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Abstract

Petrochemical installations are complex processes with high connectivity and continuously interaction between their systems and devices, which requires the control of several parameters for optimal operation. This type of process deals with hazardous substances at elevated temperatures and pressure and always faces difficulties in process control, hence failing to target operations that generate several types of risks such as explosion and fire. These safety incidents lead to serious consequences affecting people, environment and property.

To provide a high level of security and safety to these installations, different risk management strategies have featured in literature, to identify and reduce hazardous situations. However, even with the vast variety in these strategies and the combination of different techniques to deal with some limitations and cover the maximum drawbacks, other difficulties are still considered such as uncertainties in both the input and output of the analysis and the classification problem. In recent years several tools have been developed based on artificial intelligence to deal with these difficulties such as fuzzy logic that relies on membership function principle and artificial neural network that emulate the biological ones.

The objective of the thesis is to define generic methods of risk analysis based on fuzzy logic and neural network that can be appropriated for any industrial system and evaluate the different risks very well under the condition of uncertainty.

- ✓ The first: an integrated frame implemented based on HAZOP and fuzzy evaluation of risk matrix to evaluate the safety integrity level (SIL) of an industrial fired heater safety.
- ✓ The second: a novel methodology based on LOPA method and FUZZY LOGIC to increase its performance in terms of analysis and risk reduction. This approach is implemented to a real system namely naphtha-A- stabilizer after identifying risks inherent in this system by applying the HAZOP method (Hazards and Operability Study).
- ✓ The third: an approach based on Artificial Neural Networks (ANN) is developed to schedule the SIL values of the safety integrity functions (SIF) of an industrial-fired heater.

Keywords: Safety, Risk, Petrochemical installation, uncertainty, Fuzzy logic, HAZOP, SIL, Fuzzy LOPA, Neural network ...

ملخص

بعد الثورة الصناعية الرابعة زاد اهتمام الأمم بالتطور التكنولوجي لوسائل الذكاء الاصطناعي لتعزيز قدراتها وتحفيز نموها الاقتصادي. وكذا تطوير الصناعات البتروكيمياوية وتعزيز امن وسلامة مصانعها التي تعد بدورها الأكثر تعقيدا وترابطا بين أنظمتها، مما يجعل عملية التحكم بها أكثر صعوبة خاصة تحت ظل النقص في المعلومات اللازمة لذلك او عدم التأكد من دقتها.

لتوفير مستوى عالٍ من الأمن لهذه المنشآت، ظهرت استراتيجيات مختلفة لإدارة المخاطر في المراجع من خلال تحديد مختلف سيناريواتها والعمل على الحد منها، رغم التنوع الكبير في هذه الاستراتيجيات والجمع بين التقنيات المختلفة ودمجها للتعامل مع بعض القيود وتغطية الحد الأقصى من العيوب، لا تزال هناك صعوبات أخرى تؤخذ بعين الاعتبار مثل عدم اليقين في مدخلات ومخرجات طرق التقييم ومشكلة التصنيف والجدولة. في السنوات الأخيرة تم تطوير العديد من التقنيات والطرق المبنية على الذكاء الاصطناعي للتعامل مع هذه الصعوبات مثل المنطق الضبابي الذي يعتمد على مبدأ وظيفة العضوية والشبكة العصبية الاصطناعية التي تحاكي نظيرتها البيولوجية في المبدأ.

الهدف من الأطروحة هو تحديد طرق عامة لتقييم المخاطر مبنية على المنطق الغامض والشبكة العصبية والتي يمكن تخصيصها او تطبيقها على اي نظام صناعي وكذا تحسين التقييم في ظل حالات عدم اليقين.

- ✓ أولا: تكامل تم تنفيذه بناء على طريقة تحليل المخاطر وقابلية التشغيل (HAZOP) والتقييم الغامض لمصفوفة المخاطر (Fuzzy risk matrix) لتقييم مستوى سلامة السلامة (SIL) لسلامة السخان الصناعي.
- ✓ ثانيا: منهجية جديدة تعتمد على طريقة تحليل طبقات الحماية (LOPA) والمنطق الغامض لزيادة أدائها من حيث التحليل وتقليل المخاطر. يتم تطبيق هذه الأخيرة على نظام حقيقي وهو عمود استقرار الناقتا بعد تحديد المخاطر الكامنة فيه من خلال تطبيق طريقة (دراسة المخاطر وقابلية التشغيل).
- ✓ ثالثا: تم تطوير نهج يعتمد على الشبكات العصبية الاصطناعية لجدولة قيم لوظائف سلامة الامن (SIL) للسخان الصناعي.

الكلمات المفتاحية: الأمن، المخاطر، المنشآت البتروكيمياوية، عدم اليقين، المنطق الضبابي، طريقة تحليل المخاطر وقابلية التشغيل، تحليل طبقات الحماية الضبابية، الشبكة العصبية...

Résumé

Les installations pétrochimiques sont des processus complexes avec une forte connectivité et une interaction continue entre leurs systèmes et dispositifs, ce qui nécessite le contrôle de plusieurs paramètres pour un fonctionnement optimal. Ce type de processus traite des matières dangereuses à des températures et des pressions élevées, et fait face toujours à des difficultés de contrôle du processus, et donc l'incapacité de suivre les opérations ciblées, ce qui génère plusieurs types de risques tels que les explosions et les incendies. Ces incidents de sécurité entraînent des graves conséquences qui affectent les personnes, l'environnement et les biens.

Pour assurer un niveau de sécurité élevé et de sûreté à ces installations, différentes stratégies de gestion des risques ont été présentées dans la littérature, pour identifier et réduire les situations dangereuses. Cependant, même avec cette grande variété de ces stratégies et la combinaison de différentes techniques pour faire face à certaines limitations et couvrir le maximum des défauts, d'autres problèmes sont encore prises en compte, tels que les incertitudes dans les entrées et les sorties de l'analyse et le problème de classification. Plusieurs outils basés sur l'intelligence artificielle ont été développés ces dernières années pour faire face à ces problèmes, notamment la logique floue qui est basée sur le principe de la fonction d'appartenance et les réseaux neuronaux artificiels qui simulent les réseaux biologiques.

La thèse vise à établir des techniques d'analyse des risques génériques utilisant la logique floue et les réseaux de neurones qui être adaptées à tous les systèmes industriels et qui peuvent également évaluer efficacement les différents risques en cas d'incertitude :

- ✓ La première consiste à évaluer le niveau d'intégrité de sécurité (SIL) d'un four industriel en utilisant une intégration basée sur l'analyse HAZOP et d'une évaluation floue de la matrice de risques.
- ✓ La deuxième approche est basée sur la méthode LOPA et LOGIC FLOUE afin d'améliorer ses performances en terme d'analyse et de réduction des risques.

Après avoir utilisé la méthode HAZOP (Hazards and Operability Study), cette méthode est utilisée sur un système réel qui est un stabilisateur de naphta-A.

- ✓ La troisième approche basée sur les réseaux de neurones artificiels (ANN) a été créée pour prévoir les valeurs SIL des fonctions d'intégrité de sécurité (SIF) d'un four industriel.

Mots clés : Sécurité, Risque, Installation pétrochimique, incertitude, Logique floue, HAZOP, SIL, LOPA floue, Réseau de neurones ...

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Abbreviations list

AI	Artificial Intelligence
APD	Preliminary Analysis of Dangers
APR	Analysis Preliminary
C	Consequence
DRIRE	Regional Directorates of Industry, Research and the Environment
ET	Event Tree
FTA	Fault Tree Analysis
FFTA	Fuzzy Fault Tree Analysis
ETA	Event Tree Analysis
FETA	Fuzzy Event Tree Analysis
F	Consequence Frequency
FMEA	Failure Mode and Effects Analysis
FFMEA	Fuzzy Failure Mode and Effects Analysis
FMECA	Failure modes, Effects, and Criticality Analysis
FLS	Fuzzy Logic System
HAZID	Hazards Identification
HAZOP	Hazards and Operability Study
HSE	Health-Safety-Environment
IEC	International Electro-Technical Commission
ISO	International Organization for Standardization
ICI	Imperial chemical industries

ICPE	Classified Installations for the protection of environment
IOP	Internal Operation Plan
IEP	Internal Emergency Plan
IPLs	Independent Protection Layers
IT	Information Technology
GAs	Genetic Algorithms
LOPA	Layer of Protection Analysis
Ltd	Limited company
MEDD	Ministry of Ecology and Sustainable Development Department
OHSAS	International Occupational Health and Safety Management Standard
OS	Operational Safety
P	Probability of occurrence
P&ID	Piping and Instrumentation Diagram
PPI	Special Plan for intervention
PPRT	Technological Risk Prevention Plan
PFD	Probability of Failure on Demand
Probor	Probabilistic OR
R	Risk
SIF	Safety Instrumented Function
SIS	Safety instrumented system
SIL	Safety Integrity Level
UVCE	Unconfined Vapour Cloud Explosion

General Introduction

General introduction

Recently, nations have increasingly regarded to technological advances in the field of artificial intelligence as a way to enhance their military capabilities, strengthen their overall capabilities, and stimulate economic growth. Artificial intelligence plays a pivotal role in the framework of the fourth industrial revolution, particularly in the evolution of petrochemical industries and enhancing the plant security.

In this context, practicing engineers have adopted AI approaches widely, allowing them to efficiently handle with a variety of complicated challenges, such as managing uncertainties, performing classification tasks, and improving processes. The main aim of this thesis is to investigate how artificial intelligence techniques might improve safety in petrochemical facilities. In order to provide clarity regarding the scope, challenges, and objectives of this research, we have formulated two key research questions, as follows:

- ✓ What are the challenges associated with the utilization of artificial intelligence techniques in safety applications and risk assessment? This question aims to demystify the application of AI in safety contexts by highlighting the specific purposes of each technique and the problems they address.
- ✓ How do conventional methods incorporating artificial intelligence techniques propose solutions to address these challenges, particularly in the context of risk assessment, with the aim of mitigating existing issues and problems within the risk management strategy, risk analysis and evaluation, and ultimately integrating these approaches with intelligent techniques like fuzzy logic, neural networks, PSO, and genetic algorithms?"

In the last few decades, several techniques and standards have appeared in literature, to identify hazardous situations, and help companies to build up their own safety plans (Ramzan et al. 2007b). However, even the wide variety of provided techniques, they suffer from some limitations due to the limited application of some methods (taking into account the complexity of process and chemical industries) and the difficulties in generalization in other methods; hence an effective risk assessment process can be achieved only by the combination of different techniques.

The idea of integrating different methods in one frame has been extensively presented in literature, the aim is to obtain results by covering the maximum drawbacks, and respect all site-specific factors (Hu et al. 2015) (Nolan 2014) (Riad et al. 2018) (Jeerawongsuntorn et al. 2011).

Another difficulty that faces the application of these methods is the existence of uncertainties in both the output of analysis and the furnished data from the site. The uncertainties in the output of analysis means the differences between the key values in each risk assessment method and the true values. For example, in risk analysis we need to quantify the economic effect of an accident, or the number of fatalities...the fact that requires experimental data to validate the model and hence the results. which is not possible particularly in complex petrochemical plants (Bendib et al. 2019) (Zhang et al. 2015) (Chang et al. 2015). Whereas the uncertainties in the furnished data generally caused by the inability of performing adequate measurements due to sensors errors, or in some cases the operators' ignorance (Chang et al. 2015) (Zhang et al. 2015) (Bendib et al. 2019).

On the other hand, the last development in control systems characterized by the introduction of new tools based on artificial intelligence, leads to the development of effective control strategies to solve the limitations of classical control system. Among the tools the fuzzy logic, that is constructed based on the theory of fuzzy set (Mohan 2019). This theory suggested that the membership principle is the key to decision making when faced with uncertainties. Mathematically the fuzzy logic is an extension of the classical binary logic. Such that instead of exact or crisp values, membership functions with linguistic variables are used.

The mechanism to deal with any real problem using Fuzzy logic should follow three main steps, the first is fuzzification which is the conversion from the exact or crisp measures to fuzzy and membership functions, the second is rule base implementation (inference) and the last is defuzzification, the reverse process of fuzzification. The recent researches show that the fuzzy logic is a powerful tool to deal with uncertainties (Wang 1997) (Passino and Yurkovich 1998) (Ross 2016), and it is even used in risk analysis methodologies (Chun and Ahn 1992) (Dernoncourt 2013a) (Kabir and Papadopoulos 2018).

Thesis Organisation

In order to overcome all the above-mentioned aspects our present work is subdivided into four chapters.

Chapter I Sheds some light on the field safety and risk management and gives descriptions, and definitions for principles, that are generally encountered in this field. In the last part of this chapter we introduce the most known conventional risk assessment methods, such as Fault Tree Analysis (FTA), Event Tree Analysis (ETA), Hazard and Operability Analysis (HAZOP), Layer of Protection Analysis (LOPA), Safety Integrity Level analysis (SIL).

Chapter II presents the Artificial Intelligence, definitions, tools and different aspects. Since artificial intelligence is very vast area, we will focus only on the methods that are directly related to our thesis i.e. introduction to fuzzy logic and neural network technique.

Chapter III is devoted to introduce some approaches that combines between the conventional risk assessment methods and the tools of artificial intelligence such the use of fuzzy logic in SIL target evaluation, the use of Fuzzy logic in LOPA determination, the neural networks for SIL scheduling,

In chapter IV, we present the application of the previously described methods in some industrial petrochemical plants such as Fired heaters and Naphtha stabilizer

Finally, we have provided an overall conclusion concerning the investigations realized in this thesis.

Chapter I

Introduction to risk management theory

I.1 Introduction

Industries are currently dealing with serious issues that put their sustainability and objectives into question; and undoubtedly the hydrocarbons sector in particular are high risk sector (Leimeister and Kolios 2018). They are concerned with avoiding dangers that could lead to fires, explosions and other accidents that could cause damage to people, property and environment (Cruz-Campa and Cruz-Gómez 2010).

In order to ensure that their facilities operate in complete safety, industries must defend their existence by establishing a risk management strategy and developing methods for analyzing and evaluating these risks (Torres-Echeverria 2016a). The first step in risk management is to analyze the endogenous and exogenous risks that are inherent in industrial systems, starting with the identification of existing potential dangers then the estimation of the associated risks in terms of occurrence and severity (Kadja et al. 2018). The second step is to assess these risks against the risk acceptability criteria. Finally, if the risk is deemed unacceptable, new security measures and barriers will be implemented in order to control these risks (Marhavidas et al. 2020).

The objective of Algeria's law n°04-20, passed on December 25, 2004, concerning disaster management and major risk prevention in the context of sustainable development, is to establish guidelines for managing major risks and preventing them. It strengthens the concept of preventing accidents involving dangerous substances by imposing specific requirements on the operator, such as the implementation of a control system, risk management, and an organization appropriate to the hazards inherent in industrial installations. (Joubert et al. 2021) (Tixier et al. 2002)

In this chapter, we will first introduce some concepts and definitions related to risk management and describe the risk management process with an emphasis on the risk control aspect. Next, we will describe some risk analysis methods, by briefly describing their operating principles.

I.2 Concepts and definitions

Although the concepts related to risk analysis are well defined by several authors, regulatory texts and standards, it seemed useful to us to take up some fundamental concepts appearing in any risk analysis process.

I.2.1 Hazard

- The term “HAZARD” is defined in the IEC61508 standard as **an intrinsic property of a hazardous substance or a physical situation capable of causing damage to human health and/ or the environment.**
- The same term is defined according to the OHSAS 18001 standard as ‘**a source or situation that can be harmful through injury or damage to health, damage to property and the environment of the workplace or a combination of thee elements**’
- In MDAS MOSAR multimedia (griot and ayral 2002), **hazard is characterized as a state or situation that has a potential for unacceptable damage. Situation of a system when all the factors that may lead to an accident are combined.**
- The dangers associated with a system are inherent in how it operates or malfunctions, meaning they are external to the system..(Ali 2011)

Note that these definitions of hazard and others which are proposed by standards and authors, although worded differently, they have same meaning. (Liu et al. 2020)

I.2.2 Risk

The perception of potential damage associated with a dangerous situation is linked to risk concept, the term risk has several meanings:

- According to VILLEMEUR, **risk is a measure of the occurrence of an undesirable event and a measure of its effects or consequences.** (Joubert et al. 2021)
- And according to OHSAS 18001, **a risk is the combination of the probability of the event and its consequence(s)** (Joubert et al. 2021)
- In MADS MOSAR multimedia (griot and ayral 2002), **risk is characterized by a minimum three-dimensional quantity associated with an exact phase of the system and characterizing an unwanted event by the event probability, its severity (or impact on targets) and its acceptability.**(Torres-Echeverria 2016b)
- According to GOURIVEAU, **risk can be defined by the association of events, causes and consequences of a given situation.** Cause-events can be characterized by their occurrence (P) and event- effects by their impact (I) (see fig I.1). the correlation of these quantities makes it possible to construct a risk indicator (Ali 2011):

$$R=f(\text{Occurrence, Impact}) \quad (\text{I.1})$$

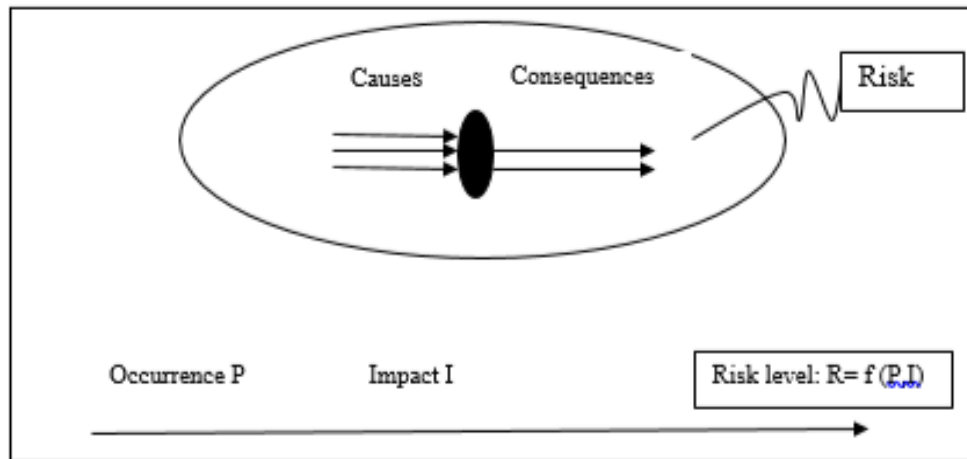


Figure I.1 Risk characterisation (Ali 2011).

In the remaining section, the risk term is unambiguously linked to the risks incurred in systems operating. Qualitatively, the risk is characterized by:

- ✓ The extent of the damage following a feared event,
- ✓ According to a gravity criterion (critical, marginal, minor, insignificant, ...). The criterion takes into account the consequences assessment in terms of human losses (injuries, death) or in terms of economic losses (cost related to damage...)
- ✓ The uncertain nature associated with the appearance of a feared event (frequent, rare, unlikely, ...) causing the damage from a determined dangerous situation.(Choi and Byeon 2020a)

I.2.3 Accident

According to OHSAS 18001, **the accident is an unexpected event that results in death, illness, injury, damage or other loss.** (Suzuki et al. 2021) (Riad et al. 2018)

I.2.4 Safety

Safety is often defined in relation to its opposite:

- According to IEC61508 standard **the absence of hazard, accident or disaster.**
- And according to the ISO/ CEI73/ISO02 guide drawn up by the ISO on risk management terminology, **safety is the absence of unacceptable risk, injury or damage to human health, directly or indirectly, resulting from damage to material or the environment.**(Cong et al. 2021)

I.3 Risk management

Although there are significant differences in terms related to risk management, the definition of risk management process is relatively identical in all ISO 1999, OHSAS18001, IEC 61511 repositories and standards as **a set of coordinated activities with the aim of reducing risk to a level deemed tolerable or acceptable** (Cruz-Campa and Cruz-Gómez 2010), which includes in particular the phases (see figure I.2)

- Risk analysis (risk identification and estimation);
- Risk assessment;
- Risk acceptance;
- Control or reduction of risk.(Ilbahar et al. 2018)

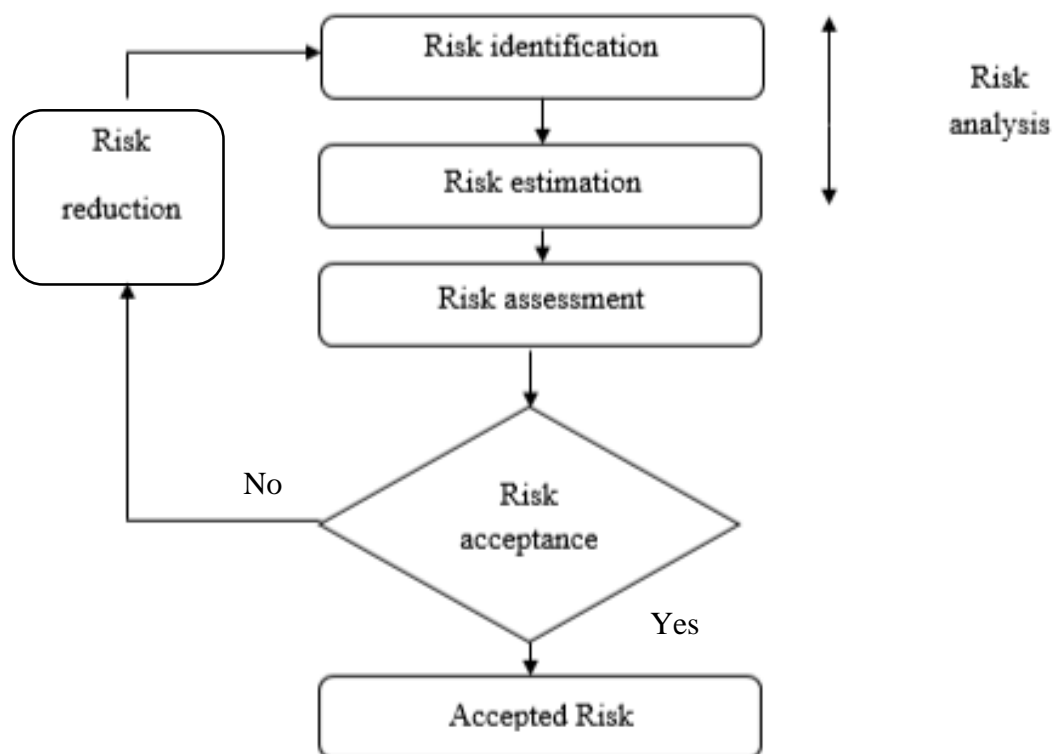


Figure I.2 Risk management process (Ilbahar et al. 2018).

Risk management is a common operation for any type of activity, the target objectives can concern for example:

- ✓ increased profits and productivity;
- ✓ cost and time management;
- ✓ the quality of a product ...(Gabriel et al. 2018)

Risk analysis and risk assessment can be performed depending on the quality of information and data collected on the system in several ways, qualitative, semi-quantitative or quantitative. In what follows, for each approach, we present some methods.(Choi and Byeon 2020b)

I.3.1 Risk analysis

Risk analysis occupies a central role in the risk management process, it is defined in ISO / IEC51 (ISO 99) as: "**The use of available information to identify dangerous phenomena and estimate risks**".(Singh and Singh 2021) (Ahn et al. 2019)

A three-level description (structural, functional, temporal) is necessary in this part to conduct an efficient analysis and achieve the desired objectives as a risk management expert.

As a first step, the primary sources of danger and the potential accident scenarios need to be determined. The complexity of certain systems requires the use of analysis tools that aid in identifying hazards (INERIS 2003), as an illustration: HAZID (hazards identification) HAZOP (hazards and operability study) APD (preliminary analysis of dangers).(Kumar and Kaushik 2020) (Zheng et al. 2012)

In a second step, risk analysis enables the identification of safety barriers existing to avoid the appearance of a hazardous situation (prevention barriers) or reduce the consequences (protection barriers). (Torres-Echeverria 2016a)

Following this identification, an estimate of the likelihood of the event occurring and the severity of its effects on people, property, and the environment may be qualitative, semi-quantitative, or quantitative. (Tixier et al. 2002)

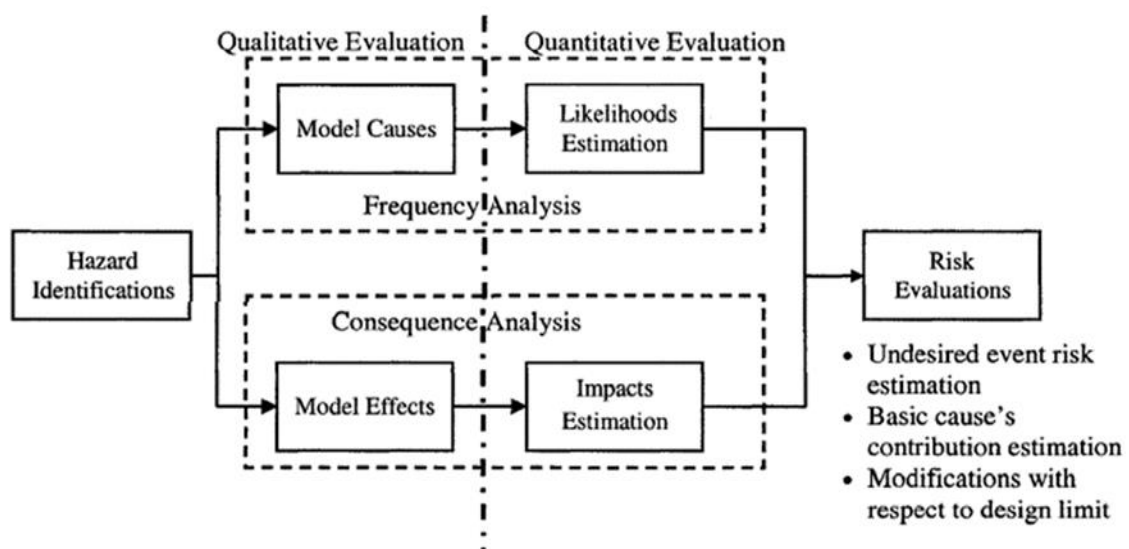


Figure I.3 Risk analysis methodology (Tixier et al. 2002).

I.3.2 Risk assessment

Once the risk has been estimated, it should be compared with the acceptability criteria previously established by the company / organization concerned. This assessment consists of determining whether the tolerable risk has been reached (ISO 99). In practice, this phase can be accompanied by a detailed and precise quantification quantities that characterize the risks (as opposed to the estimation of the risks that remains very simplified).(Khalil et al. 2012a) (Wang et al. 2019)

I.3.3 Risk acceptance

Generally, risk zones are positioned by crossing over the occurrence probability and severity levels in a criticality matrix. The Severity / Occurrence matrix is proposed by standard NF EN 50126 (NF EN 50126, January 2000): just to give an example, but in our case the SONATRACH matrix is used.(Nguyen et al. 2022) (Cui et al. 2019)

I.3.4 Risk reduction

Risk reduction (or risk control) step consists of implementing the various prevention and protection measures and barriers in order to reduce the intensity of the phenomenon (potential hazard reduction, consequences mitigation), as well as to reduce the occurrence probability by installing barriers (Kirchsteiger 1999). In a very general way, risk control measures are:

- ✓ prevention, which reduces the likelihood of occurrence of the danger situation at the origin damage;
- ✓ Protection, which is an attempt to reduce the severity of the injury.(Rausand 2014)

For as long as the risk is deemed intolerable, risk reduction strategies must be considered and implemented. In the risk management process, it is advised to regularly monitor the evolution of risks in order to maintain control and ensure the applicability of preventive measures. (INERIS 2003).

I.4 Risk analysis and assessment methods categories

In this part we will briefly describe the main methods used in risk analysis process. These methods will be classified in three main categories:

- Qualitative methods
- Quantitative method
- Semi quantitative method

I.4.1 Qualitative methods

All other analyses require qualitative risk analysis first. In fact, it enables a thorough comprehension and systematic knowledge of the system under study and all of its components (villemeur 1988). A good qualitative risk assessment draws on relevant observations about the system's state, including experience feedback and expert judgments, rather than explicitly relying on quantifiable data (kirchsteiger 1999). Therefore, using this approach requires a comprehensive understanding of all the variables and causes related to the system under study.

If this strategy is conducted appropriately and justifiably, it might be sufficient in some hazard studies to achieve the necessary goals (Crawley et al. 2008). There are many qualitative risk analysis and assessment tools available, including Bowtie analysis, HAZOP, and FMEA.

I.4.2 Semi-quantitative methods

Semi quantitative risk analysis is an approach that is neither purely qualitative nor purely quantitative (des 1995). This approach aims to remove highly the subjective aspect of the information used in the qualitative approach by giving it more precision and accuracy, and at the same time to fill the lack of robustness of the data of quantitative approach. Numerous semi quantitative analysis and evaluation methods and tools have been developed. In what follows we will present some of the most widely used methods in risk assessment.(Ramzan et al. 2007)

I.4.3 Quantitative methods

Quantitative risk analysis considered to be the most popular approach for good risk decision-making. This approach consists in characterizing the various risk analysis parameters by probabilistic measures (des 1995). Obtaining these measurements generally involves mathematical treatment (vill 1988) by taking into account the data relating to various parameters evaluated and also to the information which is of a quantitative nature. Concerning the application of this approach, particular attention must be paid to the data used, their origin and their suitability for the cases studied because a simple error will call the study into question.

We will present the most widely used quantitative methods, like the event tree and the fault tree. (Cong et al. 2021)

I.5 Fault Tree Analysis (FTA)

I.5.1 Definition

The international standard IEC 61025 defines the fault tree as a diagrammatic deductive engineering technique that is widely used to evaluate the safety and reliability of static systems based on probability theory and Boolean algebra; the applications of this technique include pipelines, petrochemical plants, nuclear reactors, aircraft, and many other industries. (Pan and Wang 2007)

Originally, H.A. Watson created it at BELL Laboratories in 1962 in response to a request from the US Air Force to assess the Minuteman intercontinental ballistic missile's Launch Command System.

Building a fault tree comes down to answering the question "how can such and such an event happen?", Or " what are all the possible sequences that can lead to this event?"(Tanaka et al. 1983)

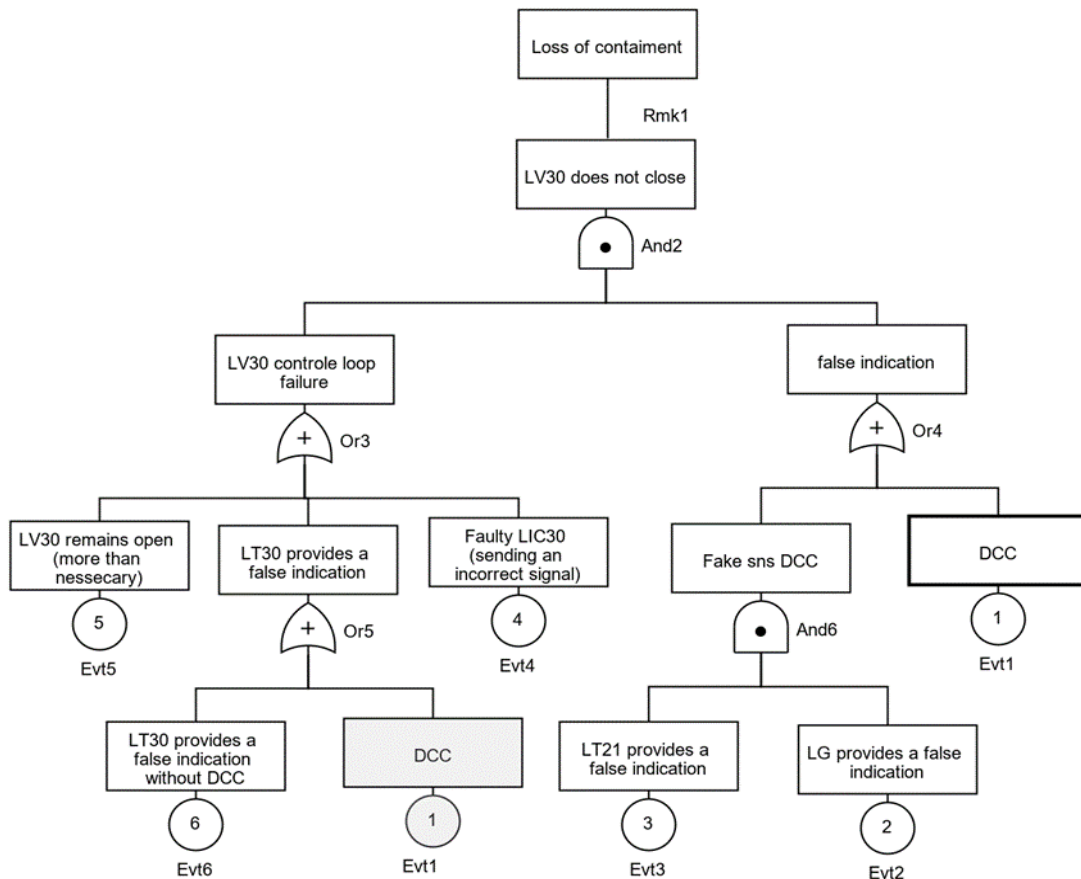


Figure I.4 FT structure

The steps of a fault tree analysis are:

- System definition
- Fault-tree construction
- Qualitative evaluation
- Quantitative evaluation.

I.5.2 Construction of a fault tree

I.5.2.1 Feared event (top event)

The first step is to define the event to investigate. In the tree, this will be the top event, and it has only one top event; it brings together all that and only that which can provoke this event. The definition of this event is completely decisive for the value of the conclusions that will be drawn from the analysis. (Zhang et al. 2015)

I.5.2.2 Intermediate events

Once the studied event has been defined, the next step is to describe it as a logical combination (conjunction or disjunction) of two or more smaller events.

We therefore observe the appearance of events less global than the summit event that we will call intermediate events and a logical connector which connects them to the top event.

