failure probabilities and severity challenging. By using fuzzy numbers, the level of uncertainty and imprecision associated with the system can be captured more accurately, leading to a more realistic and accurate representation of the potential failure modes.

In addition to the fuzzy probabilistic safety assessment approach, this thesis also proposes mapping fault trees into a deep learning framework to overcome the limitations of traditional FT analysis. Traditional FT analysis is time-consuming and complex; dealing with incomplete or missing data can be challenging. By leveraging the capabilities of ANNs, this mapping technique can provide a more effective tool for fault prediction and consequence analysis. Isolation condenser system failure is constructed in FT and then mapped into the deep neural network of each FT component. The results indicate that the two models produced output values near one another regarding accuracy and precision. The negligible disparity between the top events obtained from the BEs and the values of the top events acquired from the BEs further highlights the similarity between the models.

In summary, In this thesis, the main contributions consist of proposing a fuzzy PSA approach (based on the fuzzy logic, fuzzy operators and Pandora gates) that can improve the accuracy of traditional PSA by considering fuzzy numbers instead of crisp values for failure rates, replacing static Boolean gates with dynamics Prority-AND and Prority-OR gates and dynamic fuzzy operators. We demonstrate the applicability of this approach in a case study of CAREM-25's PRHRS using FFTA, FETA, and fuzzy FMEA. The results show that the proposed FPSA approach provides a more accurate understanding of the overall failure risk of ICS, especially under uncertainty and imprecision. Moreover, we propose a mapping technique to adopt FT into a deep learning framework to overcome the limitations of traditional FT analysis, such as the complexity and time-consuming nature of the analysis and the challenge of dealing with incomplete or missing data. Although these approaches have several advantages, some challenges still need to be addressed, including improving the methods for incorporating expert judgment, handling imprecise data, and addressing uncertainties in the overall risk assessment process.

Our research provides new insights into how fuzzy set theory and probability theory can be combined to improve safety-critical system risk assessment. Future research should address the challenges to enhance these approaches' effectiveness and accuracy. Despite this approach's advantages, challenges still need to be addressed, such as improving methods for incorporating expert judgment, handling imprecise data, and addressing uncertainties in the overall risk assessment process. However, by addressing these challenges, future research could significantly improve the effectiveness and accuracy of risk assessments for safety-critical systems.

5.2 Future Work

In future research, with respect to fuzzy PSA, incorporating expert opinion in calculating failure rates for SMRs could be a promising approach, given the comparatively lower operational expenditure of SMRs. This would enable the utilization of specialized data pertinent to specific SMR designs. Such an approach could significantly enhance the accuracy and reliability of the PSA outcomes. In addition, Neuro-fuzzy systems, as a future work possibility, combine fuzzy logic with neural networks. Neuro-fuzzy systems use neural networks to learn the relationships between inputs and outputs in a fuzzy logic system and to optimize the fuzzy logic rules for a given task. This makes neuro-fuzzy systems more flexible and adaptable than traditional fuzzy logic systems. PSA often uses them for data analysis, uncertainty modelling, decision-making, and fault diagnosis.

The current work utilized standard triangular fuzzy numbers to express the imprecise likelihood of different risk events occurring and their impact. Further research could explore the use of alternative membership function shapes to evaluate the outcomes relative to those obtained in this study. In addition, collecting data on the root causes of critical risk events could create a smart system that automatically generates fault trees.

In FMEA, the risk priority number is typically determined by multiplying the assigned scores for the probability of occurrence, severity, and detectability. By incorporating fuzzy logic into the FMEA framework, it becomes possible to enhance understanding of the complex interplay between these variables by assigning more nuanced features to the severity, occurrence, and detectability assessments. For example, rather than simply assigning a single numerical value to the severity assessment, a fuzzy FMEA approach allows for considering distinct severities associated with different elements, such as assets, people, and the environment. These severities can then be combined to provide a more comprehensive measure of overall severity within the model.

In order to improve the accuracy and efficacy of mapping FT into the ANN, further research could explore the integration of real-time RELAP and MELCOR simulations to generate relevant accident scenarios and extract data for training the ANN model. This would enable the model to more effectively identify and analyze potential system failures, ultimately improving safety and reliability in SMRs.

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