I.5.2.3 Logic connectors

The two basic logic connectors are “AND” and “OR” (figure I.4). All logical combinations are expressed with these two connectors (and the logical negation which expresses the opposite of the event it affects), but it may be convenient to use a few other connectors: n / p vote, exclusive OR ...

I.5.3 The qualitative objective

The qualitative objective is to build a synthesis of everything that can lead to a feared event and to assess the effect of a system modification, to compare the consequences of the measures that can be considered to reduce the occurrence of the feared event studied.

I.5.4 The quantitative objective

The quantitative objective is to assess the likelihood of the feared event occurrence from the combinations of elementary events that could produce it. Even in the absence of a quantification by probability, the tree allows to appreciate the number of scenarios leading to the studied event, the minimum number of events or conditions sufficient for it to occur, etc. Besides the graphical representations, a complete fault tree analysis, which is either a qualitative or quantitative assessment, ensures the following information for the process facility:

- Identify critical safety components
- Verify product requirements
- Certification of product reliability
- Product risks assessment
- Investigate accidents/incidents
- Evaluate design changes
- Display the causes and consequences of events
- Identify common cause-failures.

I.6 Event Tree Analysis (ETA)

I.6.1 Definition

Event tree analysis is an inductive and diagrammatic logical method for evaluating the various multiple decision paths in a given problem. It evolved from studies involving nuclear power plant in the 1970's. (Andrews and Dunnett 2000)

It is the commonly used tool for system reliability analysis and risk quantification to identify, characterize, and estimate risk. It uses a single probability to represent each top or initiating event. For an initiating event, if two-state modeling is used (one failure and one success), an event tree can be constructed as a binary tree with nodes representing the set of possible failure and success states. (Avena and Pitblado 1998)

An event tree includes a set of interconnected nodes and branches. Each node characterizes a random variable that addresses an uncertain event or normality (existence of negatively oriented combined planes). The branches starting from a node represent all possible events or states that could occur. Probabilities are evaluated for each branch to represent the likelihood (probability) of each event or condition. These probabilities are conditional on the occurrence of previous events to the left in the tree. (Wang et al. 2019)

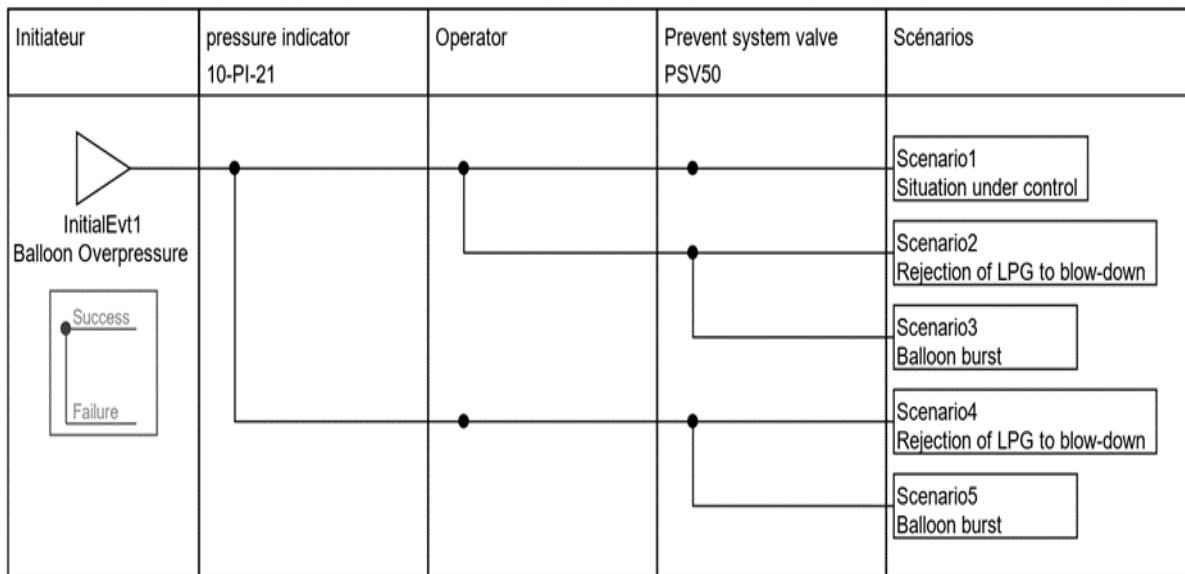


Figure I.5 The event tree structure

I.6.2 Constructing an Event Tree

Before creating an ET, the cause and consequence must be identified and each branch in the event tree must be clearly defined and represented. Multiple branch levels may be combined into a single branch level when the added resolution does not significantly improve risk understanding, estimation, or representation.

Additionally, events with relatively low and negligible probability can be excluded from the tree. (Salaheldine Darwish et al. 2020a)

The event tree structure should be designed to accommodate future requirements, such as the evaluation of risk reduction strategies to minimize duplication of effort and provide consistency in risk estimations across multiple phases of study.

Steps to create an Event Tree:

- ✓ Identify (and characterize) the related accidental (initial) event that could have undesirable outcomes.
- ✓ Identify the barriers designed to deal with the accidental event.
- ✓ Construct the event tree.
- ✓ Describe the accident sequences that may arise as a result.
- ✓ Determine the initial event frequency and the conditional probabilities of each branch in the event tree.
- ✓ Calculate the probabilities/frequencies of the identified consequences.
- ✓ Compile and present the consequences from the analysis.

I.6.3 Event Tree Analysis benefits & drawbacks

✚ Advantages:

- Visualize event chains following an accidental event.
- Visualization of barriers and grouping of initiation.
- Good basis for determining the requirements.

✚ Drawbacks:

- There is no standard for graphical representation of an event tree.
- Only one initiating event can be studied in each analysis.
- Easy to overlook subtle system dependencies.
- Common cause failures in quantitative studies are not properly handled by this method.
- There are no examples of exclusion in the event tree.

I.7 HAZOP

I.7.1 Definition

The HAZOP (Hazard and operability studies) method is part of the operational safety (OS) by proposing an approach to improve the safety and processes of a system (planned or existing industrial installation). Invented in 1965 in Great Britain by ICI (Imperial chemical industries), it was conceived as a technique and was particularly intended for the detailed engineering phase of new chemical or petrochemical installations after the catastrophic explosion in 1974 of a cloud of 40 tons of cyclohexane in Flixborough, Great Britain, killing 28 and injuring 89 others.

The following definition is used by Chemetics International Ltd in their guide to the introduction of the HAZOP approach: "... application of a formal and systematic critical examination of the process and engineering intentions of a new or existing installation in order to assess the potential for danger linked to items of equipment and their effects on the installation as a whole, as well as improper use or malfunction".(Rosner et al.) (Cruz-Campa and Cruz-Gómez 2010)

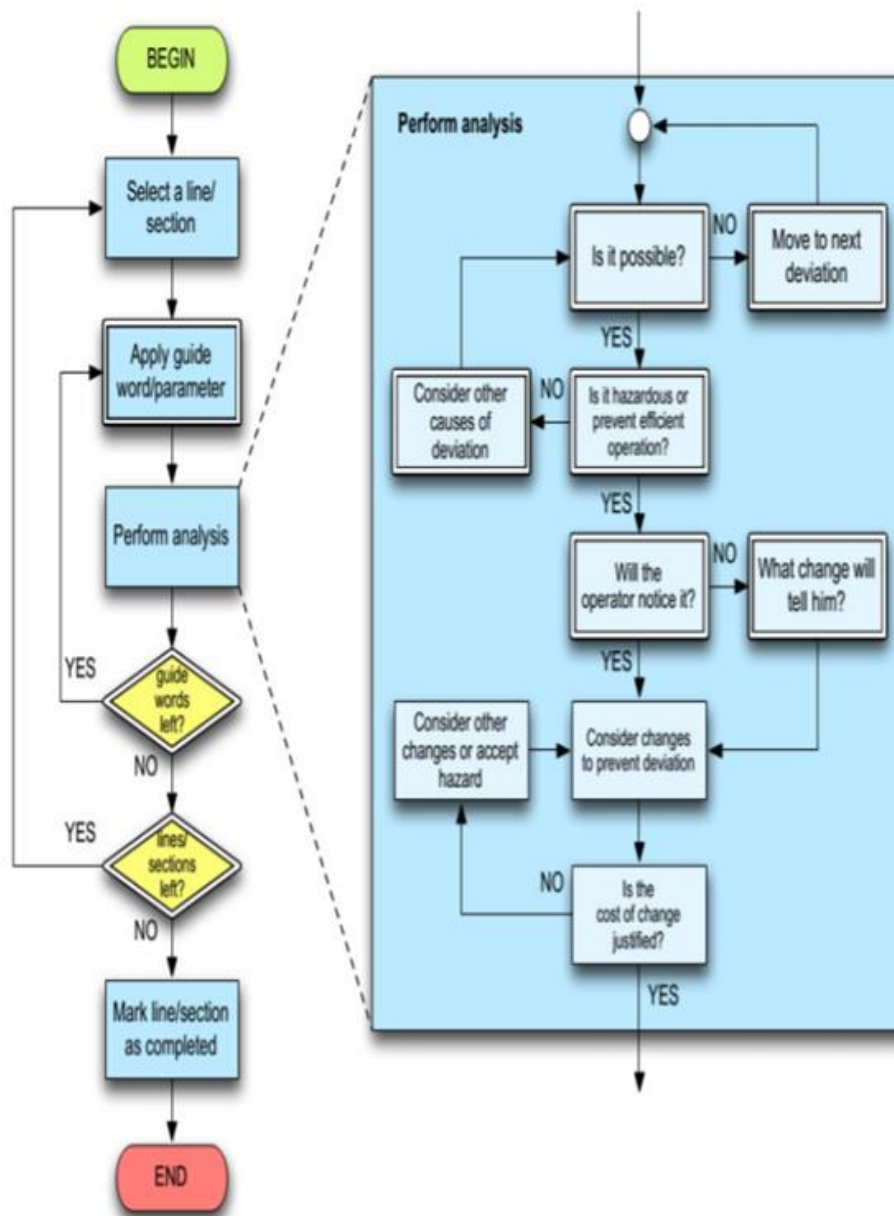


Figure I.6 HAZOP methodology (Rosner et al.).

I.7.2 Principle and development

This method requires in particular the examination of fluid flow diagrams and plans or P&ID diagrams (Piping and Instrumentation Diagram). It considered the potential drifts of the main parameters related to the operation of the installation (Choi and Byeon 2020b). For each constituent part of the system examined (line or cell), the generation of deviations is carried out systematically by the conjunction:

$$\text{Keyword} + \text{Parameterized} = \text{Deviation} \quad (\text{I.2})$$

The work group must therefore endeavor to determine the causes and potential consequences of each of these drifts and to identify the existing means to detect this drift, prevent its occurrence or limit its effects. As for the APR and FMECA presented in the previous paragraphs, a summary table is often useful to guide the reflection and collect the results of the discussions held within the working group (Pullum and Taylor 2006) .An example table is presented in the following paragraphs Table I.1: Example of a table for HAZOP

Table I.1 HAZOP table

Date:								
Line or Equipment:								
1	2	3	4	5	6	7	8	9
N'	Keyword	Parameter	causes	consequences	detection	safeguards	recommendations	observations

I.7.2.1 Parameters

The HAZOP method uses specific parameters which are expressed by simple words (nouns or verbs), characteristic of the design intention and which can be defined as: "physically measurable quantity, action or operation to be carried out". the parameters on which the analysis relates are: Temperature, pressure, flow ... Therefore, combining them with the key words makes it possible to generate drifts of these parameters. Table I.3 lists some of the most frequently used parameters in the process industry.(Rossing et al. 2010)

The HAZOP makes it difficult to analyze events resulting from the simultaneous combination of several failures.

I.7.2.2 Keywords or guide words

At the same time, the method introduces a limited number (originally seven) of keywords also called "guide words" and originally defined as follows: "... simple word or short sentence qualifying the intention in order to guide and to stimulate the creative process and thus allow the discovery of deviations ...". List of the seven keywords: - no or no (no or not); - more than (more); - less than (less); - in addition to (as well as); - in part (part of); - other than (other); - inverse (reverse).

Then four keywords have been added relating to the notions of time and sequence: - earlier than (earlier than); - later than (later than); - before (before); - after (later). So a total of eleven keywords today (Cui et al. 2008). The search for other keywords is open to the imagination.

Table I.2 Examples of the most parameters used in HAZOP

Parameter	Keyword	Examples
Negative	Undo	No part of intent is fulfilled
Quantitative modification	More	Augmentation quantitative
	Less	Diminution quantitative
Qualitative modification	In addition to	Presence of impurity- simultaneous execution of another operation
	Part of	Only part of the intention is realized
Substitution	Reverse	Applies to the reversal of flow in pipes or the reverse of chemical reaction
	Other than	A result different from the original intention is obtained
Time	Earlier	An event occurs before the scheduled time
	Later	An event occurs after the scheduled time
Sequence order	Before	An event occurs before too early in a sequence
	After	An event occurs before too late in a sequence

I.7.2.3 Deviations

The combination of key words and parameters will constitute a deviation of this parameter (see equation I.2)

Table I.3 HAZOP deviations

Deviation	
Flow	No/ Less flow
	More flow
	Reverse flow
	Misdirected flow
Pressure	More pressure
	Less pressure
Level	More pressure
	Less pressure
Temperature	More temperature
	Less temperature
Phase/ Composition	Different composition
Operations	Star-up operations
	Maintenance operation
	Shut-down operation
	Sampling operation
Other	Instrument Air failure
	Fire case
	Tube rupture

I.7.2.4 Causes and consequences

Once the deviation is considered the work team must identify the causes of this deviation, then the potential consequences of this deviation. In practice, it can be difficult to assign each keyword (and derivative) to a well-defined portion of the system, and as a result, examining potential causes can be complex in some cases (Marhavilas et al. 2020).

I.7.2.5 Safeguards and recommendation

For each deviation, the HAZOP method provides identification of the means of detecting it and the safety barriers available to reduce its occurrence or effects. If the measures taken appear insufficient, the team can propose improvements in order to mitigate these problems or at least define actions to be taken to improve safety to these precise points.(Joubert et al. 2021)

I.7.3 Objective

The objective of the HAZOP method, originally, is to identify technical and operational dysfunctions, the sequence of which can lead to unwanted events. It is therefore a question of determining, for each sub-assembly or element of a well-defined system, the consequences of operation outside the field of use for which that system was designed.

IEC 61882 defines the objectives of the original HAZOP method, which are:

- ❖ "... identification of potential dangers in the system. The danger may be limited to the immediate vicinity of the system or its effects extend beyond this, as in the case of environmental hazards ...";
- ❖ "... identification of potential operational problems posed by the system and, in particular, identification of the causes, operational disturbances and deviations in production that may lead to the manufacture of non-conforming products ...".

With the introduction of the SEVESO II Directive and the new requirements of the Ministry of Ecology and Sustainable Development (MEDD) regarding the industrial risk prevention, the original HAZOP method is insufficient for analyzing the major risks. A risk assessment phase should be added to it, this is how HAZOP method transforms from purely qualitative into semi-quantitative method, helping to improve knowledge of risks, consequently, safety of installations.

Reasons for initiating a HAZOP study on an industrial installation can meet multiple objectives and are in fact requirements:

- ❖ meeting the requirements of the "Health-Safety-Environment" (HSE) policy of the company owning the installation.
- ❖ meeting the requirements of the Administration represented, in particular, by the Regional Directorates of Industry, Research and the Environment (DRIRE): ensuring compliance with the regulations of Classified Installations for the protection of environment (ICPE), labor and environment codes, the SEVESO Directive;
- ❖ Establish emergency plans: Internal Operation Plan (IOP) for industrial installations, Internal Emergency Plan (IEP) for nuclear installations, both established under the responsibility of the operator, Special Plan for intervention (PPI) and the Technological Risk Prevention Plan (PPRT) established under the authority of the Prefect (Macdonald and Mackay 2004).

I.7.4 Limitations and advantages

The HAZOP is a particularly effective tool for thermos-hydraulic system. Like the FMEA this method has a systematic character. Considering the deviation of the operating parameters of the system, it avoids all the possible failures modes for each of the components of the system.

On other hand, HAZOP in its classic version does not allow the analysis of events resulting from the simultaneous combination of several failures. In addition, it is sometimes difficult to assign a keyword to a well-defined portion of the system to be studied. This complicates the exhaustive identification of the potential causes of the deviation. Indeed, the studied systems often consist of interconnected parts so that a deviation occurring in a line or mesh can have consequences or conversely causes in an adjacent mesh and vice versa. Of course, it is possible a priori to postpone the implications or effects of a deviation from one part of the system to another. However, this task can quickly become complex.

Finally, since the HAZOP deals with all types of risks, its implementation can be particularly time-consuming and generate an abundant production of information not relating to major accident scenarios (Riad et al. 2018).

I.8 Layers of Protection Analysis “LOPA”

I.8.1 Definition

LOPA stands for Layer of Protection Analysis, it is the newest methodology, simplified, semi quantitative method of risk assessment, of very general use, commonly used for the identification and control of risks at all phases of the design and operation of industrial installations and projects, so it can be effectively used at any point in the life cycle of a process or a facility (Markowski and Mannan 2009).

LOPA addresses the key questions: “how safe is safe enough?”; “how many independent protection layers are needed?”; and “how much risk reduction should each layer provide? LOPA build on the information developed during a qualitative hazard evaluation, it uses order of magnitude categories for initiating event frequency, consequence gravity, and likelihood of failure of independent protection layers (IPLs) in order to make consistent decisions on the adequacy of existing or proposed layers of protection against an accident scenario (Kabir and Papadopoulos 2018).

It is limited to evaluating a single cause-consequence pair as scenario, if the estimated risk is not acceptable, additional IPLs may be added. It has the advantage of being carried out in a short time and at lower costs. In addition, the accuracy of quantitative data is not required and orders of magnitude are sufficient (Khalil et al. 2012b).

I.8.2 Principal of LOPA method

The layer of protection analysis is a semi-quantitative barrier-oriented method (CCPS 2001), which is intended to control the risks of major accidents.

Generally, the principle of this method consists first of all in identifying the different accident scenarios of an installation. Indeed, it is a question of starting from a feared event defined a priori by a qualitative risk analysis of the HAZOP, FMEA type (IEC61511 2003), to determine the chain of events that could lead to this event. The next step is to assess the robustness of the protective layers put in place using a semi-quantitative approach.

The latter is used to assess the probability of failure on demand (PFD) of each layer of protection. Once the initiating events are identified and their frequencies of occurrence are adjusted, LOPA allows the determination of the frequency of occurrence of each accident scenario by multiplying the frequency of occurrence of this initiating event by the product of the PFDs of the layers of existing protection (Wei et al. 2008).

Once the accident scenario is estimated in terms of the frequency of the consequence, it remains to be decided whether this accident scenario is acceptable or not. This decision will be made through an assessment of this risk against the acceptability criteria established at the start of the analysis.

I.8.3 How the LOPA method works

LOPA can be divided into the means steps:

1. Identify the outcome to screen the scenario than assess the outcome and estimate its extent.
2. Select a scenario.
3. Identify the initiating event of the scenario and determine its frequency (occasions every year). The initiating event should prompt the outcome (given failure of the entirety of the safeguards).
4. Identify the IPLs and gauge the likelihood of failure on demand of each IPL.

5. Estimate the danger of the scenario by numerically consolidating the outcome, initiating event, and IPL information.
6. Evaluate the risk to arrive at a choice concerning the scenario.

I.8.4 Steps of the LOPA method

Step 1:

Establishment of acceptability criteria and scenario selection, this step is prior to the risk analysis, it provides a capability of limiting the duration of the study by considering only significant scenarios in terms of consequences. The establishment of acceptability criteria is made according to the context of each establishment / company concerned and also the objectives pursued in each risk management approach.

The estimation of the risk consequences allows the identification of the most important accident scenarios. For scenarios judged unacceptable, a more detailed assessment of gravity remains essential. The choice of such method is made according to the available data and also the nature of the existing accidents (Torres-Echeverria 2016a).

Step 2:

Development of accident scenarios, for LOPA, the development of accident scenarios is a main step that must be carefully designed in order to achieve good control of these scenarios. The prior application of risk analysis methods (HAZOP, FMEA) makes it possible to identify the causes, consequences and the various prevention and protection barriers.

The HAZOP table may also incorporate evaluations of the Frequency for each Cause and Gravity for every Consequence. With these evaluations a Risk Matrix can be utilized to estimate Risk for a Cause-Consequence pair (Markowski et al. 2009). Figure I.7 shows the HAZOP data and the LOPA data in graphical structure. The continuous lines show the arrangement of the HAZOP or LOPA improvement. The spotted lines show how HAZOP data is moved to the LOPA.

Remember that the effectiveness of the LOPA method remains primarily in its careful application and in the detail presented in the development of accident scenarios, these must be developed and chosen correctly in order to achieve risk control.

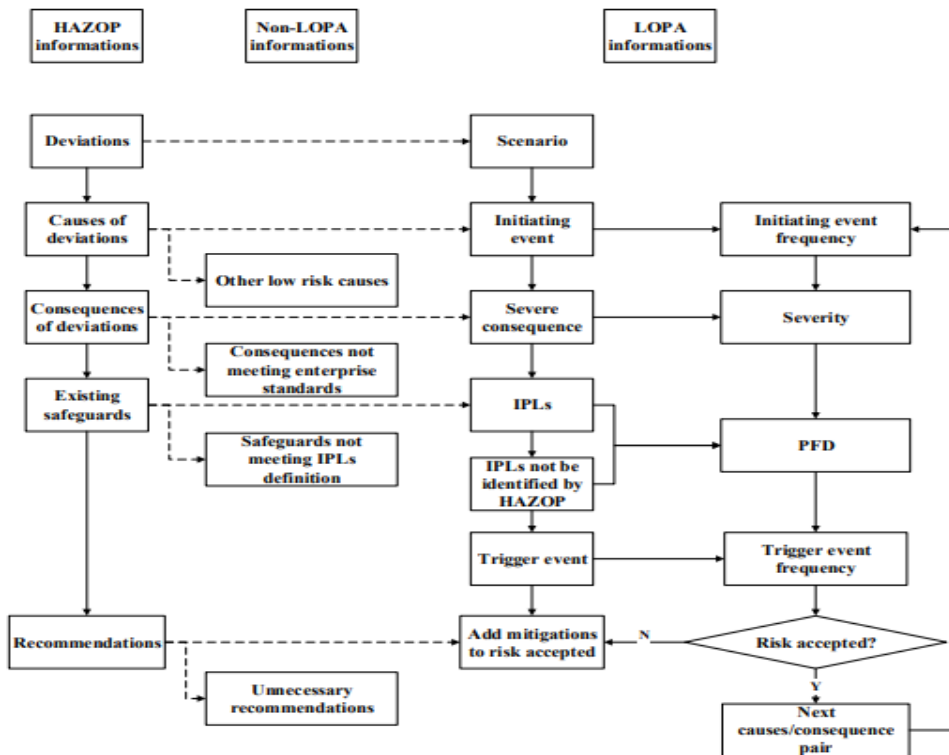


Figure I.7 Relationship between LOPA and HAZOP information (Markowski et al. 2009).

Step 3:

Identify the initiating events frequencies, identifying the initiating events frequencies is an important step that will help estimate the accident scenarios frequencies. In this step, it is important to systematically identify all the causes “initiating events” that may be at the origin of the accident scenarios (Markowski and Mannan 2009).

Step 4:

Identify independent protection layers (IPLs), LOPA is a semi-quantitative barrier-oriented method which requires in its approach an identification and evaluation of independent protection layers.

Like any security barrier, a layer protection (IPL) can be an element, system, device, action or procedure intended to perform a certain safety function in order to prevent an accident scenario and / or reduce its effects. This security barrier has a specific demand mode of operation compared to others security barriers.

An IPL should have the following significant qualities:

- a. Particularity: Able to moderate or prevent the effect of a potential hazardous event.
- b. Independence: Independent of the other protection layers identified with a particular hazardous event.

- c. Reliability (dependability): Must give protection that reduces an explicit measure of the possible hazard.
- d. Auditability: It is made to facilitate the normal adequacy of the protective functions.

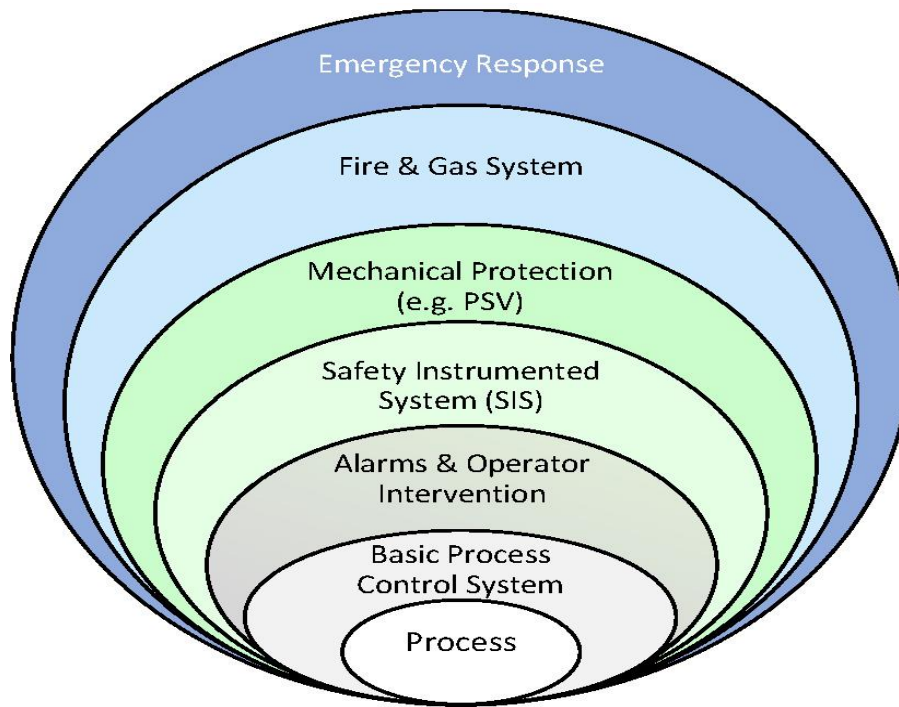


Figure I.8 Layers of protection analysis (Markowski and Mannan 2009).

Step 5:

Determination of the accident scenarios frequencies, determining the accident scenarios frequency is a key step which is used to assess the consequences of accident scenarios in terms of their occurrence probability and their consequences caused. The accident scenario frequency is given by the following equation (Vassilev 2019):

$${}^c_1f = {}^n_1f \cdot \prod_{k=1}^n PFD \tag{I.3}$$

Where:

c_1f : is the consequence frequency C of initiating event i

n_1f : is the initiating event frequency i.

PFD : is the probability of failure on demand of the same IPL which protects against the consequence C.

This procedure for the frequencies calculating of multiple accident scenarios will help us to establish the comparison against the acceptability criteria previously developed and also to judge whether these risks are acceptable or not.

Step 6:

Risk assessment against the acceptability criteria, this step consists of evaluating the estimated accident scenarios against the acceptability criteria that has been set beforehand to ensure that the scenarios are acceptable. If these accident scenarios are unacceptable, recommendations and protection layers must be implemented in order to control and reduce them to a level judged tolerable.

I.8.5 Advantages and limitations of the LOPA method

LOPA has the following advantages (CCPS 2000) (IEC61511 2003):

- LOPA is an efficient and effective tool for risk assessment and risk reduction measures.
- LOPA is a practicable and flexible tool making it possible to determine the reduction provided by each reduction measure (IPL) by assigning it probabilities of failure on demand (PFD).

However, LOPA has limitations (CCPS 2000) (IEC 61511 2003) (Markowski 2007):

- LOPA is a tool that cannot be applied for all accident scenarios, especially those with combinations of failures.
- In practice, it is often difficult to summarize a probability of failure in a single numerical value.

I.9 Safety Integrity Level study (SIL)

Current standards require that industrial installations present as few risks as possible while their operation. Two approaches enable this risk reduction: prevention by minimizing the occurrence probability of a risk, and protection by limiting the malfunction consequences. To reduce the occurrence probability of risk, Safety Instrumented Systems (SIS) are used to realize Safety Instrumented Functions (SIF) (Cruz-Campa and Cruz-Gómez 2010).

I.9.1 Safety Instrumented System (SIS)

Safety instrumented systems contribute, with other protection levels, to reduce risk in order to reach the tolerable level of risk.

A SIS, also called a safety loop, is a set of elements (hardware and software), ensure that processes are placed in a safe state (a stable state that does not pose a risk to the environment and people) when predetermined conditions are affected (a real risk for personnel and the environment e.g. explosion, fire ...) (Nait-Said et al. 2008)

I.9.2 Safety Instrumented Function (SIF)

A Safety Instrumented Function (SIF) is used to describe the safety functions implemented by a safety instrumented system. A safety instrumented function can be considered as a functional protection barrier when the safety instrumented system is considered as a system realizing this safety barrier. (Torres-Echeverria 2016a)

An instrumented safety function is realized by:

- ✓ A safety instrumented system (or a combination of the components of this system);
- ✓ A safety system based on another technology or by an external risk reduction device.

A safety instrumented function is specified to ensure that risks are maintained at an acceptable level.

I.9.3 Safety Integrity Level

A Safety Integrity Level (SIL) or Integrated Safety Level is defined as a relative level of risk reduction inherent in a safety function, or as a specification of a risk reduction target. More simply, it is a measure of the expected performance of a security function (SIF). In the case of safety instrumented systems (SIS), the safety integrity level (SIL) is used quantitatively to specify requirements for the integrity of each safety function performed by electrical, electronic or programmable electronic systems (Ioannides 2000).

Each SIL (discrete value from 1 to 4) corresponds to an increasing level of risk reduction and therefore to increasing requirements. The concept of SIL applies to the system concerned with safety in its entirety and not to a single subassembly (i.e.: a sensor). For each safety instrumented function operating in demand mode the required SIL must be specified in accordance with table I.4.

Table I.4 Safety integrity levels: Probability of failures on demand

Safety Integrity Level (SIL)	Range of PFDavg	Risk Reduction Factor (Range of RRF)
4	$10^{-5} < \text{PFD} < 10^{-4}$	10.000 < RRF < 100.000
3	$10^{-4} < \text{PFD} < 10^{-3}$	1000 < RRF < 10.000
2	$10^{-3} < \text{PFD} < 10^{-2}$	100 < RRF < 1000
1	$10^{-2} < \text{PFD} < 10^{-1}$	10 < RRF < 100.

I.9.4 The advantages of SIL

- ✓ Harmonized international procedure for the protection devices evaluation, Evaluation of process control systems with regard to systematic errors and statistical indications relating to random errors.
- ✓ "Life cycle management" defined, i.e. documentation and management of all life cycle stages relating to the equipment functions,
- ✓ Complete assessment of the entire security installation,
- ✓ The required safety can be achieved by proven instrumentation, without exhaustive modifications to process techniques. (Salaheldine Darwish et al. 2020b)

I.9.5 Determination of SIL levels

The SIL of a SIS can be determined by different methods:

- Qualitative methods: determine the level of SIL based on knowledge of the risks associated with the system.
- Semi-quantitative methods: The most used method is the risk matrix. This matrix defines the SIL level according to the risk severity and its frequency of occurrence.
- Quantitative methods: calculate the availability of SIS based on the failure and repair rates of their components. The most used methods are:
 - Simplified equations;
 - Fault trees;
 - Markovian approaches.

I.9.5.1 Risk Matrix

The procedure for determining the safety integrity level of a safety-related system is based on the following equation (Torres-Echeverria 2016b):

$$R = F \times C \tag{I.4}$$

where:

R: is the risk in the absence of safety-related systems.

F: is the frequency of the dangerous event in the absence of safety-related systems.

C: is the consequence of the dangerous event.

In our study we consider the consequences on:

1. Damage related to health.
2. Economic damage.
3. Environmental damage.

I.9.5.2 Implementation of the risk matrix

I.9.5.2.1 Reduction factors

The frequency of the hazardous event F is assumed to be the result of three factors:

- ✓ **Demand rate:** The occurrence probability of dangerous event in the absence of a safety system, this is called the probability of unwanted occurrence. To determine the demand rate, the causes of the safety function must first be defined. In the following table the different categories of demand rates are indicated.

Table I.5 Demand Rate Category

Category	Demand rate
D0	Negligible
D1	> 20 years
D2	4 – 20 years
D3	0.5 – 4 years
D4	0 – 0.5 years

- ✓ **Exposure and Possibility to avert danger:** Table I.6 and table I.7 indicate the three categories for the two factors:

Table I.6 Exposure categories

F1	Very rare (< 10 man-minutes per day)
F2	Occasional (< 6 man-hours per day)
F3	Frequent to continuously (> 6 man-hours per day)

Table I.7 Possibility to avert danger

P1	In almost all circumstances
P2	In some circumstances
P3	Little or none

I.9.5.2.2 Reduction of consequences classification

The reduction after the introduction of the two factors F and P is shown in table I.8

Table I.8 Classification consequence reduction

Possibility to avert danger	P3	-1	0	0
	P2	-1	-1	0
	P1	-2	-1	-1
		F1	F2	F3
		Exposure		

I.9.5.2.3 Personnel health & safety consequence

The SIL study determines six categories of Consequences on Personnel health & safety.

Table I.9 Personnel health & safety categories

Category	Consequence
S0	No injury or health effect S1
S1	Slight injury or health effect
S2	Minor injury or health effect
S3	Major injury or health effect
S4	Between 1 and 3 fatalities
S5	Multiple fatalities

I.9.5.2.4 Consequences on economics

The economic consequences are classified into six categories

Table I.10 consequences categories on economics

Category	Consequence
L0	No loss
L1	Slight loss (<10K USD)
L2	Minor loss (10-100K USD)
L3	Local loss (0.1-1M USD)
L4	Major loss (1-10M USD)
L5	Extensive loss (>10M USD)

I.9.5.2.5 Consequences on environment

The SIL methodology defines environmental consequences in six categories:

Table I.11 Consequences categories on environment

Category	Consequence
E0	No effect
E1	Light effect
E2	Minimal effect
E3	Local effect
E4	Major effect
E5	Massive effect

I.9.5.3 Risk matrix representation

The risk matrix used for SIL classification is as follows:

Table I.12 Risk matrix

Consequence category			Demand Rate Category				
S	E	L	D0	D1	D2	D3	D4
Health and Safety	Environment	Economic					
S0	E0	L0	-	-	-	-	
S1	E1	L1	-	-	A1	A2	A2
S2	E2	L2	-	A1	A2	1	2
S3	E3	L3	-	A2	1	2	3
S4	E4	L4	-	1	2	3	4(X)
S5	E5	L5	-	2	3	4(X)	X

I.10 Conclusion

We have devoted this chapter to the presentation of the most common and used terminologies in this field and the risk management process, and still e global description of the main analysis and risk assessment methods and their limits that make us address other techniques to solve them, such as artificial intelligence methods, which will be the topic of our next chapter.

Chapter II

Introduction to artificial intelligence

II.1 Introduction

The purpose of safety analysis is to ensure that hazards and risks that could potentially cause harm and damage are sufficiently reduced by dealing with all phases of the safety lifecycle and design of suitable safety barriers. Any error or failure to perform the function of each proposed safety barriers can cause extreme damage to the environment, facilities and human, and even loss of life(You et al. 2021). Therefore, it is necessary to ensure the effectiveness of the study or analysis like we mentioned in the previous chapter.

However, even with the major development in control system fields the problems of uncertainties, classification and optimization are still considered unsolved issues. In recent years several tools are developed based on artificial intelligence to deal with such difficulties (Pham and Pham 1999a). There are many techniques that artificial intelligence (AI) can offer, but the most important ones are as follows:

- ✓ fuzzy logic is often used to deal with lack of the information or/and uncertainty in the database; it is very difficult to estimate precise failure rates or failure probabilities of individual components or failure events due to insufficient data or ambiguity and imprecision of some basic events, which can undermine the efficacy and applicability of conventional safety and reliability assessments (Lam 2018). Fuzzy methods may be the only way to address unavailability, scarcity or uncertainty in data. In addition, an analytical method may be difficult and a simulation may require enormous computing time, in fuzzy approaches, the algebraic operations are easy and straightforward.(Raeesivand and Kasaeyan 2019)
- ✓ artificial neural networks that rely on recognition system based on machine learning/ deep learning to perform learning from observational data and discover their solutions;(Hu et al. 2015)
- ✓ genetic algorithms that simulate the natural selection process to solve optimisation problems, this is what makes them useful for adapting to complex problems; Application of genetic algorithms (GAs) to reliability optimization is relatively recent. Practically, this field of knowledge has been developed since the mid nine ties. So far, GAs for reliability problems solution, in the field of structure optimization, have been applied to three main problems: (a) redundancy allocation; (b) component-reliability allocation (alternative design); (c) multi-objective reliability optimization.(Mohan 2019) (Kabir and Papadopoulos 2018)

This chapter examines the primary artificial intelligence approaches and techniques utilized in our thesis, Fuzzy Logic and Artificial Neural Network.

II.2 Artificial intelligence

II.2.1 Definition

Artificial Intelligence has a wide range of applications, some of which we already know and encounter in our daily lives: spam filters that recognize malicious emails, search engines filters that find the “best results”, vacuum cleaner robots, or even no playable characters in video games...(Mohan 2019) (Sarbayev 2018)

The assumption that the human brain can be deemed quite comparable to computers in some ways offers the automatic basis for artificial intelligence (AI).(Pham and Pham 1999b) The concept of AI was introduced following the emergence of the concept of the Information Technology (IT) revolution, which is an attempt to replace human intelligence with machine intelligence (Bai and Wang 2006). According the Oxford dictionary, the word intelligence is derived from intellect (mind), which is the ability to know, reason and understand. Intelligent behaviour is therefore the ability to think, plan and learn, which in turn requires access to knowledge. (Mourad et al. 2022)

II.2.2 Intelligent control system structure

As Johnson Picton considered, the intelligent control system consists of three subsystems, as the figure illustrates (Wang 2003). The first is the perception subsystem, where the data are collected from the plant and the environment to be processed into the suitable form for the cognition subsystem.

The second is the cognition subsystem, and is concerned with the decision-making process under conditions of uncertainty. it includes mainly:

1. Reasoning, using:
 - Knowledge-based systems
 - Fuzzy logic
2. Strategic planning, using:
 - Optimal policy evaluation
 - Adaptive search and genetic algorithms
 - Path planning
3. Learning, using:
 - Supervised learning in neural networks

- Unsupervised learning in neural networks
- Adaptive learning (Wittwehr et al. 2020a)

The third subsystem comprises the actuators that operate in order to drive the plant into some desired states. In the event of actuator (or sensor) failure, the intelligent control system must be capable of being able to re-configure its control strategy (Zhang et al. 2021).

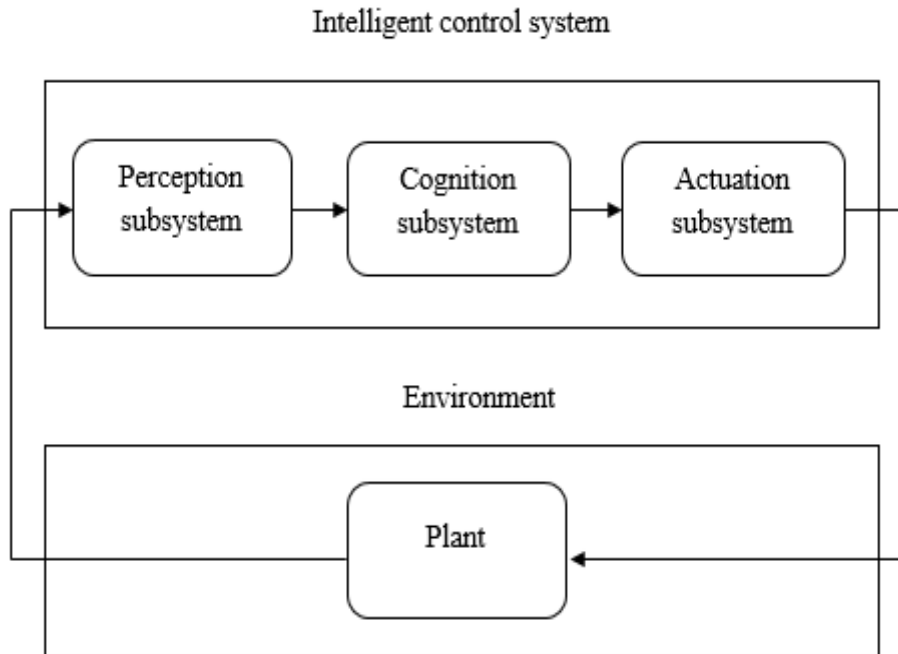


Figure II.1 Intelligent control system structure (Wang 2003).

II.3 Fuzzy logic

II.3.1 Definition

We must first understand what is meant by fuzzy logic, the word in its technical sense was initiated for the first time by Zadah, based on the idea of fuzzy sets to represent a kind of uncertainty associated with imprecision, vagueness and lack of information (Zadeh 1965).

The difference between ordinary set theory and fuzzy set theory is that the membership function in fuzzy sets, like probability theory, can have a value between 0 and 1, unlike conventional sets, it distinguishes between its elements that are members of an set and those that are not sharp or Very clear, or crisp edges (Mechri et al. 2013) (Trillas and Eciolaza 2015).

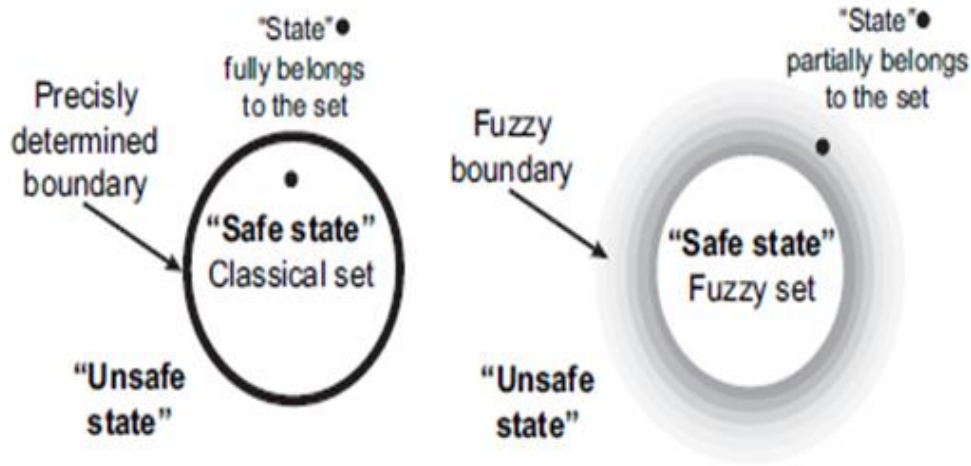


Figure II.2 Difference between fuzzy set and classical set (Mechri et al. 2013)

II.3.2 Fuzzy function and linguistic variable

Consider a limited set $X = \{x_1, x_2, \dots, x_n\}$ which will be considered the universal set in what follows. The subset A of X consisting of the single element x_i can be described by the n -dimensional membership vector $Z(A) = (1, 0, 0, \dots, 0)$, where the concept has been adopted that a 1 at the i^{th} position indicates that x_i belongs to A (Sallak et al. 2008) (Chameau and Santamarina 1987).

Membership functions are used in the fuzzification and defuzzification steps of FLS, to map the non-fuzzy input values to fuzzy linguistic terms and vice versa. The membership function is used to quantify a linguistic term that is often expressed by adjectives (nouns) or adverbs (verbs) like very, low, slight, more or less ... and so more that, and it is defined as follows:

$$\mu_A(x) = \begin{cases} 0 \leq b \leq 1 & \text{if } x \in A \\ 0 & \text{else} \end{cases} \quad (\text{II.1})$$

A is written generally in the form:

$$A = \begin{cases} \sum \frac{\mu(x_i)}{x_i} & \text{discrete case} \\ \int \frac{\mu(x_i)}{x_i} & \text{continuous case} \end{cases} \quad (\text{II.2})$$

For example, in Figure II.3, membership functions for the linguistic terms of temperature variable are plotted (Zeng et al. 2007) (Dombi 1990).

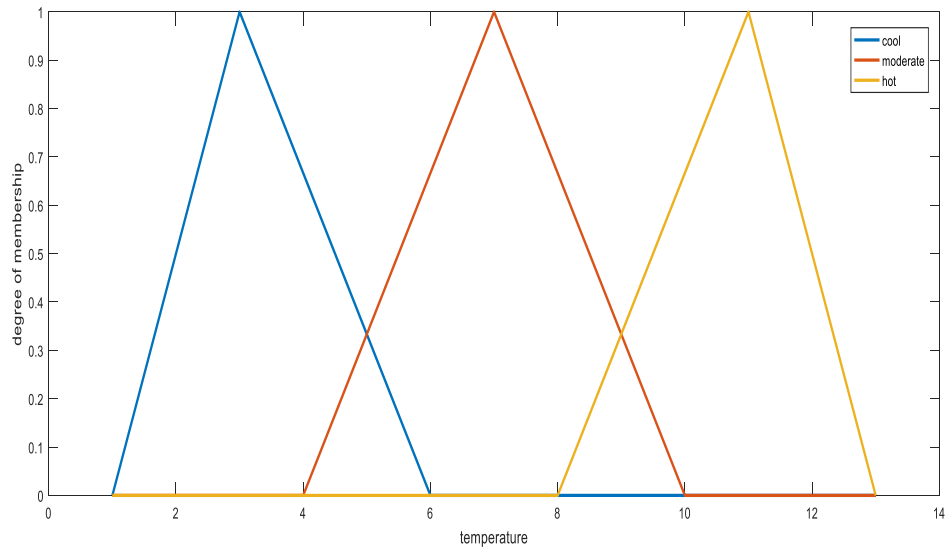


Figure II.3 Membership function for linguistic terms

A temperature value can be considered as “cold” and “moderate” at the same time, with different degree of memberships (Chen et al. 2001).

There are different forms of membership functions such as triangular, trapezoidal, piecewise linear, Gaussian, or singleton (Wang 1999). The most common types of membership function shapes as the figures illustrate are:

- Triangular:

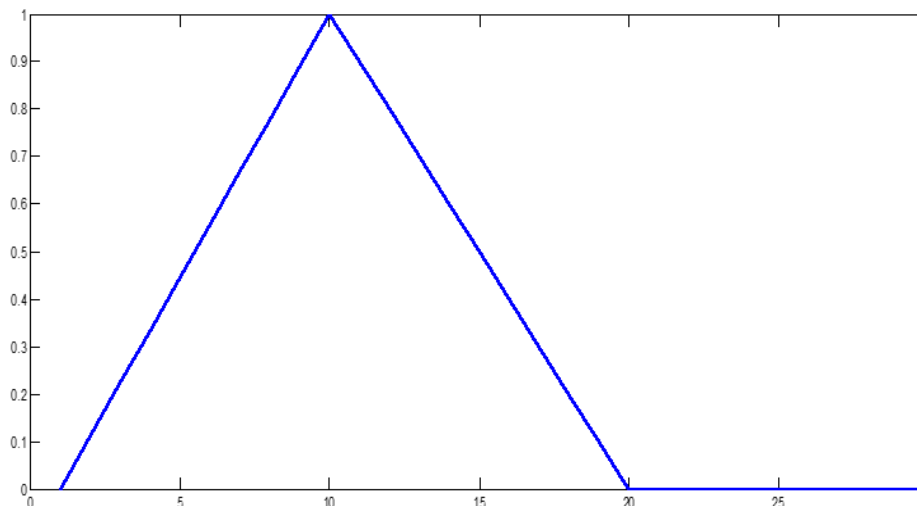


Figure II.4 Triangular membership function

- Trapezoidal:

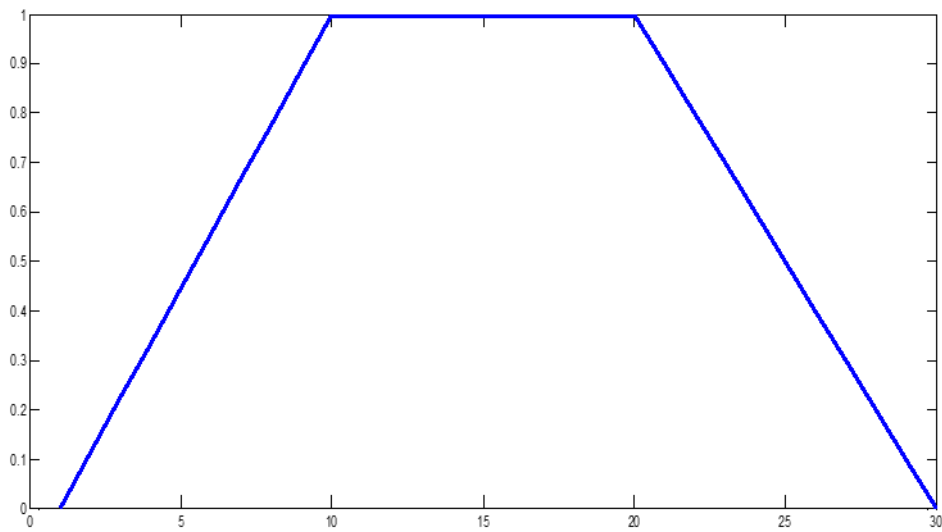


Figure II.5 Trapezoidal membership function

- Gaussian:

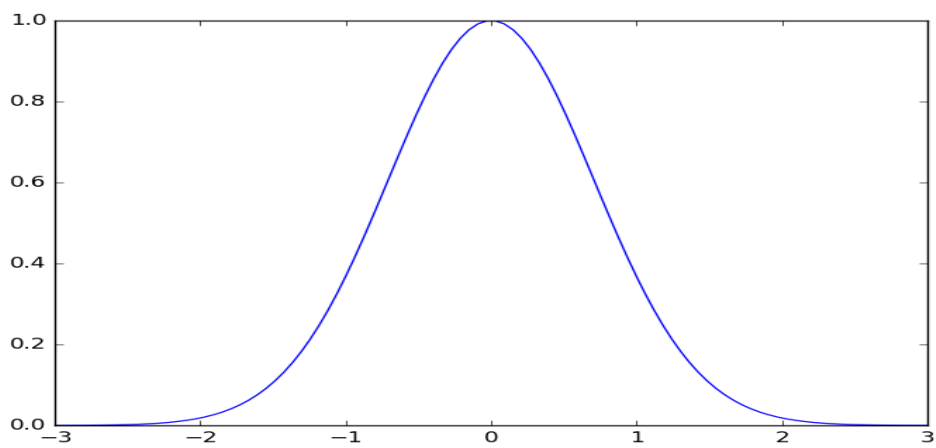


Figure II.6 Gaussian membership function

- Sigmoid:

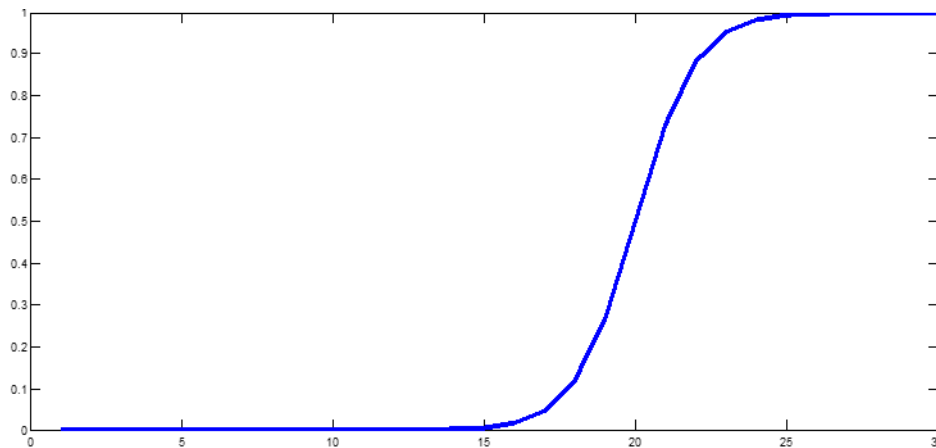


Figure II.7 Sigmoid membership function

II.3.3 Fuzzy operators

The operations on fuzzy sets are different than the operations on non-fuzzy sets. Let μ_A and μ_B are the membership functions for fuzzy sets A and B (Sal et al. 2017) (Hájek 2006).

- ✓ **complement of A** is a fuzzy set \tilde{A} in U whose membership function is defined as $\mu_{\tilde{A}} = 1 - \mu_A$

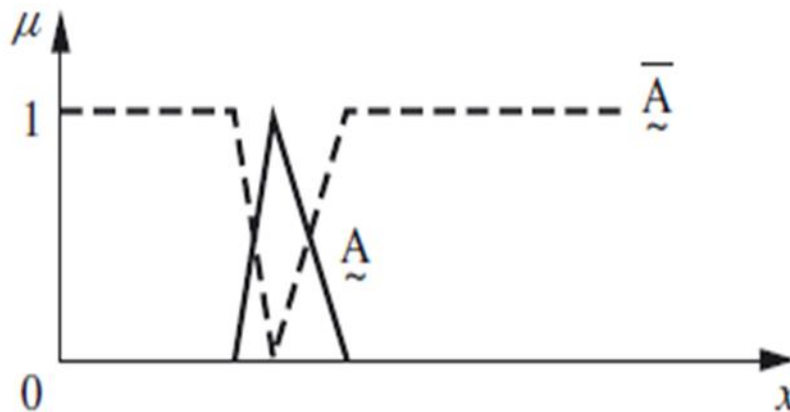


Figure II.8 The fuzzy complement of a fuzzy set

- ✓ **The union of A and B** is a fuzzy set in U, denoted by $A \cup B$, whose membership function is defined as:

$$\mu(A \cup B) = \max(\mu_A, \mu_B)$$

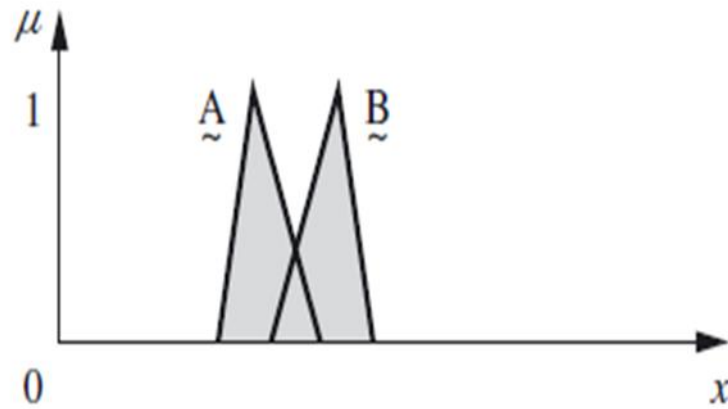


Figure II.9 The fuzzy union of A and B

- ✓ **The intersection of A and B** is a fuzzy set $A \cap B$ in U with membership function:
 $\mu(A \cap B) = \min(\mu_A, \mu_B)$

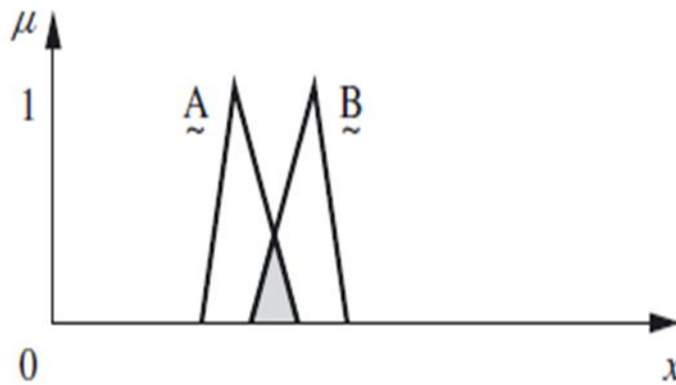


Figure II.10 Fuzzy intersections between two sets

II.3.4 Fuzzy rules

A fuzzy IF- THEN rule is a conditional statement expressed as:

IF « fuzzy proposition », THEN « fuzzy proposition »

Therefore, in order to understand fuzzy IF-THEN rules, we first must know what fuzzy propositions are (Suresh et al. 1996) (Buckley and Eslami 2002).

II.3.4.1 Fuzzy propositions

There are two types of fuzzy propositions:

- ❖ Atomic fuzzy propositions: is a single statement.
- ❖ Compound fuzzy propositions: is a composition of atomic fuzzy propositions using the connectives "and," "or," and "not" which represent fuzzy intersection, fuzzy union, and fuzzy complement, respectively:

x is A

Where x is a linguistic variable, and A is a linguistic value of x (Klir and Yuan 1995).

II.3.4.2 Structure of fuzzy rule base

A fuzzy rule base consists of a set of fuzzy IF-THEN rules. It is the heart of the fuzzy system in the sense that all other components are used to implement these rules in a reasonable and efficient manner. Specifically, the fuzzy rule base comprises the following fuzzy IF-THEN rules:

$$R_u^{(1)}: \text{IF } x_1 \text{ is } A_1^1 \text{ and } \dots \text{ } x_n \text{ is } A_n^1, \text{ THEN } y \text{ is } B^1.$$

where A_i^1 and B^1 are fuzzy sets in $U_i \in R$ and $V \in R$, respectively, and $x = (x_1, x_2, \dots, x_n)^T \in U$ and $y \in V$ are the input and output (linguistic) variables of the fuzzy system, respectively (Dubois and Prade 1993) (Pedrycz 1994).

II.3.5 Fuzzy reasoning

Since the input and output of the fuzzy system in most applications are real valued numbers, we must construct or create interfaces between the fuzzy inference and the environment. The interfaces are the fuzzification and Defuzzification (Markowski et al. 2009).

The fuzzy inference system is the procedure by which real problems are solved using fuzzy logic. The functional blocks in Figure II.11 summarizes the different functions realized in an inference engine.

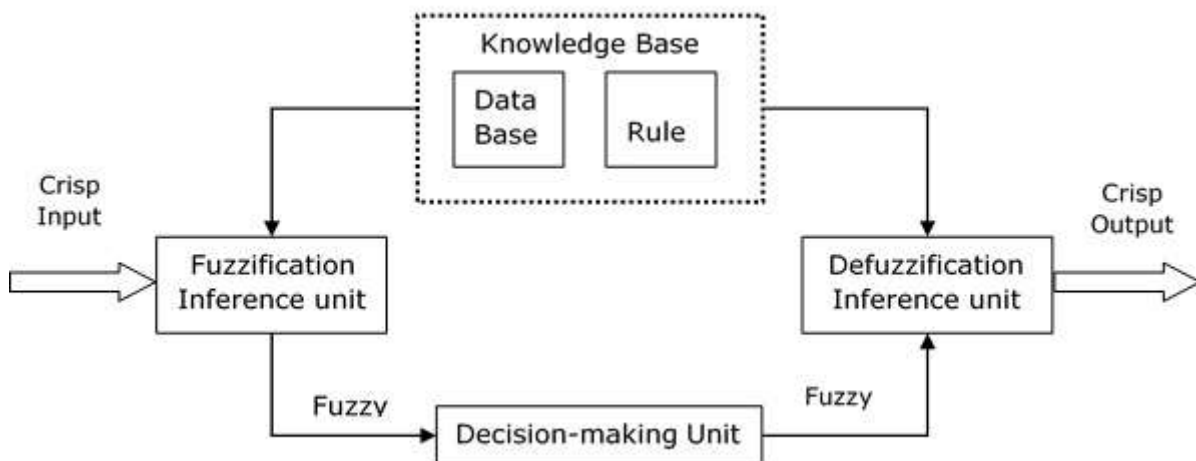


Figure II.11 Fuzzy inference engine (Markowski et al. 2009).

II.3.5.1 Fuzzification

Fuzzification is the process of making a crisp quantity fuzzy.

The fuzzifier is defined as a mapping from a real-valued point $x^* \in U \subset \mathbb{R}^n$ to a fuzzy set A' in U and convert them into linguistic variables (e.g. big, less...)

There are many fuzzifier mechanism such as Singleton, Gaussian, triangular and trapezoidal fuzzifiers.(Nait-Said et al. 2009).

II.3.5.2 Rule base

Which contains a number of fuzzy IF-THEN rules, and according to these rules we will understand the behavior mechanism of the system. The rules are generally deduced from previous experiences, or using optimization methods (Pedrycz 1994).

II.3.5.3 Data base

It defines the number and shapes of membership functions. As a common practice in engineering, membership functions have some specific shapes such as triangular, trapezoidal, Gaussian...the suited shape depends on the expert's knowledge of the application, and some recent researches has been devoted to use some of new optimization tools to find the optimal shapes (Castillo et al. 2007).

II.3.5.4 Decision making unit

Which performs the inference operations such as: evaluation and aggregation of rules. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Three built-in methods are supported:

- Max (maximum);
- Probor (probabilistic OR);
- sum (simply the sum of each rules output set) (Mizumoto 1988).

II.3.5.5 Defuzzification

Defuzzification is the conversion of a fuzzy quantity to a precise quantity, just as fuzzification is the conversion of a precise quantity to a fuzzy quantity. The output of a fuzzy process can be the logical union of two or more fuzzy membership functions defined on the universe of discourse of the output variable (Pappis and Siettos 2014). In literature different methods have been proposed such as:

- **Center of gravity (Centroid method):** This procedure is the most prevalent and physically appealing of all the defuzzification methods (Sugeno, 1985; Lee, 1990); it is given by the algebraic expression:

$$Y = \int \frac{\mu(x_i) * x_i}{x_i} \quad (\text{II.3})$$

- **Weighted average method:** The weighted average method is the most frequently used in fuzzy applications since it is one of the more computationally efficient methods. Unfortunately, it is usually restricted to symmetrical output membership functions. It is given by the algebraic expression

$$Y = \frac{\sum \mu_A(\check{Z}) * \check{Z}}{\sum \check{Z}} \quad (\text{II.4})$$

With: \check{Z} is the height of μ_A

II.4 Neural network

II.4.1 Definition

NNs consist of neurons (or nodes) distributed across layers. The way these neurons are distributed and the way they are connected to each other determines the structure of the network. Each of the links between the neurons is characterized by a weight value. A neuron is a processing unit that takes a number of inputs and gives a distinct output.

Apart from the number of its inputs, it is characterized by a function f known as transfer function. The most commonly used transfer functions are: the hard limit, the pure linear, the sigmoid and the tansigmoid function (Wang 2003) (Feng and Lu 2019).

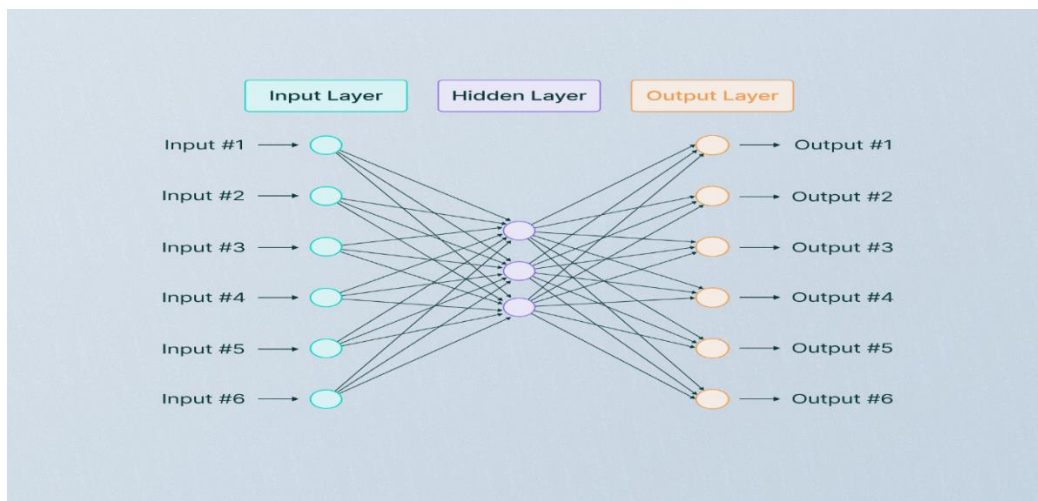


Figure II.12 Neural network structure (Feng and Lu 2019).

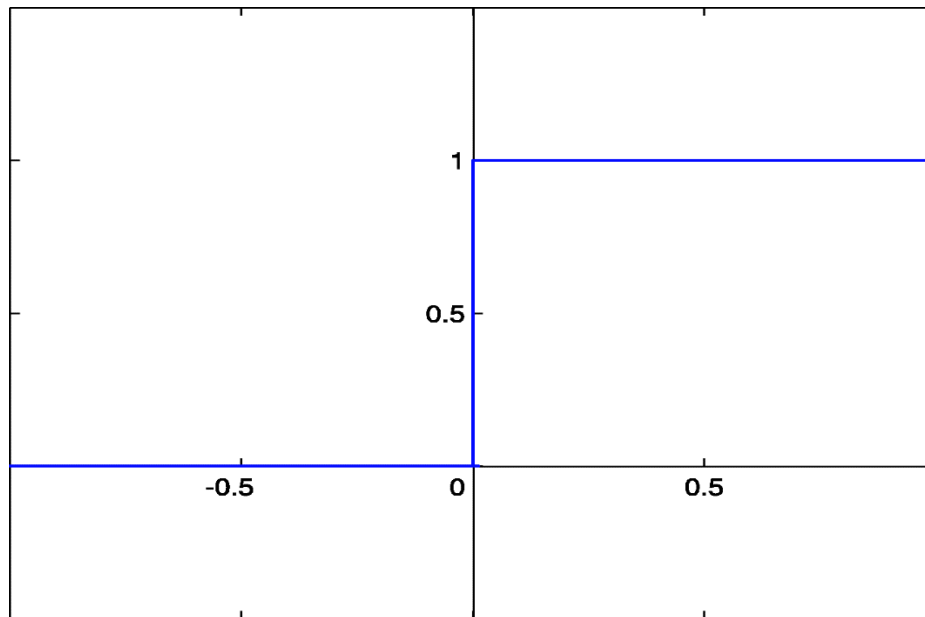


Figure II.13 Hard limit function.

II.4.2 The network layers

There are three types of layers, input layer, hidden layers, and output layer. Each network has exactly one input and one output layer. The number of hidden layers can vary from 0 to any number. The input layer is the only layer that does not contain transfer functions.

An example of a NN with two hidden layers is depicted in the next figure (Figure II.14) (Vohradsky 2001).

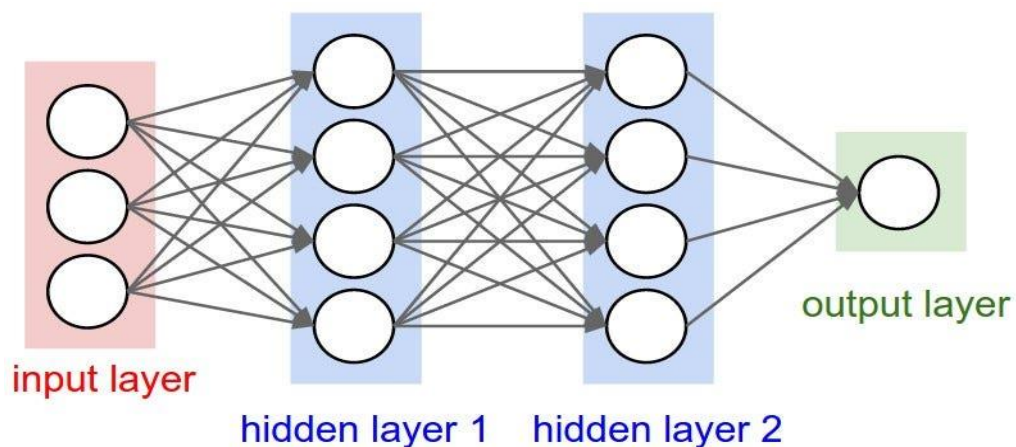


Figure II.14 Neural network with 2 hidden layers (Vohradsky 2001).

II.4.3 Concepts related to NNs

A brief description of the concepts related to NNs follows.

II.4.3.1 Neurons

A neuron is a processing unit that takes a number of inputs and gives a distinct output. The figure below depicts a single neuron with R inputs p_1, p_2, \dots, p_R , each input is weighted with a value $w_{11}, w_{12}, \dots, w_{1R}$ and the output of the neuron a equals to $f(w_{11} p_1 + w_{12} p_2 + \dots + w_{1R} p_R)$ (Hancock and Khoshgoftaar 2020).

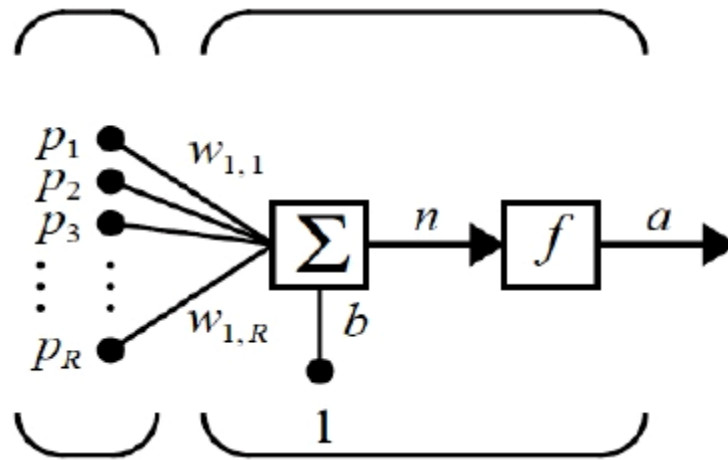


Figure II.15 A Simple neuron with R inputs (Hancock and Khoshgoftaar 2020).

Each neuron, regardless of the number of its inputs, is characterized by the function f known as transfer function. The most commonly used transfer functions are: the hardlimit, the pure linear, the sigmoid and the tansigmoid function.

II.4.3.2 Weights Adjustment and training

The power of NN models lies in the way their weights (inter unit-connection strengths) are adjusted. The procedure of adjusting the weights of a NN based on a specific dataset is referred to as the training of the network on that set (training set). The basic idea behind training is that the network will be adjusted in such a way that will be able to learn the patterns that lie in the training set. Using the adjusted network in future situations (unseen data), it will be able based on the patterns that learnt to generalize giving us the ability to make inferences. In our case we will train NN models on a part of our time series (training set) and measure their ability to generalize to the remaining part (test set). The test set size is usually selected to be 10% of available samples (Warwick 1992) (Vohradsky 2001).

The following figure shows how to train the network. Each sample consists of two parts the input parts and the target part (supervised learning). Initially the network weights are assigned random values (usually within $[-1 \ 1]$). Then the input part of the first sample is presented to the network. The network computes or calculates the output based on: the values of its weights, the number of its layers, and the type and mass of neurons per layer (Zhang et al. 2021).

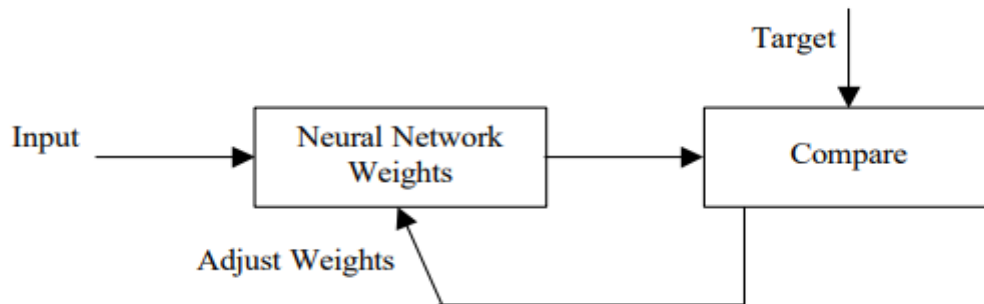


Figure II.16 The training procedure of a neural network (Warwick 1992).

This output is compared with the target value of the sample and the network weights are adjusted in such way that the measure describing the difference between outputs and targets is minimized. There are two main categories of network training: **the incremental** and **the batch training**.

During the incremental training, the network weights are adjusted and modified each time that each one of input samples is presented to the network, while in batch mode training the weights are adjusted only when all the training samples are presented to the network (Wang 2003). The number of times the training set will be fed to the network is called number of epochs.

The issues that arise related to the network training are: what exactly is the mechanism by which weights are updated, when does this iterative procedure stop, and what measure will be used to calculate the gap or the difference between the targets and the outputs? Answers to these questions are given in the next paragraphs.

II.4.3.2.1 Error Function

The error function or cost function is used to calculate the difference between the targets and the outputs of the network. The network weights are updated in the direction that makes the error function minimum.

II.4.3.2.2 Training Algorithms

The mechanism of weights update is known as the training algorithm. There are several training algorithms proposed in the literature. The algorithms described here are related to feed-forward networks. A NN is characterized as feed-forward network “if it is possible to attach successive numbers to the inputs and to all of the hidden and output units such that each unit only receives connections from inputs or units having a smaller number”. All of these algorithms use the gradient of the cost function to determine how to adjust the weights to minimize the cost function. The gradient is determined using a technique called backpropagation, which involves performing computations backwards through the network. The weights are then adjusted in the direction of the negative gradient (Pham and Pham 1999b).

II.4.3.2.3 Stop Training

A significant decision related NN training is when to stop weight adjustment. As we have explained so far, over-trained networks become over-fit to the training set and become useless in generalizing and inferring from unseen data. While under-trained networks are not able to learn all the patterns in the underlying data and for this reason they perform poorly on unseen data. Therefore, there is a trade-off between over-training and under-training our networks (Wittwehr et al. 2020b).

The methodology used to overcome this problem is called validation of the trained network. Apart from the training set, a second set is used, the validation set, which contains the same number of samples. The network weights are adjusted using only the samples in the training set. Each time the network weights are adjusted, its performance (in terms of error function) is measured on the validation set. During the initial training period, the errors in training and validation sets are reduced. This is due to the fact that the network begins to learn the patterns in the data (Cheng et al. 2008).

Through the algorithm iteration number on and off, the network will begin to confirm the training set. If this is the case, the error in the validation set will start to rise. And if this divergence persists for a number of iteration, the training is stopped. The result of this procedure will be inappropriate network (Bengio 2009).

II.5 Conclusion

In this chapter, after discussing the concept of artificial intelligence and the structure of the intelligent system, we presented its main tools and various aspects.

Since the fuzzy logic and neural network are directly related to our thesis, the chapter highlights also some definitions and concepts concerning the fuzzy logic theory and an overview of artificial neural network.

Chapter III

*Integration of artificial intelligence techniques in
safety analysis*

III.1 Introduction

Currently, fuzzy set theory is used as an effective tool to deal with the issue of imperfect data and uncertainties in information, in various fields including risk analysis, by applying the membership principle introduced by L.A Zadeh. In this context, many fuzzy applications have been developed and as an example we present below some of main conventional methods of risk analysis using this theory including the proposed methods used in the next chapter.

As a second intelligent tool considered in our thesis we will present also the use of neural network for scheduling SIL values

III.2 Fuzzy set theory application to risk analysis

III.2.1 Fuzzy Failure Mode and Effects Analysis

Failure modes and effects analysis is an effective tool for analyzing the causes and effects of failures in industrial systems, and each failure mode is evaluated based on three parameters: severity, occurrence probability and non-detection of failure mode. The development of fuzzy FMEA (FFMEA) consists of handling the imperfect data in more easy and objective way by introducing the notion of fuzzy sets and membership function principal. Fuzzy FMEA uses the linguistic variables to describe the three parameters of each failure mode as authors describe in many references (Chan et al 2007).

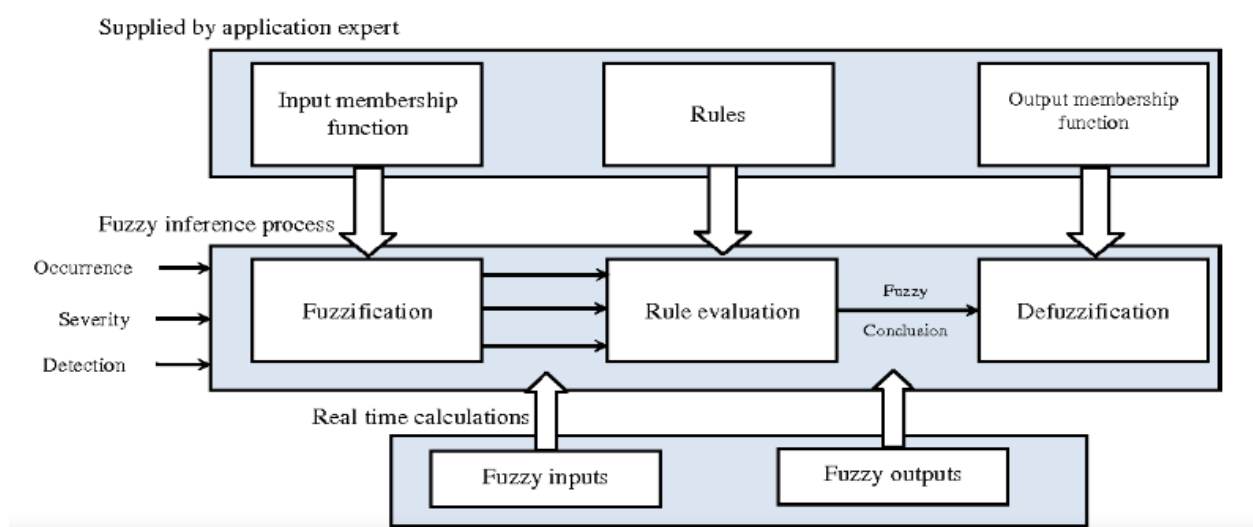


Figure III.1 overview of the fuzzy-FMEA approach (Chan et al 2007)

III.2.2 Fuzzy Fault Tree Analysis

The fault tree, as we mentioned before is the method widely used in risk analysis, which is purely quantitative analysis, requires the presence of data on operational safety parameters and risk analysis of the system. This allows it to be subject to imperfect data and knowledge and difficult to apply properly, which is why analysts have developed a fuzzy fault tree.

Fuzzy FTA (FFTA) calculates the fuzzy occurrence probability of the top event from the fuzzy occurrence probabilities of the basic events leading to the top event. In this context, several works have been developed, like Tanaka in 1983 (Tanaka et al. 1983). In 1990 Singer (Singer 1990) developed fault trees by representing the probabilities of occurrence of basic events by fuzzy numbers. In the same context and in 1993 two works appeared: Liang and Wang (Liang and Wang 1993), Soman and Misra (Soman and Misra 1993 represented the probabilities of occurrence of basic events by triangular fuzzy numbers.

III.2.3 Fuzzy Event Tree Analysis

The event tree is a quantitative method widely used in risk analysis. The probabilities and consequences in this tree are generally treated as exact values, however it is difficult to evaluate the probabilities and consequences based on feedback because generally the system history is not similar and often non-existent.

The events probabilities must be transformed into fuzzy probabilities (Dumitrescu et al 2002) represented by different shapes, trapezoidal, triangular... The fuzzy probability of each consequence is calculated by multiplying the probabilities of fuzzy events with the same path.

The result obtained is the fuzzy consequence probability, in order to obtain a more representative value for decision-making, it will be defuzzified.

III.3 Risk analysis methodologies proposed

III.3.1 Fuzzy LOPA approach

The imperfection of data and the lack of robustness in the final results are the disadvantages of the safety assessment methods, particularly LOPA method. This property is due to several specific factors: the large number of components in the studied system, as well as the structural connections and interactions, operating dependencies between these components including operating conditions and even the environmental factors that affect the state and operation of the system.

All these factors contribute to the development of a new fuzzy approach to risk estimation by introducing the concept of fuzzy sets (Marhavilas et al. 2020). In this context, the authors developed a fuzzy LOPA model that allows to assess the pipe risks and dealing with uncertainties in data used by classical LOPA.

III.3.1.1 Representation of the developed approach

The development procedure of the fuzzy LOPA consists of using fuzzy partitions to describe the parameters of LOPA scenarios. As shown in figure III.2, Each value used by the LOPA method is transformed into a fuzzy interval. The reduced outcome frequency is estimated by expanded multiplication through α -cuts method. The results are crisp values of the reduced outcome frequency calculated by defuzzification of the fuzzy frequency.

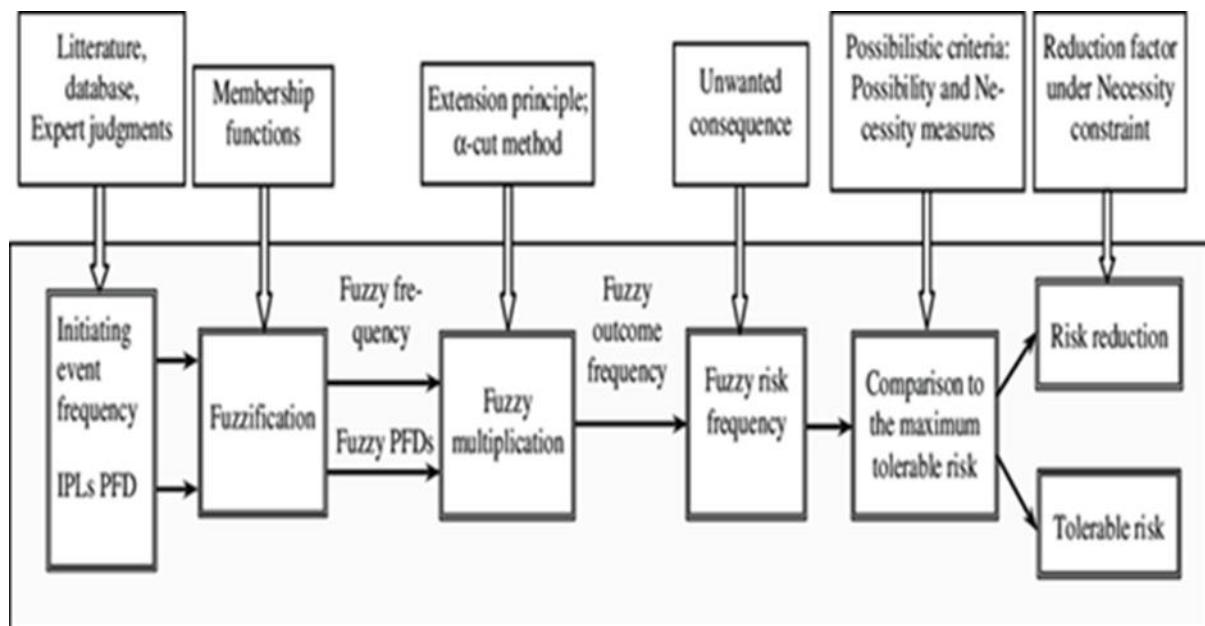


Figure III.2 Fuzzy LOPA procedure (Cui et al. 2019)

III.3.1.2 Fuzzification step

The beginning of the proposed approach "Fuzzy LOPA" is to convert the confidence intervals taken from the literature or databases (OREDA, ICSI) into fuzzy intervals (Fuzzification). The transformation is done using the concept of possibility (or fuzzy probability).

The advantage of this step is that it makes it possible to determine functions of linguistic variables. These membership functions can be expressed in different forms (triangular, Gaussian, trapezoidal, etc.). Diverse types of fuzzy sets will acquire according to membership function type. Lotfi ZADEH suggested a group of membership functions distinguished by two types of shapes, consisting of: straight lines "linear" shapes and Gaussian "curved" shapes.

III.3.1.3 Scaling and Determination of the fuzzy frequency of the reduced outcome

The next step in this approach is to calculate fuzzy interval of the reduced outcome frequency from fuzzy intervals of initiating event frequency and the probabilities of failure on demand of the independent protection layers (IPLs). The calculation of the fuzzy frequency of the reduced outcome is done using equation:

$${}^c_1f\tilde{=} = {}^n_1f\tilde{=} \otimes \prod_{k=1}^n PFD \quad (III.1)$$

Where

${}^c_1f\tilde{}$: is the fuzzy frequency of the consequence C of initiating event i

${}^n_1f\tilde{}$: is the fuzzy frequency of the initiating event i.

PFD : is the probability of failure on demand of the same IPL which protects against the consequence C.

The application of the α -cut method makes it possible to simplify the estimations by the division of the membership function into fuzzy intervals as a function of α -cuts ($0 \leq \alpha \leq 1$). The cutting is done using the α -cuts method:

$${}^c_1f\tilde{=} = \cup_{\alpha=0}^1 f_i^c = \cup_{\alpha=0}^1 f_{i\alpha} \cdot \prod_{k=1}^n \cup_{\alpha=0}^1 PFD \quad (III.2)$$

Fuzzy scales are often used to characterize and/or determine the premise and conclusion of a fuzzy rule. These scales can be linguistic or numerical (Pedrycz 1994).

In our case, the transformation concerning the initiating event frequency and the PFD values with the triangular membership functions is illustrated by figure III.3”.

The fuzzy number represented in figure 5 is written as (A, M, B):

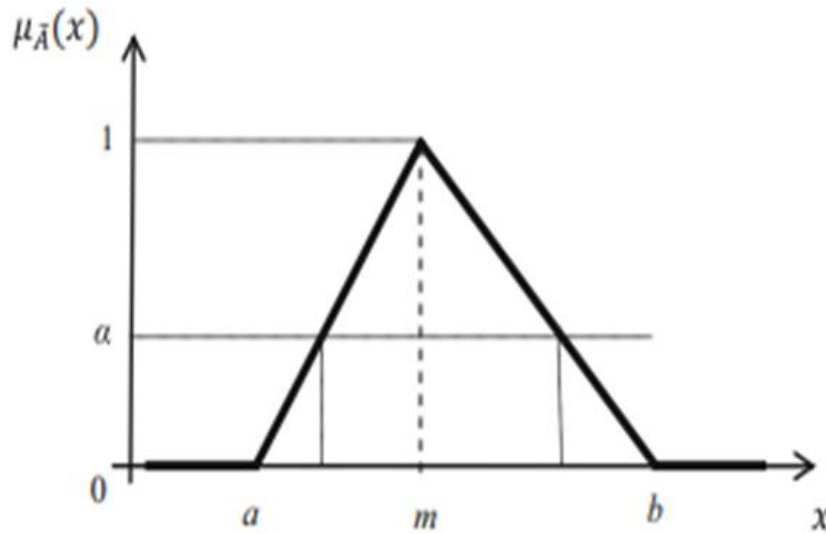


Figure III.3 Fuzzy number representation (Dubois and Prade 1993).

m is the modal value well defined by D. Dubois and H. Prade in (Dubois and Prade 1993), a and b are called the lower and upper bound, Previous works in this area focused on the fuzzification step and scaling calculation as (Markowski et al. 2009).

III.3.1.4 Defuzzification of the fuzzy frequency of the reduced outcome

The final step in this approach is to defuzzify the fuzzy frequency of the reduced outcome in order to obtain an accurate value of the reduced outcome frequency.

$$f^0 = \frac{\sum u_{f_i^c}(f).f}{\sum u_{f_i^c}(f)} \quad (III.3)$$

The Defuzzification method is described in detail in the previous chapter

III.3.2 Fuzzy SIL studies

III.3.2.1 Fuzzy logic for risk matrix evaluation

The flow chart in figure III.4 indicates the global philosophy we propose in this work, where the aim is to implement an effective safety strategy in an industrial plant. This global philosophy is based on the integration of the most known methods in the field of petrochemical studies, namely HAZOP and SIL.

We will first define the safety instrumented functions (SIF) required to bring the operation to a safe state using HAZOP study, and we will investigate the ability of the SIS to realize the safety goals using SIL.

As mentioned in the previous sections, two values of safety integrity levels must be defined, the first is the target SIL and we will use a fuzzy inference engine to specify these values, after that we consider the calculated SIL which results from calculating the average PFD of the corresponding SIS. In the last stage, we will compare the results, so whenever the target SIL is greater than the calculated SIL, a design modification is required to meet the safety requirements (our design modification should lead a target SIL smaller or equal from the required SIL).

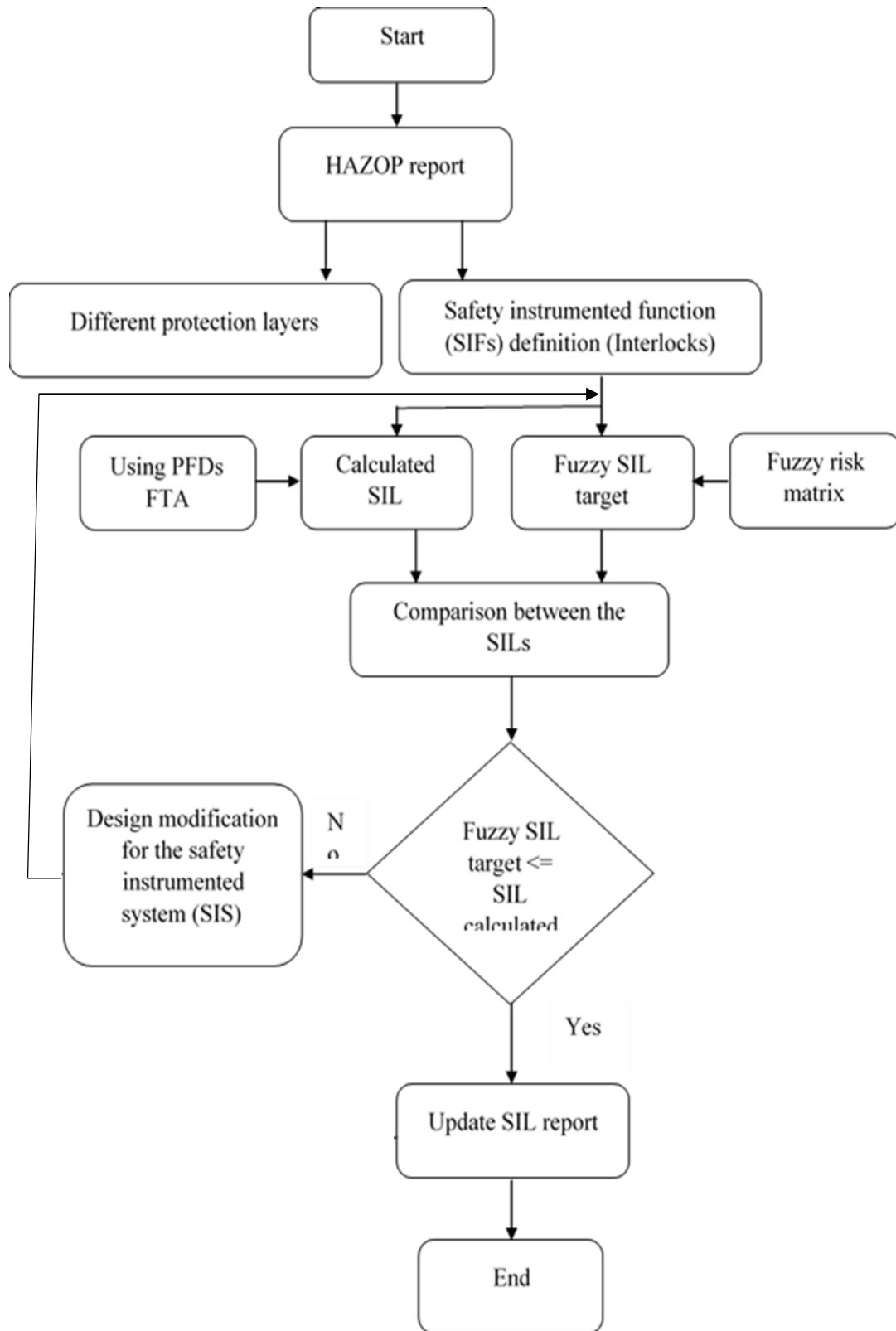


Figure III.4 Effective safety strategy based on fuzzy logic for risk assessment in an industrial plant

III.3.2.2 Fuzzy risk matrix implementation

The block diagram of figure III.5 shows a general structure of a fuzzy controller that represents the fuzzy equivalent of the risk matrix.

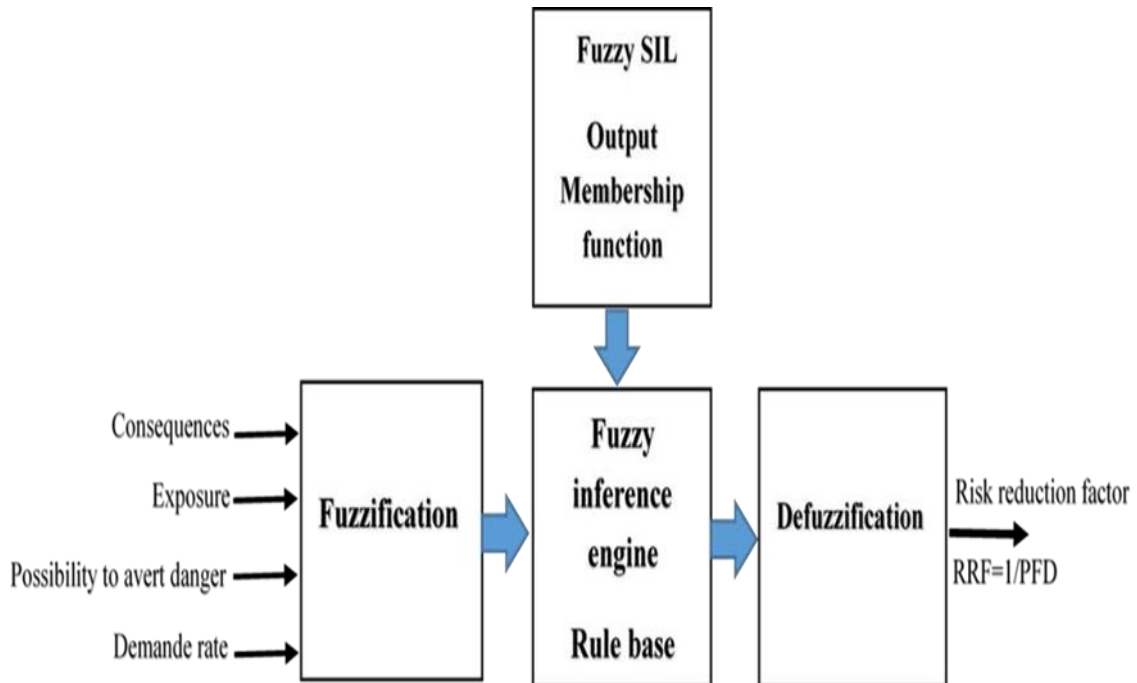


Figure III.5 Fuzzy risk matrix implementation

III.3.2.3 Scaling, fuzzy interval construction and membership function's shape determination

It should be noted that before implementing the algorithm, as it is a common practice in the design of fuzzy logic controllers, to each linguistic variable a universe of discourse and a range of variations must be assigned. In this case, the scaling of the intervals should be done to avoid computational errors and hence, bad interpretations of results.

Another important thing, the shape of any membership function is deduced based on many important factors. In our case we choose the trapezoidal shape as the basic shape (Figure III.6).

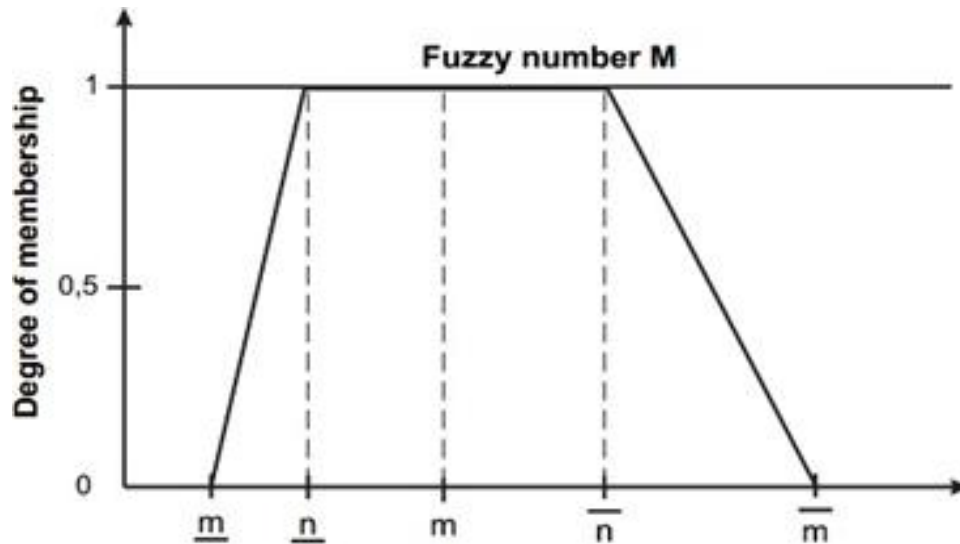


Figure III.6 Trapezoidal membership function (Markowski et al. 2009).

The linguistic term associated with this type is defined by the following equations

(III.4) (Markowski et al. 2009) :

$$\mu_M(x) = \begin{cases} 0, & x \leq \underline{m} \\ \frac{x - \underline{m}}{\underline{n} - \underline{m}} & \underline{m} \leq x \leq \underline{n} \\ 1 & \underline{n} \leq x \leq \bar{n} \\ \frac{\bar{m} - x}{\bar{m} - \bar{n}} & \bar{n} \leq x \leq \bar{m} \\ 0 & \bar{m} \leq x \end{cases} \quad (III.4)$$

The exact shape i.e. the edge calculation (defining the parameters (\underline{m} , \underline{n} , \bar{m} , \bar{n} , and \bar{m}) is based on the calculation of the fuzzy intervals.

In computing the fuzzy intervals, the following steps should be followed:

- The determination of a scaled risk matrix since all needed values are well defined in the conventional risk matrix.
- The transformation from ordinary matrix (values) to fuzzy intervals. (which is the reverse procedure of fuzzy interval mean value determination).

III.3.2.4 The rule base

The rules base is constructed following the logical sequence of the conventional SIL table (Table I.12) by translate it into fuzzy thinking (if ... then ... rule). A set of fuzzy IF-THEN rules forms the rule base engine. In fuzzy logic, this engine serves as the brain of the fuzzy

system, all other elements are used to execute these principles in a sensible and effective way. In our case, for example, regarding the personal health effect, the rule base engine is as follows:

IF the consequence S is $S2$ AND the exposure F is $F2$ AND the possibility to avert P is $P3$
 AND Demand rate D is $D4$ THEN the outcome SIL is $SIL2$.

And so on with all the rules, the same for the economic effects, the rule base engine is constructed as follows:

IF the consequence L is $L2$ AND demand rate D is $D3$ THEN the outcome SIL is $SIL1$.

Same for the Environment effects:

IF the consequence E is $E2$ AND demand rate D is $D3$ THEN the outcome SIL is $SIL1$.

III.3.3 The use of neural networks in scheduling problem

A neural network can be considered as a data processing technique that maps, or relates, some type of input stream of information to an output stream of data. Neural Networks (NNs) can be used to perform classification and regression tasks. More specifically it has been proved by Cybenko (Mitchel, 1997) that any function can be approximated to arbitrary precision by a neural network.

The concept of Artificial Neural Networks (ANN) has a biological background. ANNs imitate loosely the way that the neurons in human brain function. An ANN consists of a set of interconnected processing units, namely neurons.

The main objective of this proposition is to schedule the SILs values to the required SIL for the selected SIFs, for this reason we proposed an optimization algorithm using a multi-layer artificial network (Figure III.7).

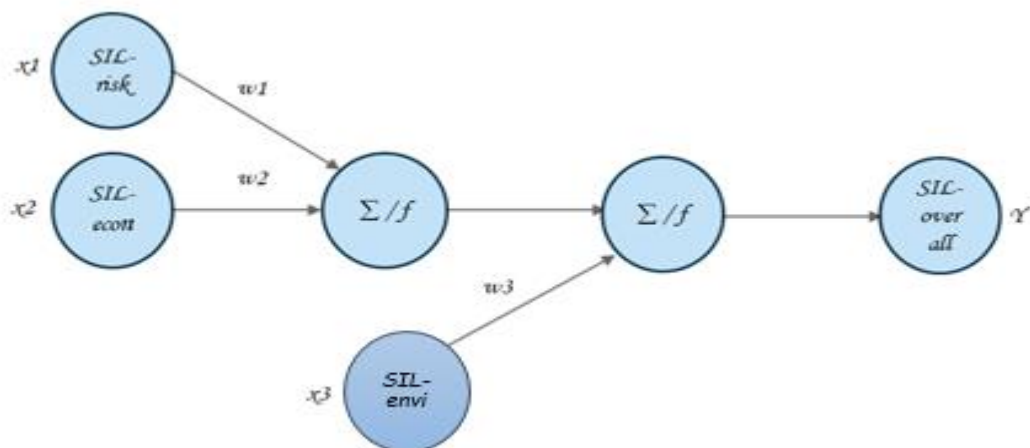


Figure III.7 Network structure for the proposed algorithm

The inputs x_1 and x_2 of the neuron are multiplied by weights w_1 and w_2 and summed up together. The resulting n is the input to the activation function f . The activation function was originally chosen to be a relay function, but for mathematical convenience a hard-limit function is used; it is defined as

$$f = \begin{cases} x_1 & \text{if } wx > 0 \\ x_2 & \text{if } wx < 0 \end{cases} \quad \text{(III.5)}$$

The output of the first node becomes an input for the second node.

We used this function in our algorithm to create neurons that make classification decisions, and the typical network is shown in Figure III.7.

The following table represents the network parameters.

Table III.1 Network parameters

Input Layer	Hidden Layer	Output Layer
x_1 : SIL-risk; x_2 : economic SIL;	Y_1 : output of first layer; x_3 : environment SIL	Y : SIL overall $F = \begin{cases} x_1 & \text{if } w \cdot x > 0 \\ x_2 & \text{if } w \cdot x < 0 \end{cases}$

III.4 Conclusion

The issue of risk management in petrochemical facilities is currently considered very attractive in light of existing uncertainties not only in the furnished data from the site but also in the output of analysis, and the classification problems.

On the other hand, the recent development in control systems focuses on the introduction of new tools based on artificial intelligence, to solve the limitations of classical methods.

It is in this context, we have presented some of them, such as the use of fuzzy logic in SIL target evaluation, the use of Fuzzy logic in LOPA determination, the neural networks for SIL scheduling, ... Which we will discuss their application to real systems in the next chapter.

Chapter IV

Improvement of the safety of industrial plants using
the proposed techniques

IV.1 Introduction

Uncertainties and incomplete / no knowledge related to process safety functions and classification tasks are important issues that faced by risk analysts. To deal with these problems, new techniques based on artificial intelligence such as fuzzy logic and neural network have been developed.

Below, we will present an industrial system (naphtha-a stabilizer 10-c-5/10v8) and integrate our fuzzy LOPA approach developed into this risks analysis method. And also another industrial system (Fired heater F201101) and apply the proposed fuzzy approach to evaluate safety integrity level to improve the heater safety followed by SIL scheduling using neural network.

IV.2 Evaluation of safety barriers for naphtha -A- stabilizer using LOPA based on Fuzzy logic.

IV.2.1 The studied system Naphtha-A-stabilizer 10-C-5 and reflex balloon 10-V8

According to the importance of the "Risk identification" part, this section of the thesis will be devoted to the technical and functional description of the "Naphtha-A stabilizer" system represented in figure IV.1 and to the analysis of the various accident scenarios.

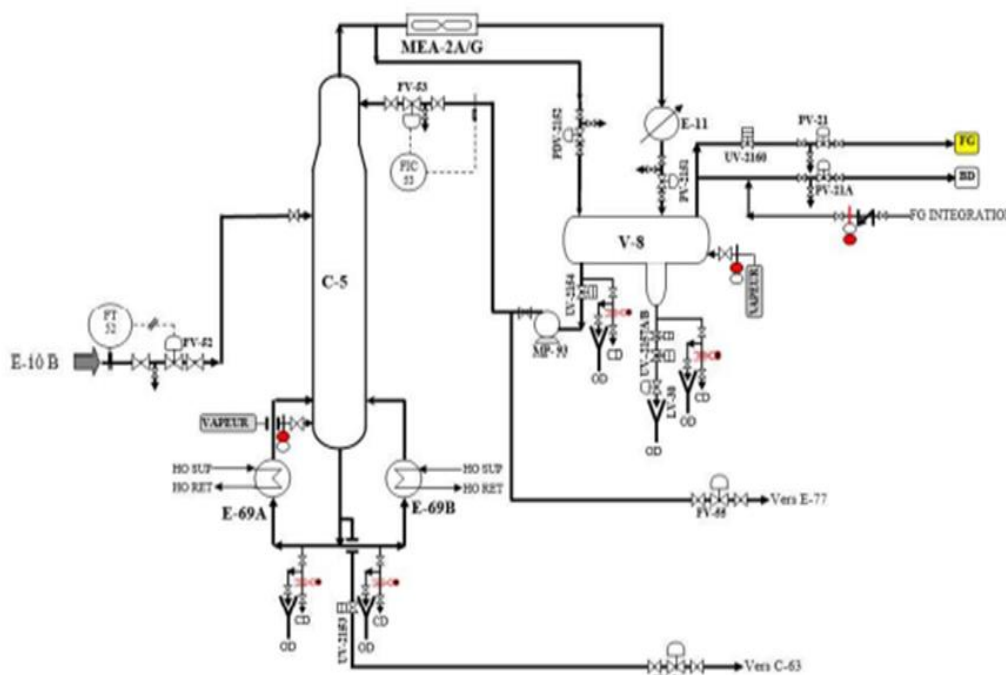


Figure IV.1 The studied system scheme.

The column operates at the temperature and pressure of 60 ° C and 7.7 kg / cm². The vapors from the top column, at the temperature indicated by 10-TI-107 (having the TAH & TAL alarm in the control room), are condensed in the air cooler of the Product Condenser at the top of Stabilizer-A (10-EA-2A~G), and the Regulating Condenser at the top of Stabilizer-A (10-E-11), and then collected in the accumulator of the Reflux Balloon of Stabilizer- A (10-V-8). The reflux balloon operates at the temperature and pressure of 43 ° C and 7.0 kg / cm². The head column was supplied with the safety valve 10-PSV-38 at the starting pressure of 9.8 kg / cm² with the discharge at Blow down.

The pressure in the column is controlled by the condenser flooded by 10-PIC-2151 via the pressure control valve 10-PV-2151. 10-PIC-2151 has been supplied with the low / high pressure alarm 10-PAL- 2151 and 10-PAH-2151. The pressure in the column is still controlled by 10-PIC-21 acting in the "split control" on valves 10-PV-21 and 10-PV-21A. The vapor flow of the uncondensed fuel gas is controlled by 10-PV-21 and the non-condensable materials accumulated in Reflux Balloon of the Stabilizer-A (10-V-8) can be Blow-down discharged by 10-PV-21A installed on line 3"-BD 10-2104-A1A. The steam line at the top is equipped with 10-FI-82. The steam line at the top of the column is affected with the injection of the corrosion inhibitor made upstream of 10-EA- 2A ~ G by the 10- pumps P-20A / B / C / D.

The liquid accumulated in the receiving tank at the top of 10-V-8 sucked by the pumps 10-P-93A / B at the temperature indicated by 10-TI-112 and transmitted to the top of the column 10-C-5 constituting in part of the production of the column at the head of unit 30 with the flow controlled by 10-FIC-55 functioned in cascade with the level controller 10-LIC-21, supplied with the alarm for the low level 10-LAH / LAL-21. The interface level between naphtha and water oily in 10-V-8 is controlled by 10-LIC-30 by control the flow rate by 10-LV-30 located in the boot discharge line. As an additional safety hydrocarbon detector 10-AI-2151 and 10-AI-2152 was equipped near the bottom the reflux balloon (10-V-8) and the reflux pump (10-P-93 A / B).

In addition, as a security part, 10-LI-2151 was supplied with the high-high and low-low alarm 10-LAHH-2151 & 10-LALL-2151. In the event that 10-LAHH-2151 lock 10-I-2164 will be activated and 10-UV-2160 in top line of 10-V-8 will be closed. In case 10-LALL-2151 gives the block signals, 10-I-2164 will activate and close the on-off valve 10-UV-2154 installed on the suction line of 10-P-93 A / B.

The bottom product of column 10-C-5, heated in Stabilizer-A 's Re-boiler (10-E-69A / B) at the temperature indicated by 10-TI-2168 & 10-TI-2151, returns to the column in below the first tray. This temperature is controlled by 10-TIC-2151 via controlling the flow of hot oil from the tube side. 10-TIC-2151 can send the temperature alarm low / high 10-TAL-2151 & 10-TAH-2151 for the control room. The level at the bottom of column 10-C-5 is controlled by 10-LIC-20 which is cascaded control with 10-FIC-54 controlling the bottom flow of gasoline stabilized in the splitter by 10-FV-54. The alarm for the low / high level 10-LAH-20/10-LAL-20 is signaled in the control room. The stabilizer bottom is sent to Splitter-I (10-C-63) (PID 1023) under flow control 10-FIC-54. 10-FIC-54 can send the 10-FAL-54 low flow alarm to the control room.

IV.2.2 Structural and functional analysis of the system

Technical and functional analysis in other words "structural and functional decomposition", this decomposition will be devoted to defining the structure of our studied system by specifying the functions of the different constituents (subsystem, equipment and components) of our global system "naphtha-A-stabilizer".

- **Technical analysis:** the technical and functional analysis of our system chosen as study case the "naphtha-A stabilizer" enabled us to decomposed it into four subsystems, namely:
 - ❖ Re-boiling subsystem (ensures the heating of the column bottom product).
 - ❖ Distillation subsystem (ensures separation between naphtha and light particles (LPG) to stabilized naphtha).
 - ❖ Condensation subsystem (ensures product condensation at the top of the column).
 - ❖ Reflux accumulation subsystem (ensures product accumulation at the top of the column)

IV.2.3 Risk analysis application and results

As a first step at all, functional structural decomposition was performed in order to define the nodes analysed in more detail by HAZOP method. (see the appendix 1).

The HAZOP table also incorporate also evaluations of the Frequency for each Cause and Gravity for every Consequence. A Risk Matrix can be utilized to assess Risk for a Cause-Consequence pair.

IV.2.3.1 Structural and functional analysis of the system

The acceptability assessment of accident scenarios is carried out by identifying the occurrence probability as well as the severity of consequences and it is based on RISK MATRIX in order to judge if the risks are unacceptable to consider actions to reduce their probability or gravity.

In this work, we used the matrix defined by SONATRACH presented in table IV.1, this matrix is compatible with the scales of (gravity and probability) as demonstrated in (table IV.2 and table IV.3).

Table IV.1 Risk matrix by SONATRACH

		Probability			
		< 10 ⁻⁴ / year (improbable)	10 ⁻⁴ to 10 ⁻² / year (unlikely)	10 ⁻² to 10 ⁻¹ /year (likely)	1/ year (very likely)
Gravity	1	Low	Low	Low	Medium
	2	Low	Low	Medium	Medium
	3	Low	Medium	Medium	High
	4	Medium	Medium	High	High
	5	Medium	High	High	high

Chapter IV *Improvement of the safety of industrial plants using the proposed techniques*

Criticality assessment: It is carried out from the gravity rating and the probability of various accident scenarios that can generated at the level of our system.

The gravity rating basis of the following table (table IV.2)

Table IV.2 Gravity rating basis

Gravity	Individual (staff)	Environment	Company	Production/goods
G5	<ul style="list-style-type: none"> - Several deaths or permanent incapacity inside and outside the plant. - Harm to the health of the surrounding population. 	<ul style="list-style-type: none"> - Long-time population out of range. - Severe damage to the ecological system of the region. 	<ul style="list-style-type: none"> - Negative image conveyed by international television news. - Information written in international press. 	<ul style="list-style-type: none"> - Partial destruction of the installation. - Site closure with authorities' decision. - Destruction of the goods outside the factory.
G4	<ul style="list-style-type: none"> - Deaths or permanent incapacity limited to plant staff. - Serious occupational disease limited to the plant person. 	<ul style="list-style-type: none"> - Uncontrolled internal pollution or pollution outside the controlled limit. - Sever damage to the environment requiring the implementation of IPL to prevent the propagation. 	<ul style="list-style-type: none"> - The whole country is informed. - Information written in the national press. 	<ul style="list-style-type: none"> - Total shutdown of production (< one week but can be restarted at the least). - Damage to equipment, lines or devices.
G3	<ul style="list-style-type: none"> - Accident with work stopping, temporary or permanent disability. - Damage to health with 	<ul style="list-style-type: none"> - Controlled internal pollution. - Limited effect to the plant environment due to the regulatory 	<ul style="list-style-type: none"> - The inhabitants of neighboring localities are informed. - Information written in the local press or communicated 	<ul style="list-style-type: none"> - partial stop of production. - Damage to an equipment, line or device.

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	loss of capacity or occupational disease declaration	thresholds exceedances.	by local radio stations.	
G2	<ul style="list-style-type: none"> - Accident without work stoppage. - Reversible health impairment. 	<ul style="list-style-type: none"> - Minor and transient effect corresponding to an isolated exceedance of rejection standards. 	<ul style="list-style-type: none"> - Impact limited to a few third parties close to the factory. - Local media impact without press article. 	<ul style="list-style-type: none"> - Interruption of production for a period of < 24 hours. - Damage to part of equipment, line or device.
G1	<ul style="list-style-type: none"> - No injury. - No harm to health. 	<ul style="list-style-type: none"> - Effect remain confined within the walls of the factory. - No exceeding of regulatory or normative thresholds. 	<ul style="list-style-type: none"> - Impact limited to factory communication. - Some third parties may be aware. 	<ul style="list-style-type: none"> - No interruption of production.

The probability rating basis of the following table (table IV.3)

Table IV.3 Probability rating basis.

Probability	Description	Frequency
P4	Very likely “has occurred frequently within Sonatrach”	1/year
P3	Likely “has occurred or could occurred within Sonatrach, could occur during the installation lifetime”	10 ⁻² to 10 ⁻¹ /year
P2	Unlikely “ could be in a company similar to Sonatrach”	10 ⁻⁴ to 10 ⁻² /year
P1	Improbable “never met or heard of but physically possible (or extremely rare)	<10 ⁻⁴ /year

Description of matrix zones and risk classification:

- ❖ Low risk (green zone): “Acceptable risk” doesn’t justify any additional action but it requires the maintenance of the existing safety barriers in well function to avert the drift of the risk to a higher level.
- ❖ Moderate risk (yellow risk): requiring action to be taken on one of the parameters (probability or gravity) which can bring the risk to a lower level, actions must be taken to reduce this parameters, if not, maintain the control measures in order to prevent the risk from drifting to a higher level.
- ❖ High risk (red zone): “Unacceptable risk” requiring urgent measures to be possessed to decrease this risk to an acceptable level

IV.2.3.2 Development of HAZOP study

Our study involves a HAZOP analysis to identify the scenarios generated by the different deviations of the operating parameters also the different causes and consequences, and their barriers that can prevent these accidents considered in such major cases. The HAZOP study is presented in the tables of the appendix 1.

The HAZOP tables allows as to identify all the risks related to the thermos-hydraulic parameters of our study system operation “naphtha-A-stabilizer”.

It revealed 2 catastrophic scenarios namely:

- Burst of the “balloon” following the increasing in pressure (pressure increasing): Augmentation in pressure due to a processes failure until it bursts when the internal pressure becomes greater than the resistance of the material constituting the storage tank.
- “UVCE” due to the drop in the water level: A cloud of GPL vapors from a leak in the 10-V-8 storage tank meets an inflammable source, the flammable vapors begin to ignite. The flame front propagates through the unburned mixture as an explosion.

IV.2.3.3 Identification of initiating events frequencies

In the following, we will identify the initiating events of these two scenarios in terms of occurrence frequency.

IV.2.3.3.1 Identification of the initiating events for scenario 01

THE overpressure caused by:

- ❖ The failure of regulation loop: auto-regulating valves; the 10-V-21 introduces the in-condensed gas to the FG system, and the 10-V-21A which releases the excess pressure to BLOW-DOWN.
- ❖ A failure in the processes by a level augmentation or a temperature augmentation; which can cause the explosion.

The initiating event frequency is calculated using the fault tree method (FTA) and the GRIF software as the figure IV.2 represents

$$FEI_1 = FEI_{(PV21)} \cdot FEI_{(PV21A)} \cdot (FEI_{\text{level augmentation}} + FEI_{\text{temperature augmentation}})$$

$$FEI_1 = 1.425 \text{ E-}8/\text{h} = 1.24 \text{ E-}4/\text{ year}$$

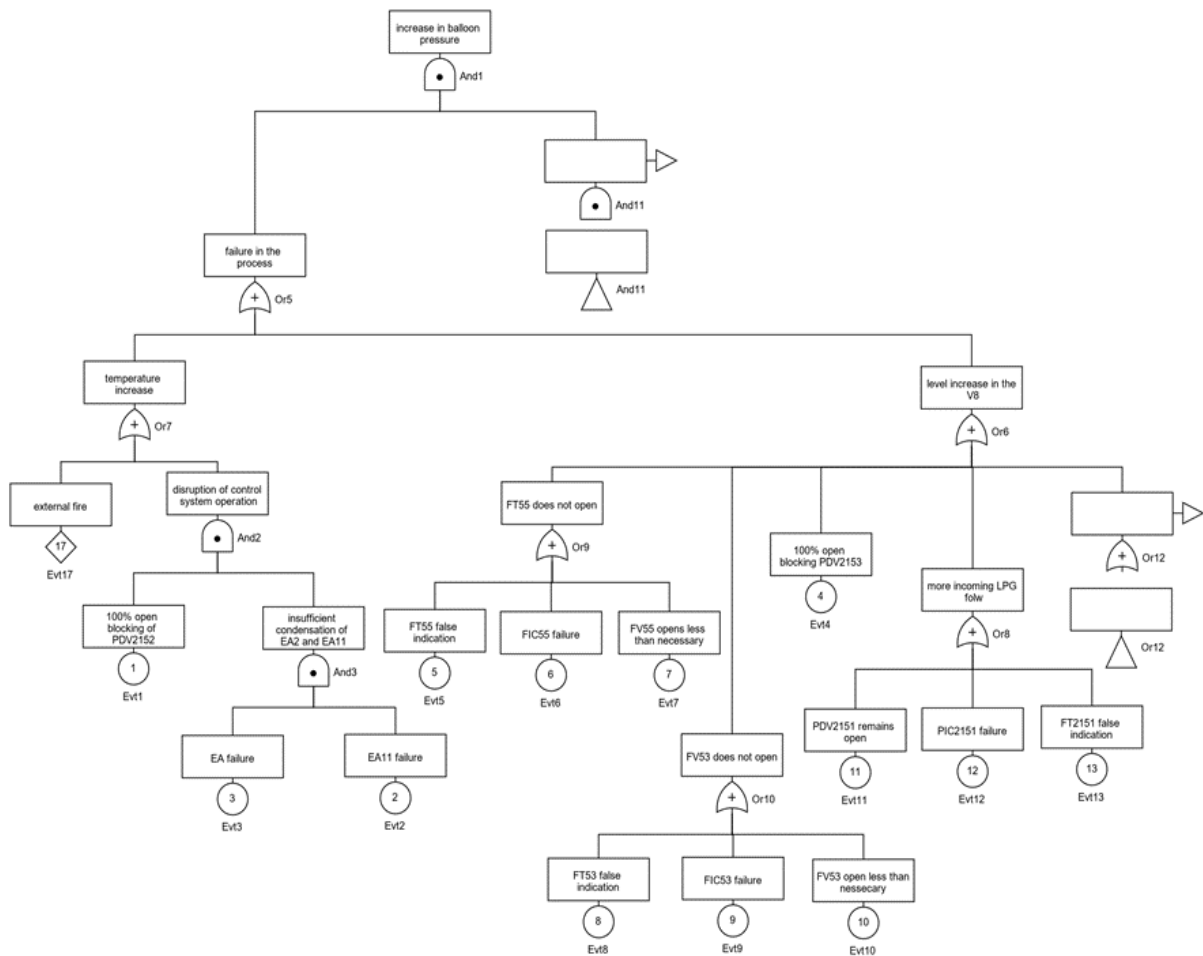


Figure IV.2 FTA application for the first scenario.

IV.2.3.3.2 Identification of the initiating events for scenario 02

The loss of containment caused by: the failure of the control loop of water level at 10-LV-30;

The frequency of this initiating event is determined using fault tree method (FTA) and GRIFF software as the figure IV.3 represents.

$$FEI2 = FEI(10-LV-30) = 3.318 \text{ E-9/h} = 2.9 \text{ E-5/ year}$$

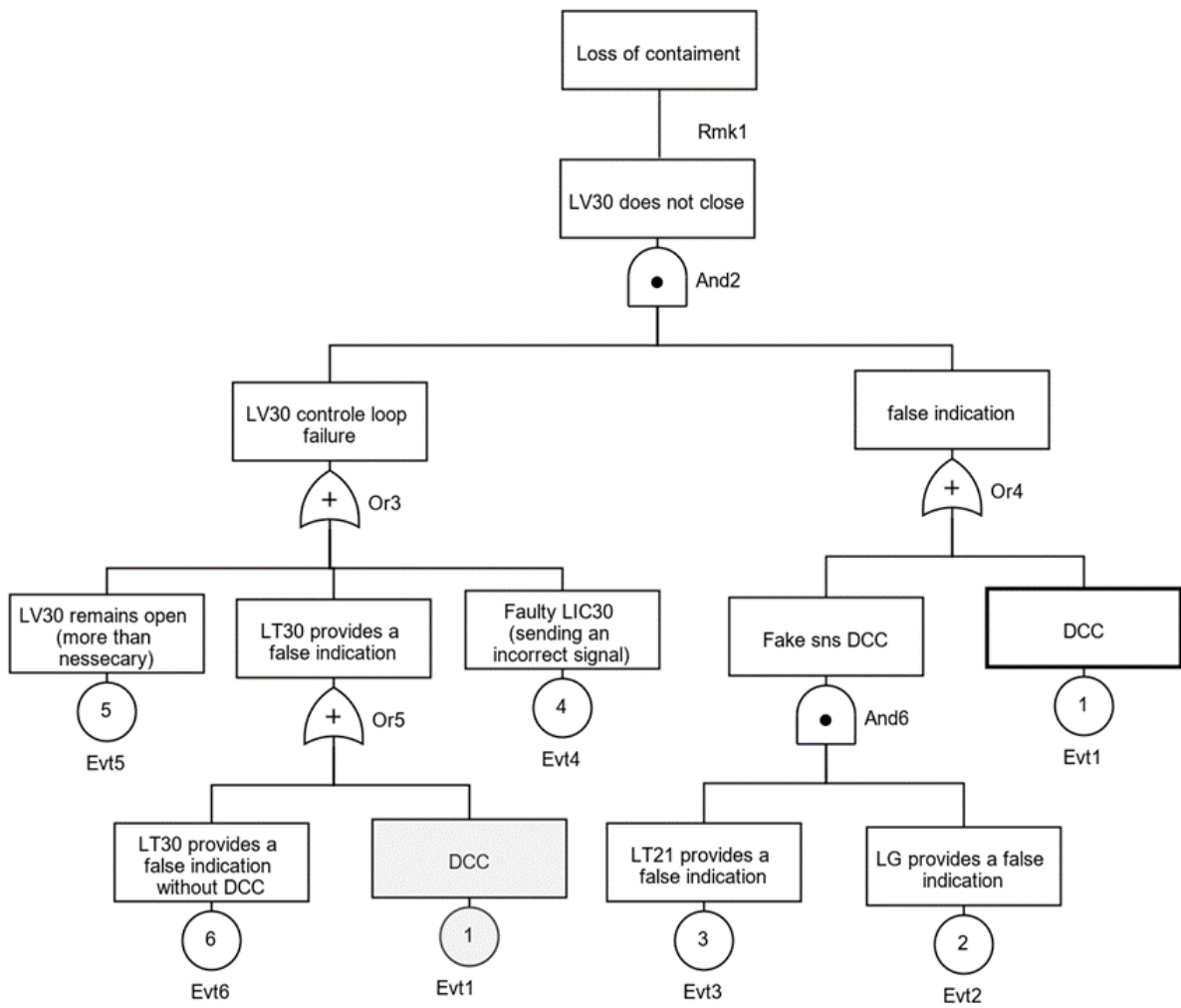


Figure IV.3 FTA application for the second scenario.

IV.2.3.4 Identification of safety barriers and their failure probabilities

The identification of independent protection layers is made based on certain specific criteria. In our study, the IPLs are as follows:

- ✓ Pressure indicator 10-PI-21.
- ✓ Human operator with a failure probability of: 0.1.
- ✓ A safety valve 10.PSV-50.
- ✓ Level indicator 10-LI-30.
- ✓ HC Gas detectors (AI-2151/ AI-2152) set off an alarm for gas detection.
- ✓ Level transmitter 10-LI-2155 (set off interlock 10-I-2165) (Safety instrumented LALL).

The used data for estimated the PFDs of safety barriers are taken from the literature, or provided by the system designer, the values are summarised in the table IV.4.

IV.2.3.5 Identification of accident scenarios

The scenarios are presented by Bow Ties, the choice of this model allows us to represent the sequence of causes and events clearly (cause & effects). The first scenario is represented by figure IV.4, and the second by figure IV.5.

IV.2.3.6 Application of the fuzzy LOPA proposed

The reduced consequence frequency is determined according to the methodology described in the above chapter.

IV.2.3.6.1 Fuzzification of confidence intervals

Referring to the data in table IV.4 and the initiating events frequency shown in section IV.2.3.3, frequency scales and PFD of IPLs are transformed into their fuzzy representations according the method described in the section III.3.1.2 (by calculating the square root value of the limit intervals).

Table IV.4 PFD values of safety barriers.

Components	Failure rate λ (h^{-1})	Periodic test T (h)	PFD = $\lambda.T/2$
10-PI-21	$1,14.10^{-5}$	4320	$2,46.10^{-2}$
Operator	-	-	10^{-1}
10-PVS-50	$4,20.10^{-6}$	25920	$5,44.10^{-2}$
10-LI-30	$1,14.10^{-5}$	4320	$2,46.10^{-2}$
10-I-2165	-	-	SIL3 = 10^{-3}
FEI 1	1.425 E-8	-	-
FEI 2	3.318 E-9	-	-

Triangular membership functions (figure IV.6) are favored as long as they allow the simple calculation of the fuzzy frequencies. Table IV.5 shows the numerical results of this transformation.

Table IV.5 Transformation from crisp values to fuzzy values for the PFDs

Scenario 01				
Fuzzy probabilities of parameters		A	M	B
FIE1		1E-8	1,425.10 ⁻⁷	2.35E-7
10-PI-21	PFD11	-1.25E-2	2.46E-2	1.675E-1
Operator	PFD12	-1.25E-2	1E-2	2.575
10-PSV-50	PFD13	-1.25E-2	5.44E-2	1.975E-1
Scenario 02				
FIE2		1E-9	1E-9	1E-9
10LI30	PFD21	-1.25E-2	2.46E-2	1.675E-1
Operator	PFD22	-1.25E-2	1E-2	2.575
10I2165	PFD23	1E-4	-	1E-3

In the case probability is a single value, the fuzzy number is defined by the lower bound, upper bound and modal value (a; b and m respectively), as is the case of scenario 02 (figure IV.7), they are considered singletons.

The average PFD of SIS characterizes its SIL and is clarified by an interval according to the standard IEC61511. In other sense, the PFD values completely possible are those belonging to this interval ($\mu\text{PFD}(p) = 1$).

For the reflux balloon 10-V-8, the functioning of SIS is under low demand mode (less than once a year) and they are purposed to reach a SIL3.

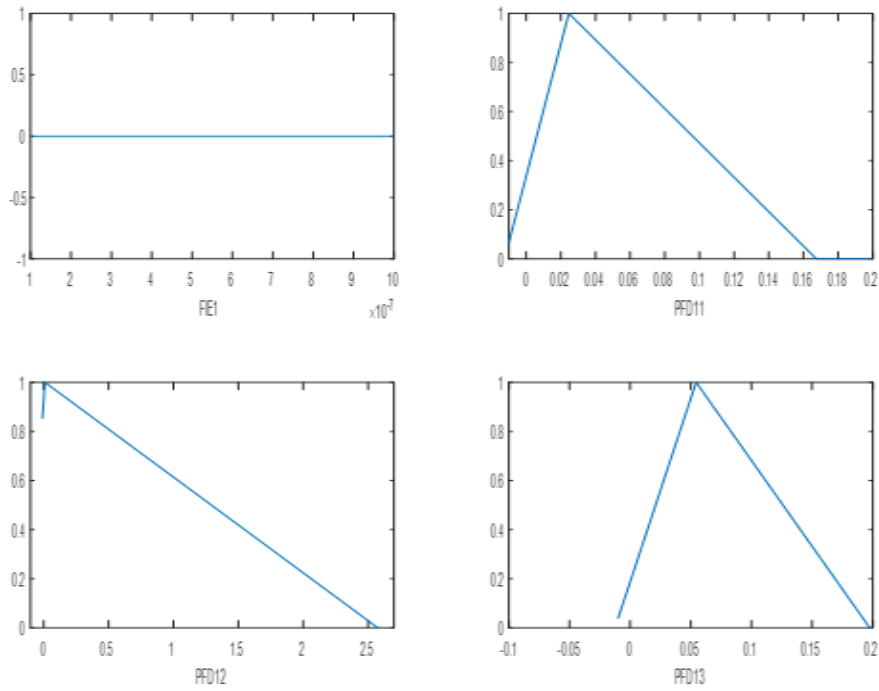


Figure IV.6 Triangular membership functions for scenario 1

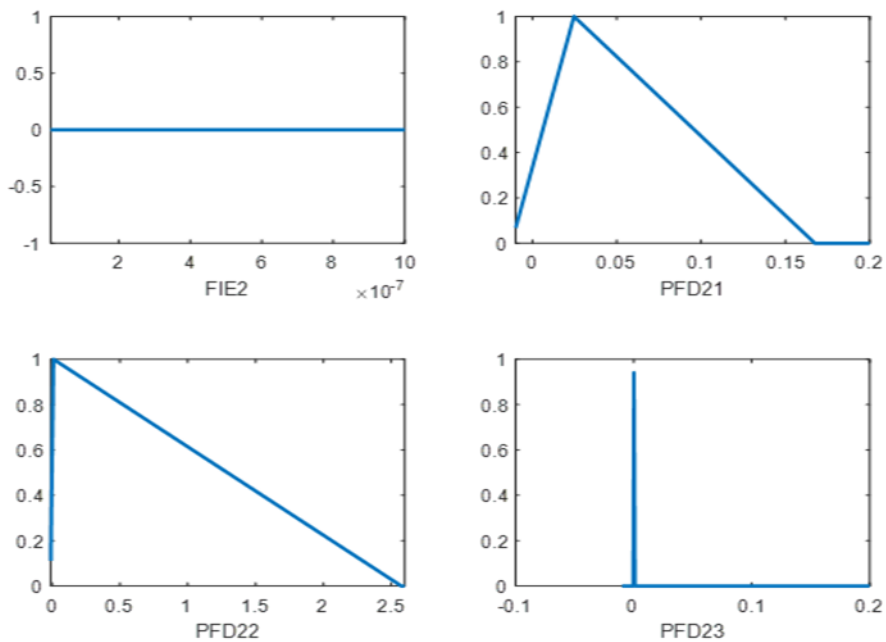


Figure IV.7 Membership functions for the second scenario.

The transformation of confidence intervals of LOPA input parameters, provided in fuzzy numbers, offers flexibility in handling uncertain data. In effect, with probability divisions represented by triangular fuzzy sets, the value of the initiating event frequency and that the PFD are subject to membership degrees belonging extending from non- membership to membership. The curves are plotted using MATLAB software.

IV.2.3.6.2 Calculate the fuzzy frequency of reduced outcome

The evaluation of the fuzzy outcome of the scenarios is made using equation (III.1). The fuzzy frequency of the reduced outcome is obtained by multiplying the fuzzy intervals of the input parameters namely the initiating events frequencies, the PFDs of IPLs and the ignition probability.

The multiplication is carried out by α -cuts according to a decadal discretization, only eleven (11) levels of the interval [0,1] are taken into consideration.

The fuzzy interval of the frequency is obtained by lower and upper bounds multiplication of the α -cuts input parameters.

IV.2.3.6.3 Defuzzification of fuzzy frequency of the reduced outcome

The final step in this model makes it possible to obtain a unique reduced outcome frequency which will be used in decision making. The results obtained by this step are given in table IV.6.

Table IV.6 Reduced outcomes frequencies

Scenario 01	$RCF_{s1} = 6.67E-2$
Scenario 02	$RCF_{s2} = 5.07E-5$

Defuzzification of the fuzzy frequency is performed according the equation (III.3) of the center of gravity method.

After accident scenarios selection and estimating their occurrence frequencies, we ended up with the evaluation of these scenarios. This evaluation, which was made using a certified company matrix (SONATRACH, RA1K) to judge the risks of the scenarios, table IV.7 shows that the second accident scenario is below the set acceptability criteria, indicative that the effectiveness of the safety barriers implemented within the studied system. Unlike the first one, it is considered as high which indicate the safety barriers are not well enough to reduce the risks.

Table IV.7 Risk evaluation of scenarios.

		Probability			
		< 10 ⁻⁴ / year (improbable)	10 ⁻⁴ to 10 ⁻² / year (unlikely)	10 ⁻² to 10 ⁻¹ /year (likely)	1/ year (very likely)
Gravity	1	Low	Low	Low	Medium
	2	Low	Low	Medium	Medium
	3	Low	Medium	Medium	High
	4	S02:“UVCE” explosion	Medium	S01: BLEVE	High
	5	Medium	High	High	high

Concerning the second scenario, some recommendations will be proposed to reduce the risk level like:

- Implement more safety instrumented functions in emergency system.
- A design modification in some of the existing instrumented functions to meet the SIL requirement (voting configuration 2out of3).

IV.3 Fuzzy safety integrity level evaluation

The under study fired heater belongs to ADRAR refinery located in the south of Algeria. The most important unit in this refinery is the CDU (crude distillation unit). The unit has a mission to separate the components of crude oil, and producing three semi-final products (Gases, Naphtha and Residues). Separation of these products is done in distillation towers; the crude is heated to reach 365 °C in the Fired Heater F-201 101 and after that is pumped to the distillation column through feed tray N°:14 (Bendib 2017)

IV.3.1 System and unit description

IV.3.1.1 Unit description

The unit under discussion is a part of ADRAR refinery, located in the south of Algeria. The refinery process 600 000 TPY of crude coming from TOUAT basin through an 8-inch pipe. The refinery is divided into three units CDU, Magnaforming and catalytic cracking unit. The most important unit is the CDU where the crude is separated to three products: NAPHTA (this product will be used as feed for the other units), gas and residue. Following the same scheme of CDUs in different refineries in the world, the crude is first stored the storage tanks and using the feed pumps is loaded to distillation tower for separation (figure IV.8). Before feeding the crude to distillation column its temperature should be augmented to reach 365 C, this is done in two steps, the first called preheating in this step the crude pass through a series of heat exchangers (E201 101,102...105) till we reach 260 °C. The second is the heating step where the fired heater F201-101 is used to rise the temperature to approximately 360 °C (the crude at this stage is partially vaporized). In this location we can see that the three elements of fire triangle are gathered i.e. the fuel (crude), the heat (365 °C) and the oxygen. In the fired heater the fuel gas or (natural gas) is burned to provide the necessary energy to heat the crude.

Some important thing that should be mentioned here is that the fired heater plays a very important role in the CDU unit and hence all the refinery. The shut-down of the heater means shut-down of all the plant, bad operation in the heater means off-spec products.

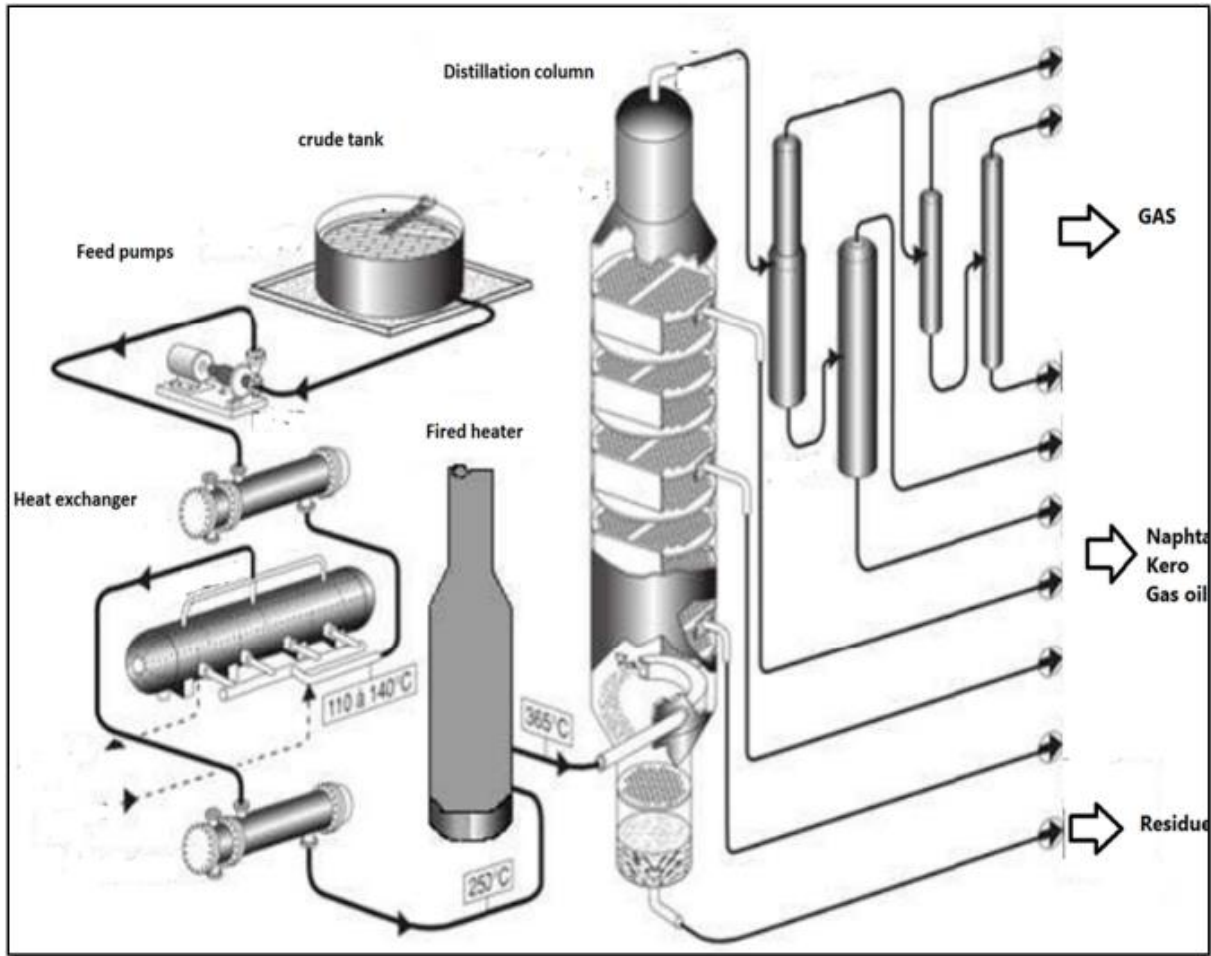


Figure IV.8 Process diagram for crude distillation unit

IV.3.1.2 Fired heater operation philosophy

In petrochemical refineries, fired heaters (Figure IV.9) are used to heat up the crude to reach high temperatures (in our case 365 °C). For safe operation, the following parameters should be controlled:

- ✓ The product flow in each pass (in our case, the heater has two passes). The control is realized through simple control loops FIC (Flow Indicator Controller). In some heaters the flow in each pass combined with the skin temperature of the corresponding tubes are both used to control the flow. In this case we use ratio control principle.

- ✓ The temperature for both product and internal tubes: Concerning the product, this temperature should be controlled such that the set point is 365 °C, and this is done by the use of a cascade type controller, that controls the outlet temperature through the burners fuel gas pressure. For the tubes' temperature, special type sensors are used which called skin points. The skin temperatures are in direct relation with the product's flow inside the tubes in case there is no flow or less flow in the tubes, the skin temperature increases automatically.
- ✓ Pressure: fuel gas pressure in both burner and pilot lines and the pressure inside the heater's combustion room.

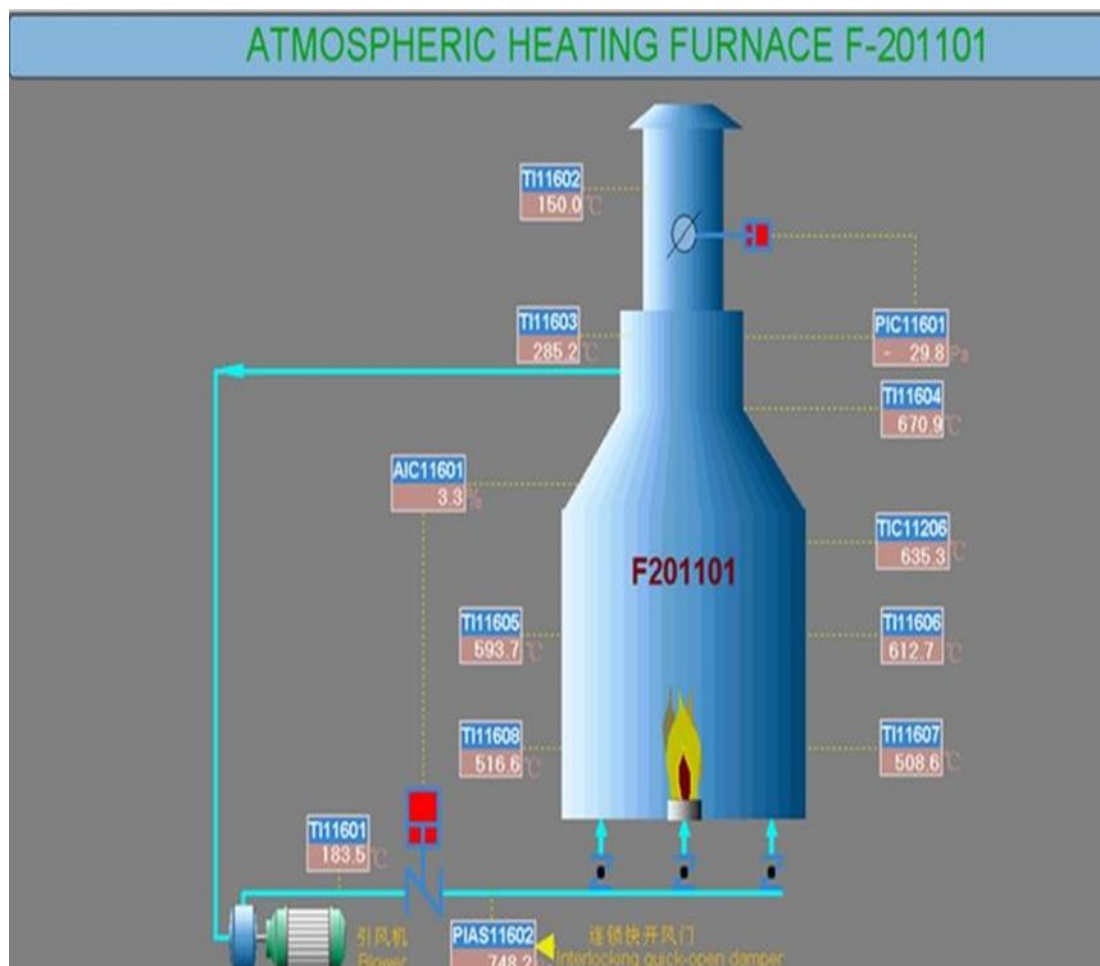


Figure IV.9 Fired Heater F201101

The above parameters are used as key words in HAZOP study to describe the safety-instrumented functions (SIFs).

Following the flow chart described in the above section, application of HAZOP study will give the safety-instrumented functions mentioned in Table IV.8. The case status in table IV.8 means whether the function already exists in the plant or it is just a HAZOP recommendation for future work. A more detailed HAZOP report is given in (Bendib 2017) (Riad et al. 2018), where all guidewords are considered along with different scenarios.

Table IV.8 Deduced SIFs from HAZOP study report

SIF	Definition	Status	Scenario
PS11203	Low / low pressure in the fuel gas and pilot gas lines.	Existing	Burner can extinguish at low fuel gas pressure and possible flammable material accumulation inside the heater. There is a possibility of explosion during heater restart-up. The existing protection to avoid this scenario is explosion windows of the heater.
TAHH 1	Skin Temperature High/High in the tube	New	High/high temperature in the tube may lead to tube failure and explosion in case where the tube is damaged (presence of hydrocarbons with fire). The existing protection is the low pressure vapor to extinguish the fire inside the heater.
FS11204 FS11205	Low/ low flow of the crude in each pass	Existing	Low/low flow of the product in each pass will lead to increase in the skin temperature of the corresponding heater tube which will lead to tube damage. Fire and explosion is expected .

PAHH-2	High/High alarm in the pressure of both fuel gas and pilot lines	New	Burner can extinguish at high/high fuel gas pressure as a result of gas blowing, and possible flammable material accumulation inside the heater. There is a possibility of explosion during heater restart-up.
TS11207	High/High temperature in the heater box	Existing	Prolonged exposure to high temperature may cause tube failure which will lead to explosion and unit shutdown. High temperature of the crude may lead to perturbation of distillation column operation, and it may cause harm for the column internal in future.
PAHH-3	High/High pressure in the heater box	New	Increasing the pressure inside the heater box may lead to explosion. The existing physical protection is the explosion windows.

IV.3.1.3 The heater’s emergency shutdown philosophy

Heater’s safety is designed to simultaneously realize the following sequences in case of any deviation (through the activation of at least one of the previous safety functions)

1. Stop the feed of fuel gas by the closure the safety valve XCY-11201(fully closing)
2. Stop the product feed by the closure of the safety valve XCV-11202.
3. Full opening of the heater damper TSV-11206

Figures IV.10, IV.11 and IV.12 illustrate the implementation of the safety functions TAHH1, PAHH-2 and PAHH-3 using FTA analysis.

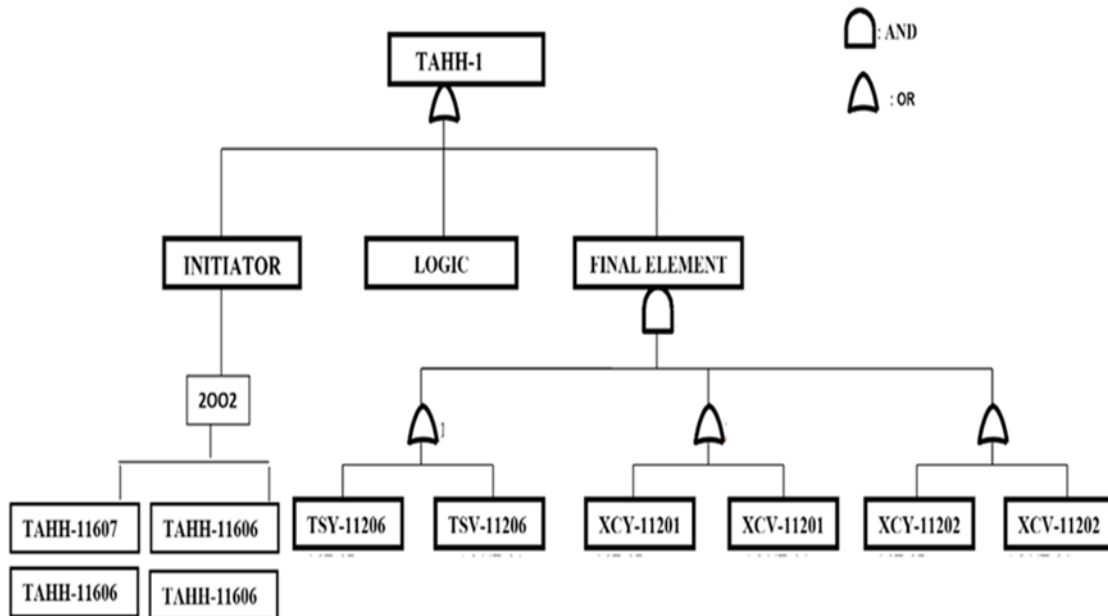


Figure IV.10 Implementation of SIF TAHH-1 using FTA

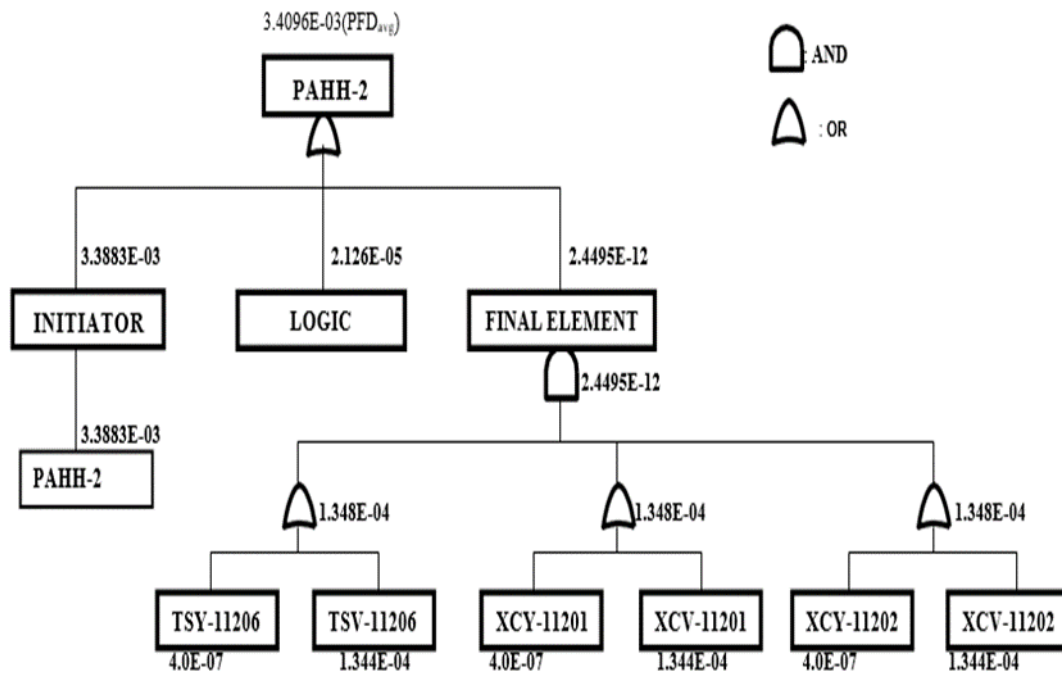


Figure IV.11 Implementation of SIF PAHH-2 using FTA

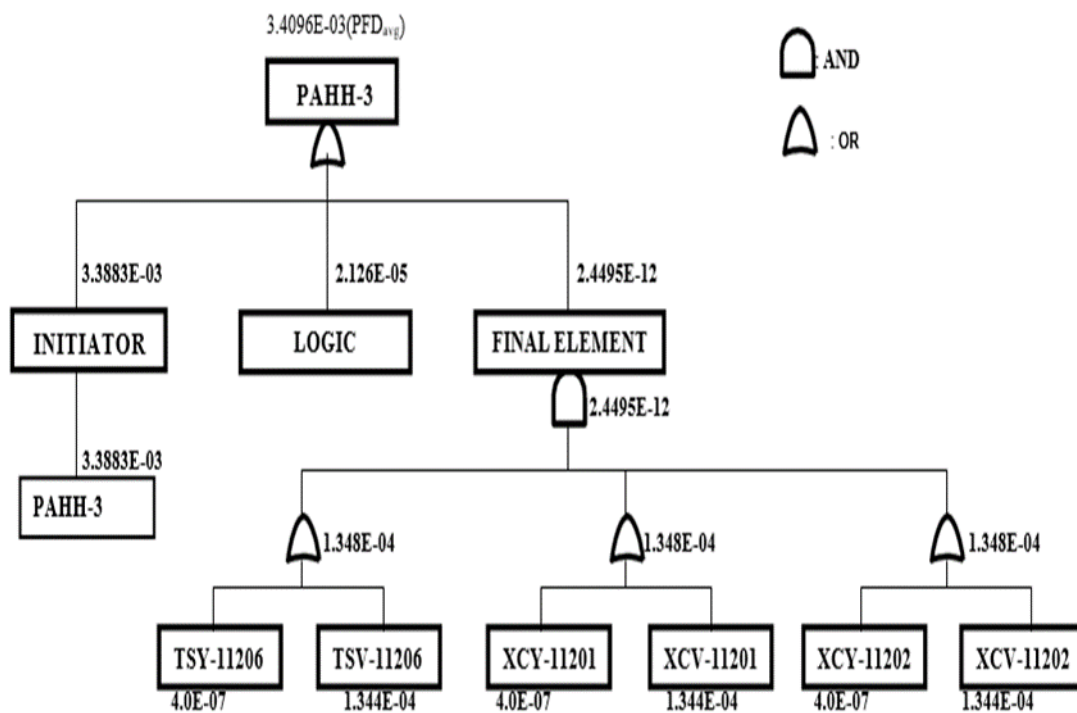


Figure IV.12 Implementation of SIF PAHH-3 using FTA

The PFD (the instruments' probability under demand) values for the existing instruments as furnished in the Refinery documents (Report 2007) are summarized in Table 9 (Riad et al. 2018).

Table IV.9 PFD values for the existing instrument

Initiators		Logic Solver		Final elements	
Type	PFD	Type	PFD	Solenoid valve	Valve
Pressure Transmitter	Simple 3.3883E-03	TRICONEX TMR Triple Modular redundant	2.125E-05	High flow direct acting valve	On-off valve 1.344E-04
	Voting 2oo3 8.1873E-06				
Differential pressure transmitter (Flow)	Simple 6.7746E-03			4.0E-07	
	Voting 2oo3 7.7764E-05				
Temperature	Simple 2.5411E-03				
	Voting 2oo3 6.0662E-06				

Remark

Above values are used in to define the calculated SIL based on the calculation of the PFD average for each safety instrumented function. Table 7 summarizes the calculated SILs for all defined SIFs. Knowing in case of On-off valves (safety valves) we consider both values for PFD (PFD for the solenoid and the valve), which can be achieved using an OR logic function.

IV.3.2 Fuzzy safety integrity level evaluation

The fuzzy safety integrity level (SIL) is determined according to the methodology described in the above chapter.

IV.3.2.1 The fuzzy system parameters

The following parameters should be specified

IV.3.2.1.1 The system's inputs

Four inputs for our algorithm are considered, these inputs are chosen following the guidelines for constructing the conventional risk matrix. These parameters are:

- ❖ **Consequences:** which means the resulted consequences when the safety instrumented function does not work, there are three categories of these consequences.
- ✓ **The first is (S):** the effect on people where six linguistic variables are considered, S0, S1... S5 the corresponding membership functions are given in Figure IV.13



Figure IV.13 Membership functions for consequences on safety and health of persons

- ✓ **The second is the economic effects (L):** in this case six linguistic variables are considered which are L0, L1...L5, the membership functions are shown in figure IV.14.

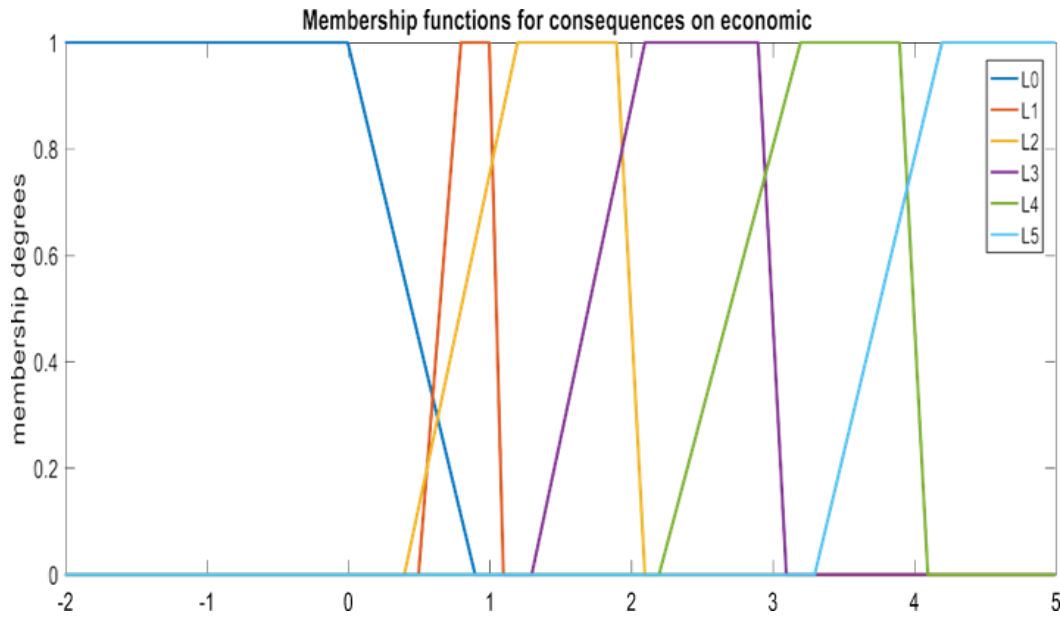


Figure IV.14 Membership function for consequences on economy

✓ **The third parameter:** is the environmental effects (E) which also contains six linguistic variables E0, E1...E5, the corresponding membership functions are shown in figure IV.15

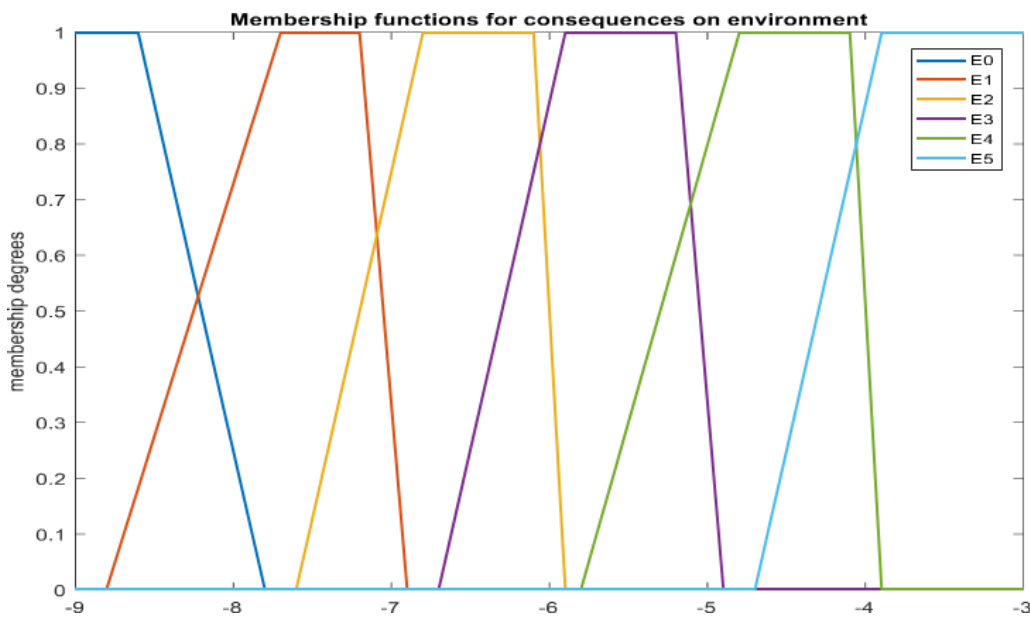


Figure IV.15 Membership functions for consequences on environment

❖ **Exposure (F):** Duration of presence (exposure) of personnel in the area affected by the hazardous situation, three linguistic variables are assigned to this input F1, F2, F3 the corresponding membership functions are shown in figure IV.16.

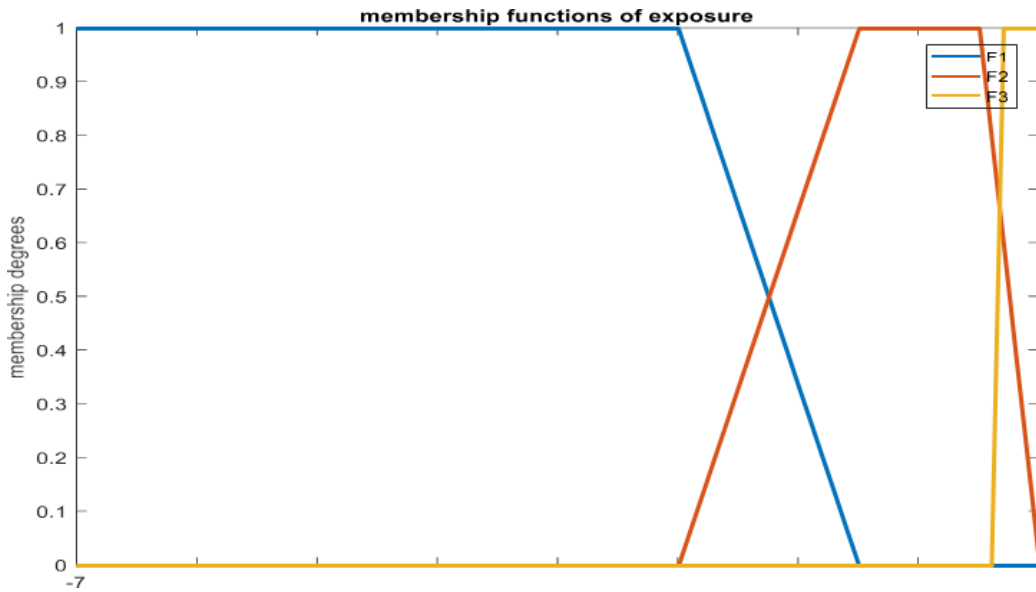


Figure IV.16 Membership functions of exposure

❖ **Possibility to avert the danger (P):** means Possibilities for the person(s) who may be injured to avert the hazardous situation. This considers the existence of alarming tools and possibility of escape from the area. Three linguistic variables are considered P1, P2 and P3 the corresponding membership functions are shown in figure IV.17.

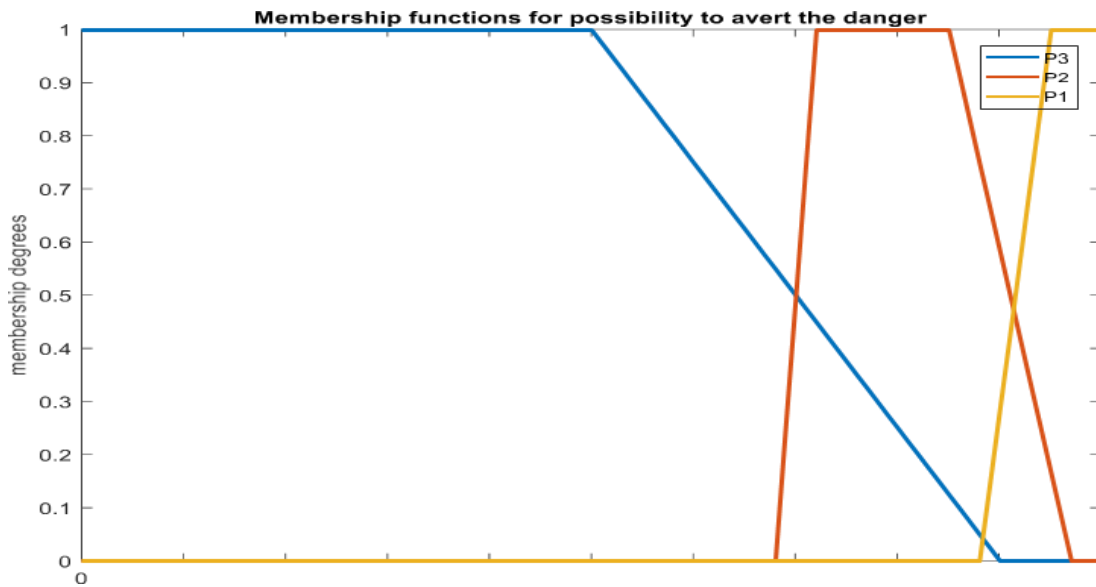


Figure IV. 17 Membership functions for possibility to avert the danger

- ❖ **Demand rate(D)**: this factor means the rate by which the demand is placed on the safety instrumented function or SIF. Five linguistic variables are considered D1, D2...D4. The corresponding membership functions are shown in figure IV.18.

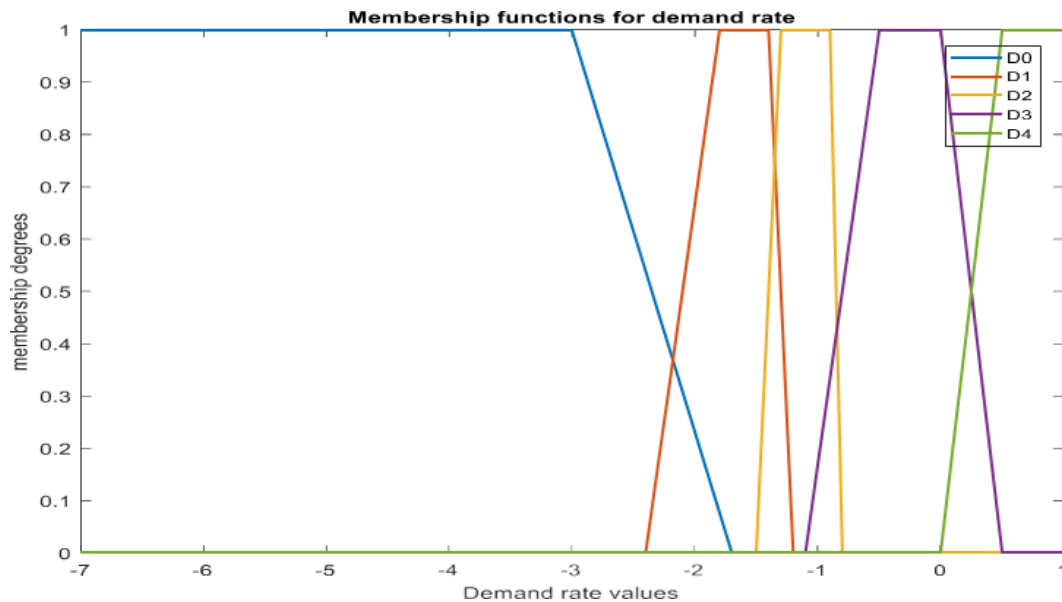


Figure IV.18 Membership functions for demand rate

IV.3.2.1.2 The system's output

The output of our system is the safety integrity level and six linguistic variables are considered SIL1, SIL2, SIL3, SIL4, a (no special safety requirements) and NR (situation to be avoided). The corresponding membership functions are shown in figure IV.19.

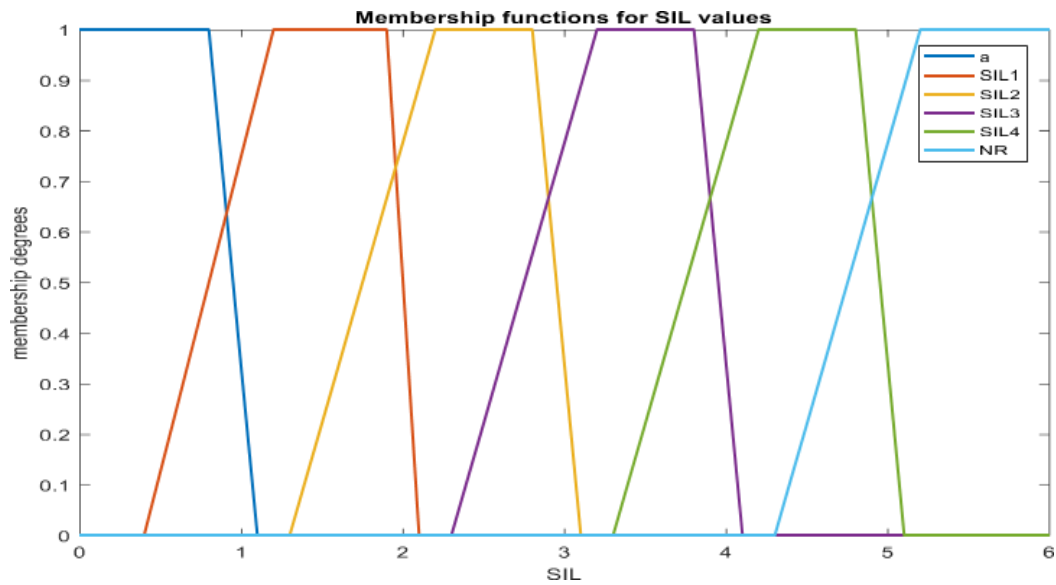


Figure IV.19 Membership functions for SIL values

IV.3.2.2 The rule base

The tables are constructed based on the conventional risk matrix and the rule base (see chapter III section III.3.2.4). Table IV.10, table IV.11 and table IV.12 summarize the chosen rules.

Table IV.10 Rule base engine for fuzzy risk matrix- Personal health effect

Rule	Consequences	Exposure	Possibility to avert danger	Demand rate	SIL
1	S2	F2	P3	D4	SIL2
2	S2	F3	P3	D4	SIL2
3	S2	F3	P2	D4	SIL2
4	S3	F2	P3	D4	SIL2
5	S3	F3	P3	D4	SIL3
6	S3	F3	P2	D4	SIL3
7	S3	F2	P3	D3	SIL2
8	S3	F3	P3	D3	SIL2
9	S3	F3	P2	D3	SIL2
10	S3	F1	P3	D4	SIL2
11	S3	F1	P2	D4	SIL2
12	S3	F2	P2	D4	SIL2
13	S3	F2	P1	D4	SIL2
14	S3	F3	P1	D4	SIL2
15	S4	F2	P3	D2	SIL2
16	S5	F2	P3	D1	SIL2
17	S5	F3	P3	D1	SIL2
18	S5	F3	P2	D1	SIL2
19	S5	F2	P3	D2	SIL2
20	S5	F3	P3	D2	SIL3
21	S5	F3	P2	D2	SIL3

Table IV.11 Rule base engine for fuzzy risk matrix- Economic effect

Rule	Consequences	Demand rate	SIL
1	L2	D3	SIL1
2	L3	D4	SIL2
3	L3	D2	SIL1
4	L3	D3	SIL2
5	L4	D4	SIL3
6	L4	D1	SIL1
7	L4	D2	SIL2
8	L5	D3	SIL3
9	L5	D1	SIL2
10	L5	D2	SIL3

Table IV.11 Rule base engine for fuzzy risk matrix- Environment effects

Rule	Consequences	Demand rate	SIL
1	E2	D3	SIL1
2	E2	D4	SIL2
3	E3	D2	SIL1
4	E3	D3	SIL2
5	E3	D4	SIL3
6	E4	D1	SIL1
7	E4	D2	SIL2
8	E4	D3	SIL3
9	E5	D1	SIL2
10	E5	D2	SIL3

IV.3.2.3 The fuzzy required SIL for the defined safety functions

In defining the required fuzzy (target) SIL the following tasks are performed (Ross 2016):

- ✚ Using MAMDANI (min/Max) inference engine, we evaluate the rules

- ✚ The aggregation between the rules is done via MAMDANI's rule
- ✚ At the end, the CENTROID is used in the Defuzzification step to find the exact SIL values.
- ✚ The Fuzzy toolbox in MATLAB is used to implement the algorithm.

The above steps are repeated for Personal, Economic and Environment effects of any safety- instrumented function. Figure IV.16, figure IV.17 and figure IV.18 show the application the fuzzy engine to determine the Required SILs for the Safety function TAHH-1.

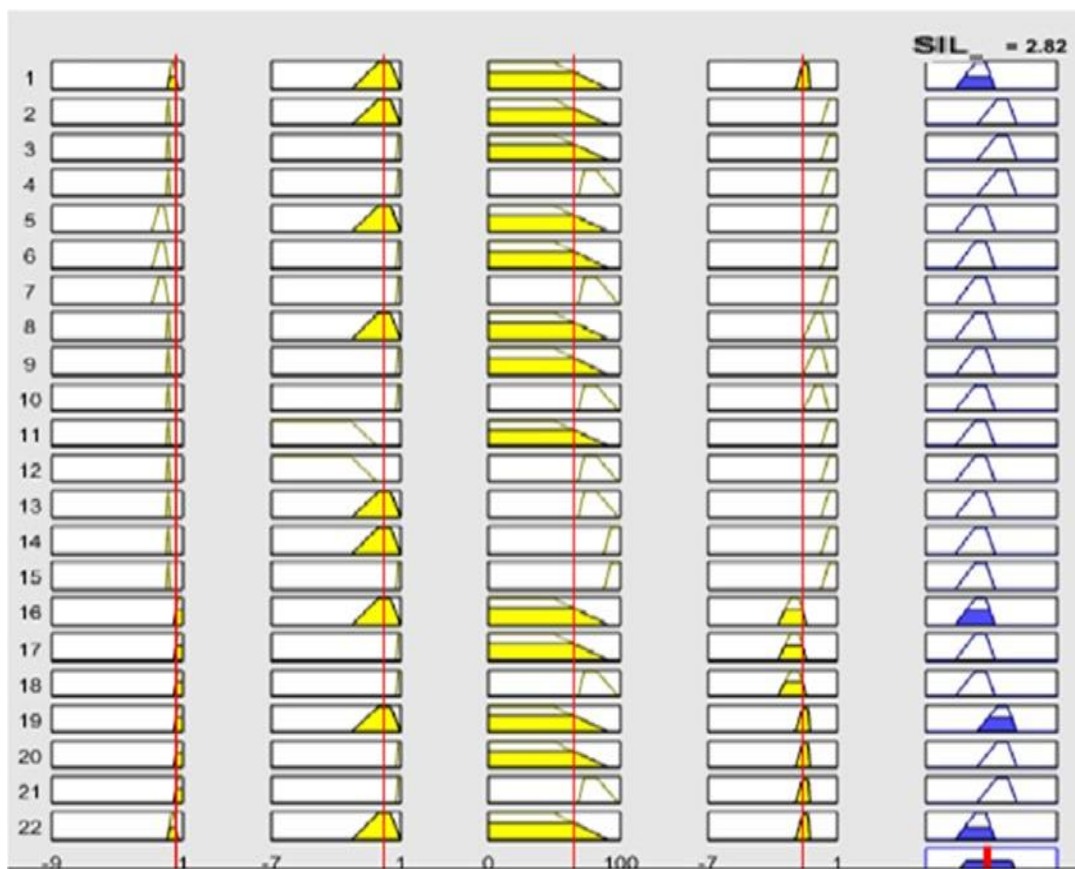


Figure IV.16 The inference Engine for SIL determination (Rule base evaluation)- Personal health effect

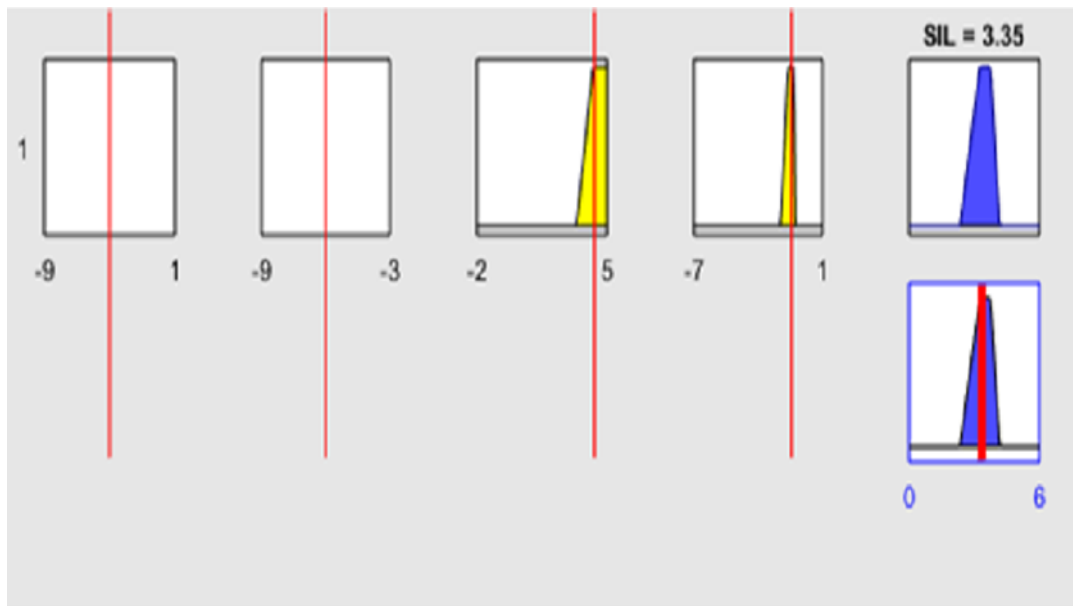


Figure IV.17 The inference Engine for SIL determination (Rule base evaluation)- Economic effects

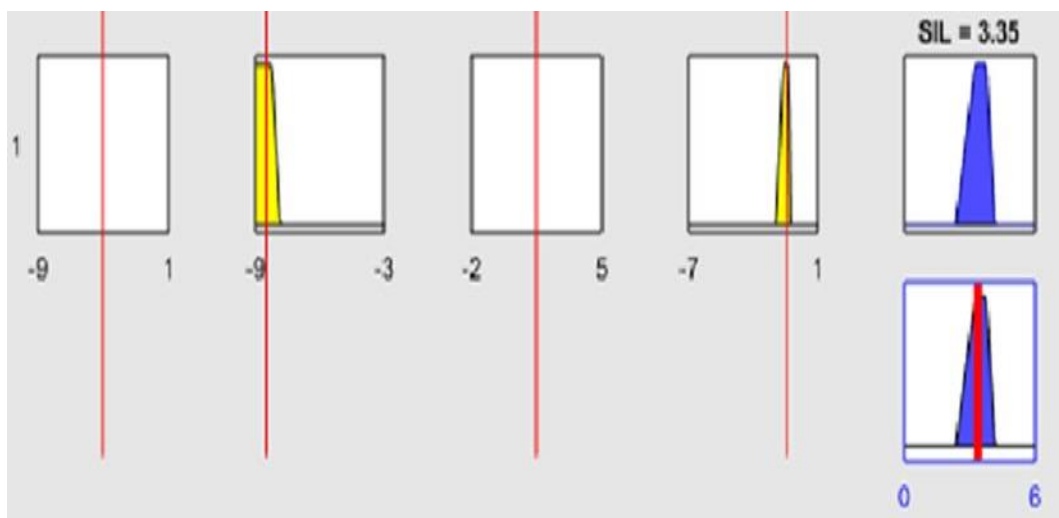


Figure IV.18 The inference Engine for SIL determination (Rule Base evaluation)- Environment Effects

For other safety functions the results for the fuzzy target SIL are included in Table 13.

Table IV.13 The calculated SIL versus Target SIL

SIF	Calculated SIL		Fuzzy Target SIL				Recommendations
	PFD	SILcal	health	economic	environment	Over all SIL	
PS11203	3.4096E-03	2	0.48	2.35	0.474	2	Since the Target SIL equals to the calculated SIL, hence no design modification on the SIF component is required
TAHH 1	2.2431E-05	3	2.82	3.35	3.35	3	The same remark as above, no design modification is required.
FS11204 FS11205	6.7959E-03	2	3	3.35	0.474	3	The calculated SIL is smaller than the Target SIL hence design modification is required. In this case, we recommend the use of voting system (2oo3), which designed using three initiators.
	2oo3 vote 1.0E-04	3					The condition is satisfied the target SIL equals the calculated SIL
PAHH-2	3.4096E-03	2	0.502	2.35	0.469	2	Since the Target SIL equal to the calculated SIL so no design modification on the SIF component is required
TS11207	3.5624E-03	2	2.47	2.35	0.518	2	Since the Target SIL equal to the calculated SIL so no design modification on the SIF component is required
PAHH-3	3.409E-03	2	2.82	3.35	0.469	3	The calculated SIL is smaller than the Target SIL hence design modification is required in this case we recommend the use of the vote (2oo3) between three initial sensors.
	2oo3 vote 2.95E-05	3					The condition is satisfied SILtarget equal SILcalculated

The following assumptions are considered in SIL determination process:

- ❖ In calculating the target SIL, the maximum value among the personal, economic and environment effects is chosen as the overall SIL. However, in case the results contain decimal numbers the value is rounded to the nearest one (if it is greater than 0.5 it is rounded to 1, whereas in case it is smaller than 0.5 it is rounded to zero).
- ❖ The tag number of the new SIFs are chosen randomly depending on its existence in the HAZOP report.
- ❖ For the SIF TAHH-1 the initiator is chosen as 2oo2 (two out of two) voting configuration, because generally when we deal with the skin points temperature, the tube's temperature is measured in both the input and the output of each pass.

IV.4 Scheduling the SIL values using neural network

In this section, an approach based on Artificial Neural Networks (ANN) is developed to schedule the SIL values of the safety integrity functions (SIF) of an industrial-fired heater (Fired Heater F201101). The SIFs are first deduced from HAZOP study for the fired heater. The SIL risk of the consequences related to personnel health and safety, the economic SIL and environment SIL are considered as inputs of the multilayer network with a predefined hard limit activation function.

The SIL values are summarized in table IV.14

Table IV.14 SIL values for each SIF

SIF 1/ PS11203		
Economic Risk SIL	Environment Risk SIL	Personnel health SIL
2	(-) no safety requirement	(-) no safety requirement
SIF 2/ TAHH1		
Economic Risk SIL	Environment Risk SIL	Personnel health SIL
3	(-) no safety requirement	2
SIF 3/ FS11204, FS11205		
Economic Risk SIL	Environment Risk SIL	Personnel health SIL
3	(-) no safety requirement	2
SIF 4/ PAHH2		
Economic Risk SIL	Environment Risk SIL	Personnel health SIL
2	(-) no safety requirement	(-) no safety requirement
SIF 5/ TS11207		
Economic Risk SIL	Environment Risk SIL	Personnel health SIL
2	(-) no safety requirement	1
SIF 6/ PAHH3		
Economic Risk SIL	Environment Risk SIL	Personnel health SIL
3	(-) no safety requirement	2

The aim of this application is to create a cognition and decision system that classify the SILs values with a predefined activation function to define the overall SIL or the required SIL.

The work is conducted using MATLAB based in the proposed approach in chapter III section III.3.3 and results are presented in the below table (Table IV.15).

Table IV.15 The overall SIL values for SIFs.

SIF	SIL_{overall}
PS 11203	SIL2
TAHH 1	SIL3
FS11204 FS11205	SIL3
PAHH 2	SIL2
TS 11207	SIL2
PAHH 3	SIL3

As it is shown in the table, the safety integrity level of the heater's safety instrumented function are classified. The next step to ensure the safety of the fired heater is to compare the obtained results with the calculated SIL resulted from the calculation of the equivalent probability failure under demand of the corresponding safety integrity system. Depending on this comparison, recommendations for the safety system design are raised (i.e., keeping the existing component or proceeding to design configuration in case the calculated SIL is smaller than the required SIL).

The parameters of the considered ANN are obtained during the learning step and they are suitable to be used in any complex system, as in the case of petrochemical plants.

IV. Conclusion

In this chapter, we applied 3 approaches based on intelligent techniques, the first is Fuzzy LOPA, the second is Fuzzy evaluation of SIL values for different system (naphtha stabilizer and fired heater, respectively), and the third is a continuation of the second method for the same system which is a SIL values scheduling based on neural network.

- ✓ The Fuzzy LOPA has been proposed to take into account the uncertainties to give more precise results and evaluate the different parameters of accident scenario such as the initiating events frequencies and the failure probabilities of independent protection layers.

some recommendations will be suggested to reduce the risk level, such as:

- Implementing more safety instrumented functions (SIF) in emergency system.

- Design modification in some existing instrumented functions to meet the SIL requirements (voting configuration 2out of3).
 - ✓ The comparison between the values of the calculated SIL and target SIL, and HAZOP recommendations give the following results:
- More safety-instrumented functions should be implemented in the emergency shutdown system, such as TAHH1, PAHH2 and PAHH3.
- A design modification should be added in some of the existing instrumented functions to meet the SIL requirement (FS11204, FS11205), here we recommend the use of three sensors with a voting configuration 2out of 3.
- For the new SIF PAHH3 three initiators with a voting 2oo3 configuration should be envisaged.
- For the new SIF TAHH-1 two sensors with a 2oo2 vote configuration (one in the entrance and the other in the output of each pass) should be considered
 - ✓ Finally, we should mention that the application of neural network to create a cognition and decision system that classify the SILs values with a predefined activation function to define the overall SIL or the required SIL is an important stage to save costs and time

General Conclusion

Due to the vast increase in scales and the complexity of modern chemical industries, particularly those petrochemical, it has become harder to control their systems and chemical accidents. Therefore, the safety management theory that reduce the likelihood of process accidents, mitigates its consequences, and ensure its safe operation, has a high priority.

Risk management consists of analyzing all the risk of industrial systems by identifying the existing potential hazards first then estimating the associated risks in terms of occurrence and severity. Then evaluating these risks against risk acceptability criteria. Finally, if a risk is deemed unacceptable, new measures and security barriers will be implemented to control risk.

Therefore, it is necessary to ensure the effectiveness of study or analysis. However, even with the major development in the fields of control system, the problem of uncertainties and classification is still considered an unsolved issue.

Lack of detailed information on failure rates, uncertainties in available data, inaccuracies and ambiguities lead to uncertainty in results which affect the risk level of process by underestimated or overestimated it. In recent years, several tools have been developed based on artificial intelligence to deal with such difficulties such as fuzzy logic and neural network.

Based on this context, this thesis is part of the Contribution in the improvement of petrochemical plant safety using artificial intelligence methods. To this objective, we proposed two approaches based on fuzzy logic. The first, a novel methodology based on LOPA method and FUZZY LOGIC to increase its performance in terms of analysis and risk reduction. This approach consists of modeling the inaccuracies and / or uncertainties in initial events frequencies, the PFD (Probability of Failure on Demand) of the independent protection layers by fuzzy intervals or fuzzy numbers and consequently, determining the fuzzy frequencies of the reduced consequences of the scenarios using fuzzy calculation techniques.

This approach is implemented to a real system namely naphtha-A- stabilizer after identifying the risks inherent in this system by applying the HAZOP method (Hazards and Operability Study). As a perspective to give more precise results and evaluate different parameters of the accident scenario such as the initiating events frequencies and the failure probabilities of independent protection layers.

Some recommendations will be suggested to reduce the level of risks, such as:

- Implementing more safety instrumented functions (SIF) in emergency system.
- Design modification in some of the existing instrumented functions to meet the SIL requirement (voting configuration 2out of3).

In the second approach, we first presented a new general comprehensive framework for risk assessment in industrial facilities based on the integration of three most well-known methods HAZOP, SIL and FTA. This integration allows identifying of potential hazards, determining the required safety integrity levels for various safety instrumented function (SIF), and finally deciding on the architecture of the safety instrumented system (SIS). The approach uses Fuzzy logic methods in the Risk matrix construction, fuzzy logic is a powerful tool to deal with uncertainties that may be caused by lack of information or data in the SIL target assessment stage (determination of the safety level depends on expert judgment and the nature of each level that depends on the accident consequences, which is given in an approximate way in the standards).

This approach was applied to improve the safety of a fired heater located in ADRAR refinery in the South of Algeria. Special attention should be given to risk assessment in fired heaters since the three important factors for generating a fire/or explosion have already been combined (the oxygen, energy and hydrocarbons). A detailed HAZOP report for the under study fired heater is indicated in (Bendib 2017), where all the required safety instrumented function to ensure a safe operation of the fired heater are listed.

The MAMDANI inference engine is used in the rule base calculation, and target SIL determination for each SIF. In the other hand, the FTA method is used in the calculated SIL determination. The PFDs of each component are defined in the Refinery construction report (Report 2007 the instruments data sheets).

A method based on artificial neural networks (ANN) has also been developed to schedule the SIL values of the safety integrity functions (SIF) for the same fired heater. SIFs are first deduced from HAZOP study. SIL risks and consequences related to personnel health and safety, economic SIL and environmental SIL are considered as inputs to the multilayer network with a predefined hard limit activation function.

The comparison between the values of the calculated SIL and target SIL, and HAZOP recommendations give the following results:

- More safety-instrumented functions should be implemented in the emergency shutdown system, such as TAHH1, PAHH2 and PAHH3.
- A design modification should be added in some of the existing instrumented functions to meet the SIL requirement (FS11204, FS11205), here we recommend the use of three sensors with a voting configuration 2out of 3.
- For the new SIF PAHH3 three initiators with a voting 2oo3 configuration should be envisaged.
- For the new SIF TAHH-1 two sensors with a 2oo2 vote configuration (one in the entrance and the other in the output of each pass) should be considered

Finally, we should mention that the presented approach is a very powerful tool to improve the safety of any industrial plants however we need more theoretical analysis to improve the approach particularly if we consider that the uncertainties may exist not only in the risk matrix determination but in the FTA construction which may lead to use the fuzzy logic in this stage ((Kumar and Kaushik 2020)) or the use of Fuzzy logic in HAZOP study ((Cheraghi et al. 2022)).

We propose therefore the application of the type 2 fuzzy engine process to model membership degree uncertainty. In addition to replace the used qualitative method with one that is more accurate in defining scenarios and giving more accurate data about initiating events, the safety barriers and their frequencies such as layers of protection analysis (LOPA).

Regarding the shape chosen to the membership function in our study we suggest to use the genetic algorithm as an optimization tool to find the best shape to give more precise results as a further work.

Publications

The thesis is expanded from published papers, in journal and conferences, which are listed below:

- Two papers published in international journals respectively International Journal of System Assurance Engineering and Management (Int J Syst Assur Eng Manag), and Multidisciplinary Digital Publishing Institute (MDPI):
 - ✓ Fuzzy approach for safety integrity level evaluation to improve the safety of an industrial fired heater. International Journal of System Assurance and Engineering Management “Int J Syst Assur Eng Manag”. <https://doi.org/10.1007/s13198-023-02103-y>
 - ✓ An intelligent Optimization Algorithm for Scheduling the Required SIL Using Neural Network. Engineering proceedings MDPI 2023. <https://doi.org/10.3390/engproc2023029005>.
- One paper published in national journal “Algerian Journal of Signals and Systems”:
 - ✓ Evaluation of safety barriers deduced from the HAZOP study of fired heater F201-101, ADRAR refinery, Algeria using ETA method. Algerian Journal of Signals and Systems 2020. <https://doi.org/10.51485/ajss.v5i1.95>.
- Six Papers published in international conferences:
 - ✓ Analytical evaluation of Safety Integrity Levels of fired heater F201-101, ADRAR refinery, Algeria using Risk Graph Method. International Conference On Maintenance and Industrial Safety CIMSI’ 2019. Skikda.
 - ✓ Evaluation of safety barriers deduced from the HAZOP study of fired heater F201-101, ADRAR refinery, Algeria using ETA method. The International Conference on Advanced Engineering in Petrochemical Industry (ICAEPI’19). Skikda, Algeria.
 - ✓ Evaluation of the identified IPLs to “UVCE explosion” scenario under uncertainty using fuzzy logic. The International Conference on Advanced Engineering in Petrochemical Industry (ICAEPI’21). Skikda, Algeria.
 - ✓ An intelligent optimization algorithm for scheduling the required SIL using neural network. The 2nd International Conference on Computational Engineering and Intelligent Systems ICCEUS 2022. BOUMERDES, Algeria.
 - ✓ A Quantitative Analysis of Catastrophic Scenarios Deduced from HAZOP for an Industrial System by Bowtie Method. The 4th International Conference on Electromechanical Engineering ICEE’2022, SKIKDA- Algeria.

- ✓ Risk analysis of HAZARD scenarios for the industrial system naphtha a stabilizer. 2 ND International Seminar on industrial engineering and applied mathematics ISIEAM'22. Skikda, Algeria.
 - Two Papers published in national conferences:
- ✓ Modified LOPA method using FUZZY logic for naphtha-A-stabilizer. Conférence National sur le Control et la Sécurité des Systèmes Industriels CNCSSI' 2021. Skikda, Algeria.
- ✓ Classification of Safety Integrity Level using neural networks. Conférence National sur le Control et la Sécurité des Systèmes Industriels CNCSSI' 2022. Skikda, Algeria

Appendix

Appendix 01

Equipement : colonne distillation 10-C-5 (fond de colonne).

Paramètre : Débit

Guide Word	deviation	Causes	Consequences	Safeguards	G	Recommendation
Not	No hot oil flow	-UV-2151/59 does not close due to loss of AI.	Loss of temperature in the re-boiler, and the column will stagnate, resulting in a high level in the column, and a loss of pressure in the head of the column, resulting in slight peculiarities in the stabilized naphtha.	-TAL on TIC-2151 sets off the alarm on Column bottoms. -LAH on the LIC-20 setting off an alarm on the column bottoms. -AAH on AI-2101 sets off alarm in case of high C4 content in stabilized naphtha -PAL on PIC-2151 sets off the alarm on the column head. -TAL on TI-107 sets off the alarm on the column head. -When the UV-2151 closes, the TV-2151B opens and bypasses the hot oil around the Re-boiler, and sets off the I-2151 which closes.	2	
			Possibility of loss of level in the receiver of the column	-LAL on the LIC-21 sets off the alarm	2	

			Possibility of loss of reflux flow if the level is lost, causing a disturbance in the column, with an overpressure potential in the column.	-LAL on the LIC-21 sets off the alarm	2	
		TV-2151A does not close due to loss of AI.	Loss of temperature in the re-boiler, and the column will stagnate, resulting in a high level in the column bottom, and a loss of pressure in the column head, resulting in slight peculiarities in the stabilized naphtha.	-TAL on TIC-2169 sets off the alarm on Column bottoms. -LAH on the LIC-20 sets of the alarm on the column bottoms. -AAH on the AI-2101 alarm in case of high content of C4 in stabilized naphtha. -PAL on PIC-2151 sounds the alarm on the Column head. -TAL on TI-107sets off the alarm on the column head.	2	
			Possibility of loss of level in the receiver of the column. Possibility of loss of reflux flow if the level is lost, causing a disturbance in the column, with an overpressure potential in the column.	-LAL on the LIC-21 sets off the alarm -LAL on the LIC-21 sets off the alarm	2	
	No bottom flow product	UV-2153 does not shut down due to loss of AI	increase in the level in the bottom section of the stabilizer column, and possibly flooding of the column causing overpressure	-LAH on the LIC-20 sets off the alarm -AAH on AI-2101 alarm in case of high C4 content of stabilized naphtha	2	
		The FV-54 does not close because of a loss of AI	Increased level in the bottom section of the stabilizer column and possibly flooding of the column causing overpressure	-LAH on the LIC-20 sets off the alarm -AAH on AI-2101 alarm in case of content	2	

				high in C4 stabilized naphtha		
More	More hot oil flow	TV-2151A blocked open or bypass open on the re-boiler hot oil flow.	Increase in the temperature in the column, with more heavy parts (C5) in the LPG stream at the top of the column.	-OTP to manage the bypass -Daily LPG sampling in the laboratory -TAH on TIC-2151 sets off alarm on table 3 -TAH on TI-107 sets off the alarm on the column head -TAH on TI-2169 sets off the alarm when the re-boiler returns	2	
			High pressure potential in the head of the column and maximum reflux, causing flooding due to maximum descending reflux and maximum re-boiling causing an increase in production in the column	The OTP to manage the bypass -The PAH on the PIC-2151 sets off the alarm -PAHH on PI-2168A / B / C-2003 sets off the alarm and I-2151 which closes the UV valves on the hot oil to the re-boiler, and opens the bypass around the hot oil to the re-boiler. -The PSV-38A / B set at 9.8 kg / cm ² g allows discharge to Blow-down.	2	
			Possibility of low level in column due to excessive re-boiling, but column overpressure reaction would occur first.	-OTP to manage the bypass -LAL on the LIC-20 sounds the alarm	2	
	More flow Fund Product	FV-54 blocked open or bypass open	Low level potential at the bottom of the column, with the possibility of steam entering the separator	-OTP to manage the bypass -LAL on the LIC-20 sets off the alarm -LALL on the LI-2153 sets off the alarm and the I-2163 which shuts off the UV-2153 to maintain the level and prevent gas leakage	2	

less	Less hot oil flow	Hot oil leak in the naphtha stabilizer "A" at the bottom re-boiled	Increase in the temperature entering the column due to the hot oil at 290 ° C which penetrates at the bottom of the column, which leads to the contamination of the stabilized naphtha by high melting point materials.	-Analysis of samples in the laboratory every 8 hours will eventually allow the detection of high melting point materials in the naphtha C. Possibility of discolouring the naphtha if the leak is significant -Exchanger designed for TEMA and HTRI Standards.	3	
	Less product flow from funds	No causes				
	Reverse flow	No causes				

Parameter: Pressure

Guide word	Deviation	Causes	Consequences	Safeguards	G	Recommendations
More	More pressure	No causes				
Less	Less pressure	No causes				

parameter: Temperature

Guide word	Deviation	Causes	Consequences	Safeguards	G	Recommendations
More	More temperature	The TT-2151 fails, causing TV-2151A to fail to open and TV 2151B to fail to close	See "flow" of this node for the effect on Stabilization Column. Possibility of reducing the temperature of the hot oil available for column C6, with a probability of C3 in stream C4.	-The diagnostic alarm is set off and the valve switches to manual mode and locks in the last position (if the cause is a transmitter failure). - TAL on TIC-2180 sets off the alarm	2	
Less	Less temperature	TT-2151 fails, resulting in failure TV-2151B fails to open and TV-2151A fails to close	See "flow" of this node for the effect on Stabilization Column. Excess temperature in the hot oil at Column C6, requiring the TIC Bypass of the Column C6 re-boiler to be fully opened without serious consequences		2	

Parameter: Level

Guide word	Deviation	Causes	Consequences	Safeguards	G	Recommendations
Less	No / Low level	LT-20 fails, causing the FV-54 to open completely	low level potential at the bottom of the column, with the possibility of steam entering the separator	-OTP to manage the bypass -LAL on the LIC-20 sets off the alarm -LALL on the LI-2153 sets off the alarm and the I-2163 which shuts off the UV-2153 to maintain the level and prevent gas leakage	2	
More	More level	LT-20 fails, causing the FV-54 to shut down completely	Increase in the level in the bottom section of the stabilizer column, and possibly flooding of the column causing overpressure	-LAH on the LIC-20 sets off the alarm -AAH on AI-2101 alarm in case of high C4 content of stabilized naphtha	2	

Equipment: 10-C-5 distillation column and 10-V reflux balloon

Parameter: Flow

Guide word	Deviation	Causes	Consequences	Safeguards	G	Recommendations
No	No flow at the top of the column	No causes				
	No discharge flow	UV-2154 on reflux pump suction does not close due to loss of A.I.	No cooling at the top of the column, and rapid increase in pressure at the top of the column, with heavy parts greatly exceeding the capacity of the cooling system, and the level of the reflux flask increases rapidly, and overflows towards the FG system, causing the flow of liquid out of the heater burners, and the possibility of causing an external fire.	-FAL on the FIC-53 sets off the alarm -FAL on FIC-55 sets off alarm on product flow -PAH on the PIC-2151 sets off the alarm -LAHH on the LI-2154 sets off an alarm and engages the interlock I-2164, which closes the PV21 and opens the PV 21A to stop the flow of liquid in the FG system -The PV-21 opens when the pressure on the PIC-21 increases -PAHH on PI-2168A / B / C - 2003 sets off the alarm and activates I-2151 which closes the hot oil to the re-boilers and opens the bypass. -The PSV-38A / B set at 9.8 kg / cm ² g allows discharge to the torch.	3	
		The 10-P-93A / B pump fails due to loss of electrical energy or mechanical reasons	No cooling at the top of the column, and rapid increase in pressure at the top of the column, with heavy parts greatly exceeding the capacity of the cooling system, and the level of the reflux flask increases rapidly, and	-Alarm and pump status indication on DCS Spare pump available. -The FAL on the FIC-53 sets off the alarm -The FAL on the FIC-55 sets off the alarm on the flow of products	2	

			overflows towards the FG system, causing the flow of liquid out of the heater burners, and the possibility of causing an external fire	-The PAH on the PIC-2151 sets off the alarm -LAH on LIC-21 sets off the alarm. -LAHH on LI-2151 sets off the alarm. -The PV-21A opens when the pressure on the PIC-21 increases -PAHH on PI-2168A / B / C - 2003 sets off the alarm and activates I-2151 which closes the hot oil to the re-boilers and opens the bypass. -The PSV-38A / B set at 9.8 kg / cm2g allows discharge to the torch		
		The FV-53 is stuck in the closed position	No cooling at the top of the column by reflux, and rapid increase in pressure at the top of the column, with heavy parts greatly exceeding the capacity of the cooling system.	-the bypass available -FAL on the FIC-53 sets off the alarm -The PAH on the PIC-2151 sets off the alarm -The PV-21A opens when the pressure on the PIC-21 increases -PAHH on PI-2168A / B / C - 2003 sets off the alarm and I-2151 which closes the hot oil to the re-boiler and opens the bypass -The PSV-38A / B set at 9.8 kg / cm2g allows clearance to torch	2	
			Possibility of passing heavy parts from the bottom of the column above the head and increasing the level of the reflux flask, with consequences of the high pressure in the head of the column	-LAH on LIC-21 sets off alarm -LAHH on LI-2151 sets off alarm	2	
No Product flow	The 10-P 93A / B pump fails due	No cooling at the top of the column, and rapid increase in pressure at the	Alarm and pump status indication on DCS Spare pump available.		2	

		to loss of electrical power or mechanical reason	top of the column, with heavy parts greatly exceeding the capacity of the cooling system, and the level of reflux flask rises rapidly, and overflows to the FG system, causing liquid to flow out of the heater burners, and the possibility of causing an external fire.	-The FAL on the FIC-53 sets off the alarm -The PV-21A opens when the pressure on the PIC-21 increases -PAHH on PI-2168A / B / C - 2003 sets off the alarm and activates I-2151 which closes the hot oil to the re-boiler and opens the bypass. -The PSV-38A / B set at 9.8 kg / cm ² g allows discharge to the torch.		
		FV-55 fails to close due to loss of AI	The level will rise in the reflux flask and overflow to the FG system, with the ability to back up into the column head and increase column pressure.	-The FAL on the FIC-55 sets off the alarm on the product flow -LAH on LIC-21 sets off alarm -LAHH on LI-2151 sets off alarm -The PAH on the PIC-2151 sets off the alarm -The PV-21A opens when the pressure on the PIC-21 increases -PAHH on PI-2168A / B / C - 2003 sets off the alarm and the I-2151 which closes the hot oil to the re-boiler and opens the bypass -The PSV-38A / B set at 9.8 kg / cm ² g sets off towards the torch.	2	
More	More flow from the column head.	No causes				
	More reflux flow	FV-53 does not open due to loss of AI or bypass open	The reflux flow rate increases, and the pressure in the column decreases, with less material passing over it, and the level in the reflux flask decreases, resulting in a build-up in the column,	-LAH on the LIC-20 sets off the alarm -The PAHs on the PIC-2151 set off an alarm, and if the pressure continues to rise, the PAHHs on the PI 2168A / B / C-2003 stop the hot oil to the re-boiler.	2	Configure the FAH to the FIC-53 reflux flow

			then the pressure increases, and the column overflows to the reflux tank			
More Product throughput	FV-55 blocked in open position or bypass open	The liquid level in the reflux flask decreases, which can result in a loss of suction for the product / reflux pump, and therefore a lack of discharge flow and significant column disturbance.	-LAL on the LIC-21 sets off the alarm -LALL on the LI-2151 sets off the alarm	2		
	Increased LPG flow in Stabilizer A	No causes				
No more residual gas flow (off-gas)	PV-21A open	Loss of C3, C4 gas to blow-down, without serious consequences				
More AW flow	LV-30 blocked or bypass open	C3 and C4 flow in ATM under the reflux tank, with a major risk of significant fire in the event of ignition	-LAL on the boot interface for the LIC-30 sets off the alarm -LALL on LI-2155 closes UV-2157 on water drainage -AAH on AI-2151 sets off an alarm if HC gas is detected at the reflux pump -AAH on AI-2152 at reflux pump 10-P-93A / B sets off alarm for gas detection	4	install a deluge system on the reflux flask 10-V-8 Stabilizer A for fire protection	
Less	Less column head flow	No causes				
	Less reflux flow	Partially clogged filter on ref 10P-93A / B pump	Decreased reflux flow, even if the FIC is fully open	- Standby pump available -OTP to ensure the cleaning of the pumps filters	0	

	Less product throughput	Partially filter clogged on the reflux pump	Decreased reflux flow, even though the FIC is completely open	-Spare pump available -OTP to ensure cleaning pump filters	0	
	Less residual gas flow	No causes				
	Less AW flow					

Parameter: pressure

Guide word	Deviation	Causes	Consequences	Safeguards	G	Recommendations
More	More pressure	T-21 fails, causing PV21/21A to shut down	Increased pressure in the reflux balloon and possibility of balloon bursting	-The PAH, PAHH and PSV are intended to alert operators in the event of overpressure and the column will be shut down (Shut down)	4	
Less	Less pressure	PT-21 fails, causing the opening of the PV21/21A	Loss of C3, C4 gas to Blow down, without serious consequences			

parameter: Temperature

Guide word	Deviation	Causes	Consequences	Safeguards	G	Recommendations
More	More temperature	Loss of Air Cooler function for all coolers	Increase in temperature at the head of the column, with increase in pressure, and maximum cooling by exchanger 10-E-11	<ul style="list-style-type: none"> -Aero-coolers are equipped with a VAHH to set off the alarm and a VSHH-2152A N to cut off the power. - 50% of Aero-coolers are equipped with variable-speed motors which make it possible to meet any cooling demand. -Parallel stabilizers make it possible to adjust the feed rate to minimize the consequences of Aero cooler failure. -TAH on TI-2156 sets off the alarm on the Aero coolers output. - PAH on the PIC-2151 sets off the alarm. -PV-21A opens when pressure on PIC 21 increases PAHH on PI-2168A/B/C - 2oo3 sets off alarm and sets off I-2151 which closes hot oil to re-boiler and opens by- pass. -The PSV-38A/B set to 9.8 kg/cm²g to relieve towards torch. 	1	
Less	Less temperature	Loss of cooling water to 10-E-11	Insufficient condensation of the column head and significant loss of C3/C4 towards blow-down.	-Parallel stabilizers allow the feed rate to be adjusted to minimize the consequences of a failure of a cooled Aero	1	

Parameter: Level

Guide word	Deviation	Causes	Consequences	Safeguards	G	Recommendations
Less	No / Low level					
More	More level					

References

References

- Ali R (2011) When SIL suitability is required for final control elements
- Ahn J, Noh Y, Joung T, et al (2019) Safety integrity level (SIL) determination for a maritime fuel cell system as electric propulsion in accordance with IEC 61511. *International Journal of Hydrogen Energy* 44:3185–3194. <https://doi.org/10.1016/j.ijhydene.2018.12.065>
- Akyuz E, Arslan O, Turan O (2020) Application of fuzzy logic to fault tree and event tree analysis of the risk for cargo liquefaction on board ship. *Applied Ocean Research* 101:102238. <https://doi.org/10.1016/j.apor.2020.102238>
- Andrews JD, Dunnett SJ (2000) Event-tree analysis using binary decision diagrams. *IEEE Transactions on Reliability* 49:230–238. <https://doi.org/10.1109/24.877343>
- Avena T, Pitblado R (1998) On risk assessment in the petroleum activities on the Norwegian and UK continental shelves. *Reliability Engineering & System Safety* 61:21–29. [https://doi.org/10.1016/S0951-8320\(98\)80002-1](https://doi.org/10.1016/S0951-8320(98)80002-1)
- Badida P, Balasubramaniam Y, Jayaprakash J (2019) Risk evaluation of oil and natural gas pipelines due to natural hazards using fuzzy fault tree analysis. *Journal of Natural Gas Science and Engineering* 66:284–292. <https://doi.org/10.1016/j.jngse.2019.04.010>
- Bendib R (2017) Optimization And Improvement Of The Overall Performance Of An Industriale Plant. M'hamed Bougara
- Bendib R, Zennir Y, Mechhoud E-A, Bouziane S (2019) Risk assessment for a steam generator (1050 G1) Skikda refinery Algeria, using HAZOP and RQA methods. In: 2019 International Conference on Advanced Systems and Emergent Technologies (IC_ASET). pp 262–267
- Bengio Y (2009) Learning Deep Architectures for AI. *MAL* 2:1–127. <https://doi.org/10.1561/22000000006>
- Buckley JJ, Eslami E (2002) *An Introduction to Fuzzy Logic and Fuzzy Sets*. Springer Science & Business Media
- Cong G, Lu D, Liu M, et al (2021) A New Semi-Quantitative Process Safety Assessment Method and Its Application for Fluorochemical Industry. *Processes* 9:1695. <https://doi.org/10.3390/pr9101695>
- Crawley F, Preston M, Tyler B (2008) *HAZOP: Guide to Best Practice: Guidelines to Best Practice for the Process and Chemical Industries*. IChemE
- Cruz-Campa HJ, Cruz-Gómez MJ (2010) Determine SIS and SIL using HAZOPS. *Proc Safety Prog* 29:22–31. <https://doi.org/10.1002/prs.10293>
- Cui L, Zhao J, Qiu T, Chen B (2008) Layered digraph model for HAZOP analysis of chemical processes. *Proc Safety prog* 27:293–305. <https://doi.org/10.1002/prs.10266>

References

- Cui Z, Tian W, Wang X, et al (2019) Safety integrity level analysis of fluid catalytic cracking fractionating system based on dynamic simulation. *Journal of the Taiwan Institute of Chemical Engineers* 104:16–26. <https://doi.org/10.1016/j.jtice.2019.08.008>
- Chang K, Kim S, Chang D, et al (2015) Uncertainty analysis for target SIL determination in the offshore industry. *Journal of Loss Prevention in the Process Industries* 34:151–162. <https://doi.org/10.1016/j.jlp.2015.01.030>
- Chen L, Fan D, Zheng J, Xie X (2022) Functional Safety Analysis and Design of Sensors in Robot Joint Drive System. *Machines* 10:360. <https://doi.org/10.3390/machines10050360>
- Cheraghi M, Eslami Baladeh A, Khakzad N (2019) A fuzzy multi-attribute HAZOP technique (FMA-HAZOP): Application to gas wellhead facilities. *Safety Science* 114:12–22. <https://doi.org/10.1016/j.ssci.2018.12.024>
- Cheraghi M, Eslami Baladeh A, Khakzad N (2022) Optimal selection of safety recommendations: A hybrid fuzzy multi-criteria decision-making approach to HAZOP. *Journal of Loss Prevention in the Process Industries* 74:104654. <https://doi.org/10.1016/j.jlp.2021.104654>
- Choi J-Y, Byeon S-H (2020) HAZOP Methodology Based on the Health, Safety, and Environment Engineering. *IJERPH* 17:3236. <https://doi.org/10.3390/ijerph17093236>
- Chun M-H, Ahn K-I (1992) Assessment of the potential applicability of fuzzy set theory to accident progression event trees with phenomenological uncertainties. *Reliability Engineering & System Safety* 37:237–252. [https://doi.org/10.1016/0951-8320\(92\)90130-D](https://doi.org/10.1016/0951-8320(92)90130-D)
- Cui L, Shu Y, Wang Z, et al (2012) HASILT: An intelligent software platform for HAZOP, LOPA, SRS and SIL verification. *Reliability Engineering & System Safety* 108:56–64. <https://doi.org/10.1016/j.res.2012.06.014>
- Dernoncourt F (2013a) Introduction to fuzzy logic
- Dernoncourt F (2013b) Introduction to fuzzy logic
- Dubois D, Prade H (1987) The mean value of a fuzzy number. *Fuzzy Sets and Systems* 24:279–300. [https://doi.org/10.1016/0165-0114\(87\)90028-5](https://doi.org/10.1016/0165-0114(87)90028-5)
- Gabriel A, Ozansoy C, Shi J (2018) Developments in SIL determination and calculation. *Reliability Engineering & System Safety* 177:148–161. <https://doi.org/10.1016/j.res.2018.04.028>
- Ilbahar E, Karaşan A, Cebi S, Kahraman C (2018) A novel approach to risk assessment for occupational health and safety using Pythagorean fuzzy AHP & fuzzy inference system. *Safety Science* 103:124–136. <https://doi.org/10.1016/j.ssci.2017.10.025>
- Ioannides A (2000) SAFETY INTEGRITY LEVELS OF FAIRGROUND RIDE CONTROL SYSTEMS:
- Joubert F, Steyn E, Pretorius L (2021) Using the HAZOP Method to Conduct a Risk Assessment on the Dismantling of Large Industrial Machines and Associated Structures: Case

References

- Study. *Journal of Construction Engineering and Management* 147:05020021. [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001942](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001942)
- Hu J, Zhang L, Cai Z, Wang Y (2015) An intelligent fault diagnosis system for process plant using a functional HAZOP and DBN integrated methodology. *Engineering Applications of Artificial Intelligence* 45:119–135. <https://doi.org/10.1016/j.engappai.2015.06.010>
- Kadja M, Zaatri A, Chemani H, et al (2018) Approche QRA pour modéliser des conséquences des scénarios d'accidents fireball et VCE cas Bac de stockage GPL In *Aminas Algérien*. 9
- Khalil M, Abdou MA, Mansour MS, et al (2012a) A cascaded fuzzy-LOPA risk assessment model applied in natural gas industry. *Journal of Loss Prevention in the Process Industries* 25:877–882. <https://doi.org/10.1016/j.jlp.2012.04.010>
- Khalil M, Abdou MA, Mansour MS, et al (2012b) A cascaded fuzzy-LOPA risk assessment model applied in natural gas industry. *Journal of Loss Prevention in the Process Industries* 25:877–882. <https://doi.org/10.1016/j.jlp.2012.04.010>
- Kumar M, Kaushik M (2020) System failure probability evaluation using fault tree analysis and expert opinions in intuitionistic fuzzy environment. *Journal of Loss Prevention in the Process Industries* 67:104236. <https://doi.org/10.1016/j.jlp.2020.104236>
- Leimeister M, Kolios A (2018) A review of reliability-based methods for risk analysis and their application in the offshore wind industry. *Renewable and Sustainable Energy Reviews* 91:1065–1076. <https://doi.org/10.1016/j.rser.2018.04.004>
- Liu C, Yang S, Cui Y, Yang Y (2020) An improved risk assessment method based on a comprehensive weighting algorithm in railway signaling safety analysis. *Safety Science* 128:104768. <https://doi.org/10.1016/j.ssci.2020.104768>
- Macdonald D, Mackay S (eds) (2004) 7 - Hazard analysis methods. In: *Practical Hazops, Trips and Alarms*. Newnes, Oxford, pp 180–192
- Marhavilas PK, Filippidis M, Koulinas GK, Koulouriotis DE (2020) A HAZOP with MCDM Based Risk-Assessment Approach: Focusing on the Deviations with Economic/Health/Environmental Impacts in a Process Industry. *Sustainability* 12:993. <https://doi.org/10.3390/su12030993>
- Markowski A, Mannan MS, Bigoszevska A (2009) Fuzzy logic for process safety analysis. *Journal of Loss Prevention in the Process Industries* 22:.. <https://doi.org/10.1016/j.jlp.2008.11.011>
- Markowski AS, Mannan MS (2009) Fuzzy logic for piping risk assessment (pfLOPA). *Journal of Loss Prevention in the Process Industries* 22:921–927. <https://doi.org/10.1016/j.jlp.2009.06.011>
- Nait-Said R, Zidani F, Ouzraoui N (2008) Fuzzy Risk Graph Model for Determining Safety Integrity Level. *International Journal of Quality, Statistics, and Reliability* 2008:1–12. <https://doi.org/10.1155/2008/263895>
- Macdonald D (2004) *Practical Hazops, Trips and Alarms*. Elsevier

References

- Marhavilas PK, Filippidis M, Koulinas GK, Koulouriotis DE (2020a) A HAZOP with MCDM Based Risk-Assessment Approach: Focusing on the Deviations with Economic/Health/Environmental Impacts in a Process Industry. *Sustainability* 12:993. <https://doi.org/10.3390/su12030993>
- Marhavilas PK, Filippidis M, Koulinas GK, Koulouriotis DE (2020b) An expanded HAZOP-study with fuzzy-AHP (XPA-HAZOP technique): Application in a sour crude-oil processing plant. *Safety Science* 124:104590. <https://doi.org/10.1016/j.ssci.2019.104590>
- Marszal EM, Scharpf EW (2002) Safety Integrity Level Selection - Systematic Methods Including Layer of Protection Analysis
- Mendel JM (1995) Fuzzy logic systems for engineering: a tutorial. *Proceedings of the IEEE* 83:345–377. <https://doi.org/10.1109/5.364485>
- Nguyen H-T, Safder U, Kim J, et al (2022) An adaptive safety-risk mitigation plan at process-level for sustainable production in chemical industries: An integrated fuzzy-HAZOP-best-worst approach. *Journal of Cleaner Production* 339:130780. <https://doi.org/10.1016/j.jclepro.2022.130780>
- Pan N-F, Wang H (2007) Assessing Failure of Bridge Construction Using Fuzzy Fault Tree Analysis. In: *Fourth International Conference on Fuzzy Systems and Knowledge Discovery (FSKD 2007)*. IEEE, Haikou, China, pp 96–100
- Pullum L, Taylor BJ (2006) Risk and Hazard Analysis for Neural Network Systems. In: *Methods and Procedures for the Verification and Validation of Artificial Neural Networks*. Kluwer Academic Publishers, Boston, pp 33–49
- Ramzan N, Compart F, Witt W (2007) Methodology for the generation and evaluation of safety system alternatives based on extended Hazop. *Proc Safety prog* 26:35–42. <https://doi.org/10.1002/prs.10161>
- Rausand M (2014) *Reliability of Safety-Critical Systems: Theory and Applications*, 1st edition. Wiley, Hoboken, New Jersey
- Riad B, Hamid B, Hind R, Youcef Z (2018) Design Of an integration Frame HAZOP-SIL for safety Optimization of a Fired Heater. In: *2018 International Conference on Electrical Sciences and Technologies in Maghreb (CISTEM)*. pp 1–6
- Rosner E, Brissaud F, Declerck B, et al Différences entre approches semi-quantitative et quantitative pour l'évaluation probabiliste des risques technologiques
- Rossing N, Lind M, Jensen N, Jørgensen S (2010) A functional HAZOP methodology. *Computers & Chemical Engineering* 34:244–253. <https://doi.org/10.1016/j.compchemeng.2009.06.028>
- Salaheldine Darwish A, Salem Mansour M, Farag H, Ezzat KH (2020a) Applying LOPA and fuzzy logic to identify SIL requirement for safety critical functions in a direct reduction iron industry. *Alexandria Engineering Journal* 59:3575–3585. <https://doi.org/10.1016/j.aej.2020.06.003>

References

- Salaheldine Darwish A, Salem Mansour M, Farag H, Ezzat KH (2020b) Applying LOPA and fuzzy logic to identify SIL requirement for safety critical functions in a direct reduction iron industry. *Alexandria Engineering Journal* 59:3575–3585. <https://doi.org/10.1016/j.aej.2020.06.003>
- Suzuki T, Izato Y, Miyake A (2021) Identification of accident scenarios caused by internal factors using HAZOP to assess an organic hydride hydrogen refueling station involving methylcyclohexane. *Journal of Loss Prevention in the Process Industries* 71:104479. <https://doi.org/10.1016/j.jlp.2021.104479>
- Tanaka H, Fan LT, Lai FS, Toguchi K (1983) Fault-Tree Analysis by Fuzzy Probability. *IEEE Transactions on Reliability* R-32:453–457. <https://doi.org/10.1109/TR.1983.5221727>
- Tixier J, Dusserre G, Salvi O, Gaston D (2002) Review of 62 risk analysis methodologies of industrial plants. *Journal of Loss Prevention in the Process Industries* 15:291–303. [https://doi.org/10.1016/S0950-4230\(02\)00008-6](https://doi.org/10.1016/S0950-4230(02)00008-6)
- Torres-Echeverria AC (2016a) On the use of LOPA and risk graphs for SIL determination. *Journal of Loss Prevention in the Process Industries* 41:333–343. <https://doi.org/10.1016/j.jlp.2015.12.007>
- Torres-Echeverria AC (2016b) On the use of LOPA and risk graphs for SIL determination. *Journal of Loss Prevention in the Process Industries* 41:333–343. <https://doi.org/10.1016/j.jlp.2015.12.007>
- Vassilev A (2019) BowTie – A deep learning feedforward neural network for sentiment analysis. National Institute of Standards and Technology, Gaithersburg, MD
- Wang G, Xu Y, Qin S (2019) Basic Fuzzy Event Space and Probability Distribution of Probability Fuzzy Space. *Mathematics* 7:542. <https://doi.org/10.3390/math7060542>
- Wei C, Rogers WJ, Mannan MS (2008) Layer of protection analysis for reactive chemical risk assessment. *J Hazard Mater* 159:19–24. <https://doi.org/10.1016/j.jhazmat.2008.06.105>
- Zeng J, An M, Smith NJ (2007) Application of a fuzzy based decision making methodology to construction project risk assessment. *International Journal of Project Management* 25:589–600. <https://doi.org/10.1016/j.ijproman.2007.02.006>
- Zhang Y, Zhang W, Zhang B (2015) Automatic HAZOP analysis method for unsteady operation in chemical based on qualitative simulation and inference. *Chinese Journal of Chemical Engineering* 23:2065–2074. <https://doi.org/10.1016/j.cjche.2015.10.004>
- Zheng G, Zhu N, Tian Z, et al (2012) Application of a trapezoidal fuzzy AHP method for work safety evaluation and early warning rating of hot and humid environments. *Safety Science* 50:228–239. <https://doi.org/10.1016/j.ssci.2011.08.042>
- Mechri W, Simon C, Bicking F, Ben Othman K (2013) Fuzzy multiphase Markov chains to handle uncertainties in safety systems performance assessment. *Journal of Loss Prevention in the Process Industries* 26:594–604. <https://doi.org/10.1016/j.jlp.2012.12.002>

References

- Mohan C (2019) An Introduction to Fuzzy Set Theory and Fuzzy Logic, Second Edition, New edition, Second. MV Learning
- Mourad A, Youcef Z, Tolba C (2022) Cost and Risk Prediction in Road Transportation of Hazmat by ANFIS Trained with PSO, FA, HBBO and ICA. *IJSSE* 12:429–439. <https://doi.org/10.18280/ijssse.120403>
- Pham DT, Pham PTN (1999a) Artificial intelligence in engineering. *International Journal of Machine Tools & Manufacture* 39:937–949
- Pham DT, Pham PTN (1999b) Artificial intelligence in engineering. *International Journal of Machine Tools and Manufacture* 39:937–949. [https://doi.org/10.1016/S0890-6955\(98\)00076-5](https://doi.org/10.1016/S0890-6955(98)00076-5)
- Raesivand A, Kasaeyan M (2019) New fuzzy uncertainty assessment approach of target SIL evaluation by risk graph optimization. *Life Cycle Reliab Saf Eng* 8:291–302. <https://doi.org/10.1007/s41872-019-00093-0>
- Sal R, Nait-Said R, Bourareche M (2017) Dealing with uncertainty in effect analysis of test strategies on safety instrumented system performance. *Int J Syst Assur Eng Manag* 8:1945–1958. <https://doi.org/10.1007/s13198-017-0636-2>
- Sallak M, Simon C, Aubry J-F (2008) A Fuzzy Probabilistic Approach for Determining Safety Integrity Level. *IEEE Trans Fuzzy Syst* 16:239–248. <https://doi.org/10.1109/TFUZZ.2007.903328>
- Sarbayev M (2018) APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PROCESS SAFETY ASSESSMENT
- Suresh PV, Babar AK, Raj VV (1996) Uncertainty in fault tree analysis: A fuzzy approach. *Fuzzy Sets and Systems* 83:135–141. [https://doi.org/10.1016/0165-0114\(95\)00386-X](https://doi.org/10.1016/0165-0114(95)00386-X)
- Wittwehr C, Blomstedt P, Gosling JP, et al (2020) Artificial Intelligence for chemical risk assessment. *Computational Toxicology* 13:100114. <https://doi.org/10.1016/j.comtox.2019.100114>
- You M, Li S, Li D, Xu S (2021) Applications of artificial intelligence for coal mine gas risk assessment. *Safety Science* 143:105420. <https://doi.org/10.1016/j.ssci.2021.105420>
- Hong T-P, Lee C-Y (1996) Induction of fuzzy rules and membership functions from training examples. *Fuzzy Sets and Systems* 84:33–47. [https://doi.org/10.1016/0165-0114\(95\)00305-3](https://doi.org/10.1016/0165-0114(95)00305-3)
- Jeerawongsuntorn C, Sainyamsatit N, Srinophakun T (2011) Integration of safety instrumented system with automated HAZOP analysis: An application for continuous biodiesel production. *Journal of Loss Prevention in the Process Industries* 24:412
- Jin Zhao, Bose BK (2002) Evaluation of membership functions for fuzzy logic controlled induction motor drive. *IEEE 2002 28th Annual Conference of the Industrial Electronics Society IECON 02* 1:229–234. <https://doi.org/10.1109/IECON.2002.1187512>
- Jose LD (2013) Integral management of abnormal situations in complex process plants ” PHD thesis Poltecnic university Madrid. PhD thesis

References

- Kabir S, Papadopoulos Y (2018) A review of applications of fuzzy sets to safety and reliability engineering. *International Journal of Approximate Reasoning* 100:29–55. <https://doi.org/10.1016/j.ijar.2018.05.005>
- Kletz TA (2018) *Hazop & Hazan: Identifying and Assessing Process Industry*
- Nigel H (2004) *Guidelines for process hazards analysis, hazards identification and risk analysis*, 1st edn.
- Nolan DP (2014) *Safety and Security Review for the Process Industries: Application of HAZOP, PHA, What-IF and SVA Reviews*, 4th edition. Gulf Professional Publishing, Amsterdam
- Passino KM, Yurkovich S (1998) *Fuzzy control*. Addison-Wesley, Menlo Park, Calif
- Ramzan N, Compart F, Witt W (2007a) Application of extended Hazop and event-tree analysis for investigating operational failures and safety optimization of distillation column unit. *Process Safety Progress* 26:248–257. <https://doi.org/10.1002/prs.10202>
- Ramzan N, Compart F, Witt W (2007b) Methodology for the generation and evaluation of safety system alternatives based on extended Hazop. *Proc Safety prog* 26:35–42. <https://doi.org/10.1002/prs.10161>
- Report (2007) *The instruments data sheet*
- Ross TJ (2016) *Fuzzy Logic with Engineering Applications*, 4th edition. Wiley
- Simon D (2002) Sum normal optimization of fuzzy membership functions. *Int J Unc Fuzz Knowl Based Syst* 10:363–384. <https://doi.org/10.1142/S0218488502001533>
- Singh P, Singh LK (2021b) Engineering Education for Development of Safety-Critical Systems. *IEEE Trans Educ* 64:398–405. <https://doi.org/10.1109/TE.2021.3062448>
- Sotoodeh K (2019) Safety Integrity Level in Valves. *J Fail Anal and Preven* 19:832–837. <https://doi.org/10.1007/s11668-019-00666-2>
- Voskoglou M (ed) (2021) *Fuzzy Sets, Fuzzy Logic and Their Applications 2020*. MDPI - Multidisciplinary Digital Publishing Institute
- Wang L-X (1997) *A Course in Fuzzy Systems and Control*. Prentice Hall PTR
- (2003) IEC 61511-1:2016 | IEC Webstore | cyber security, functional safety, smart city, smart manufacturing, industrie 4.0, industry 4.0, automation. <https://webstore.iec.ch/publication/24241>. Accessed 24 Dec 2022
- Bai Y, Wang D (2006) Fundamentals of Fuzzy Logic Control — Fuzzy Sets, Fuzzy Rules and Defuzzifications. In: Bai Y, Zhuang H, Wang D (eds) *Advanced Fuzzy Logic Technologies in Industrial Applications*. Springer, London, pp 17–36
- Buckley JJ, Eslami E (2002) *An Introduction to Fuzzy Logic and Fuzzy Sets*. Springer Science & Business Media

References

- Castillo O, Melin P, Kacprzyk J, Pedrycz W (2007) Type-2 Fuzzy Logic: Theory and Applications. In: 2007 IEEE International Conference on Granular Computing (GRC 2007). pp 145–145
- Chameau J-L, Santamarina JC (1987) Membership functions I: Comparing methods of measurement. *International Journal of Approximate Reasoning* 1:287–301. [https://doi.org/10.1016/S0888-613X\(87\)80003-8](https://doi.org/10.1016/S0888-613X(87)80003-8)
- Deng J, Deng Y (2021) Information Volume of Fuzzy Membership Function. *INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL* 16:
- Dombi J (1990) Membership function as an evaluation. *Fuzzy Sets and Systems* 35:1–21. [https://doi.org/10.1016/0165-0114\(90\)90014-W](https://doi.org/10.1016/0165-0114(90)90014-W)
- Dubois D, Prade H (1993) FUZZY NUMBERS: AN OVERVIEW. In: *Readings in Fuzzy Sets for Intelligent Systems*. Elsevier, pp 112–148
- Feng J, Lu S (2019) Performance Analysis of Various Activation Functions in Artificial Neural Networks. *J Phys: Conf Ser* 1237:022030. <https://doi.org/10.1088/1742-6596/1237/2/022030>
- Gaines BR (1976) Foundations of fuzzy reasoning. *International Journal of Man-Machine Studies* 8:623–668. [https://doi.org/10.1016/S0020-7373\(76\)80027-2](https://doi.org/10.1016/S0020-7373(76)80027-2)
- Hájek P (2006) Why Fuzzy Logic? In: Jacquette D (ed) *A Companion to Philosophical Logic*, 1st edn. Wiley, pp 595–605
- Hancock JT, Khoshgoftaar TM (2020) Survey on categorical data for neural networks. *Journal of Big Data* 7:28. <https://doi.org/10.1186/s40537-020-00305-w>
- Klir GJ, Yuan B (1995) *Fuzzy sets and fuzzy logic: theory and applications*. Prentice Hall PTR, Upper Saddle River, N.J
- Lam HK (2018) A review on stability analysis of continuous-time fuzzy-model-based control systems: From membership-function-independent to membership-function-dependent analysis. *Engineering Applications of Artificial Intelligence* 67:390–408. <https://doi.org/10.1016/j.engappai.2017.09.007>
- Mizumoto M (1988) Fuzzy controls under various fuzzy reasoning methods. *Information Sciences* 45:129–151. [https://doi.org/10.1016/0020-0255\(88\)90037-0](https://doi.org/10.1016/0020-0255(88)90037-0)
- Pappis CP, Siettos CI (2014) Fuzzy Reasoning. In: Burke EK, Kendall G (eds) *Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques*. Springer US, Boston, MA, pp 519–556
- Park D, Kandel A, Langholz G (1994) Genetic-based new fuzzy reasoning models with application to fuzzy control. *IEEE Transactions on Systems, Man, and Cybernetics* 24:39–47. <https://doi.org/10.1109/21.259684>
- Pedrycz W (1994) Why triangular membership functions? *Fuzzy Sets and Systems* 64:21–30. [https://doi.org/10.1016/0165-0114\(94\)90003-5](https://doi.org/10.1016/0165-0114(94)90003-5)
- Picton P (1994) What is a Neural Network? In: Picton P (ed) *Introduction to Neural Networks*.

References

Macmillan Education UK, London, pp 1–12

Szandala T (2021) Review and Comparison of Commonly Used Activation Functions for Deep Neural Networks. In: Bhoi AK, Mallick PK, Liu C-M, Balas VE (eds) *Bio-inspired Neurocomputing*. Springer, Singapore, pp 203–224

Tanaka H, Asai K (1984) Fuzzy linear programming problems with fuzzy numbers. *Fuzzy Sets and Systems* 13:1–10. [https://doi.org/10.1016/0165-0114\(84\)90022-8](https://doi.org/10.1016/0165-0114(84)90022-8)

Trillas E, Eciolaza L (2015) An Introduction to Fuzzy Control. In: Trillas E, Eciolaza L (eds) *Fuzzy Logic: An Introductory Course for Engineering Students*. Springer International Publishing, Cham, pp 175–202

Tzung-Pei Hong, Jyh-Bin Chen (1999) Finding relevant attributes and membership functions. *Fuzzy Sets and Systems* 103:389–404. [https://doi.org/10.1016/S0165-0114\(97\)00187-5](https://doi.org/10.1016/S0165-0114(97)00187-5)

Vohradsky J (2001) Neural network model of gene expression. *FASEB j* 15:846–854. <https://doi.org/10.1096/fj.00-0361com>

Wang G (1999) On the logic foundation of fuzzy reasoning. *Information Sciences* 117:47–88. [https://doi.org/10.1016/S0020-0255\(98\)10103-2](https://doi.org/10.1016/S0020-0255(98)10103-2)

Wang S-C (2003) Artificial Neural Network. In: Wang S-C (ed) *Interdisciplinary Computing in Java Programming*. Springer US, Boston, MA, pp 81–100

Wang Y, Li Y, Song Y, Rong X (2020) The Influence of the Activation Function in a Convolution Neural Network Model of Facial Expression Recognition. *Applied Sciences* 10:1897. <https://doi.org/10.3390/app10051897>

Warwick K (1992) Neural networks: an introduction. In: Warwick K, Irwin GW, Hunt KJ (eds). Peter Peregrinus on behalf of IET

Wu Y, Feng J (2018) Development and Application of Artificial Neural Network. *Wireless Pers Commun* 102:1645–1656. <https://doi.org/10.1007/s11277-017-5224-x>

Yen J (1999) Fuzzy logic-a modern perspective. *IEEE Trans Knowl Data Eng* 11:153–165. <https://doi.org/10.1109/69.755624>

Yu J, Yang L, Xu N, et al (2018) Slimmable Neural Networks

Zhang Y, Tiño P, Leonardis A, Tang K (2021) A Survey on Neural Network Interpretability. *IEEE Transactions on Emerging Topics in Computational Intelligence* 5:726–742. <https://doi.org/10.1109/TETCI.2021.3100641>

Bengio Y (2009) Learning Deep Architectures for AI. *MAL* 2:1–127. <https://doi.org/10.1561/22000000006>

Buckley JJ, Eslami E (2002) *An Introduction to Fuzzy Logic and Fuzzy Sets*. Springer Science & Business Media

Castillo O, Melin P, Kacprzyk J, Pedrycz W (2007) Type-2 Fuzzy Logic: Theory and Applications. In: 2007 IEEE International Conference on Granular Computing (GRC 2007). pp

References

145–145

Chameau J-L, Santamarina JC (1987) Membership functions I: Comparing methods of measurement. *International Journal of Approximate Reasoning* 1:287–301. [https://doi.org/10.1016/S0888-613X\(87\)80003-8](https://doi.org/10.1016/S0888-613X(87)80003-8)

Chen G, Pham TT, Boustany N (2001) Introduction to Fuzzy Sets, Fuzzy Logic, and Fuzzy Control Systems. *Applied Mechanics Reviews* 54:B102–B103. <https://doi.org/10.1115/1.1421114>

Cheng J, Li QS, Xiao R (2008) A new artificial neural network-based response surface method for structural reliability analysis. *Probabilistic Engineering Mechanics* 23:51–63. <https://doi.org/10.1016/j.probenmech.2007.10.003>

Dombi J (1990) Membership function as an evaluation. *Fuzzy Sets and Systems* 35:1–21. [https://doi.org/10.1016/0165-0114\(90\)90014-W](https://doi.org/10.1016/0165-0114(90)90014-W)

Dubois D, Prade H (1993) FUZZY NUMBERS: AN OVERVIEW. In: *Readings in Fuzzy Sets for Intelligent Systems*. Elsevier, pp 112–148

Feng J, Lu S (2019) Performance Analysis of Various Activation Functions in Artificial Neural Networks. *J Phys: Conf Ser* 1237:022030. <https://doi.org/10.1088/1742-6596/1237/2/022030>

Hájek P (2006) Why Fuzzy Logic? In: Jacquette D (ed) *A Companion to Philosophical Logic*, 1st edn. Wiley, pp 595–605

Hancock JT, Khoshgoftaar TM (2020) Survey on categorical data for neural networks. *Journal of Big Data* 7:28. <https://doi.org/10.1186/s40537-020-00305-w>

Hu J, Zhang L, Cai Z, Wang Y (2015) An intelligent fault diagnosis system for process plant using a functional HAZOP and DBN integrated methodology. *Engineering Applications of Artificial Intelligence* 45:119–135. <https://doi.org/10.1016/j.engappai.2015.06.010>

Kabir S, Papadopoulos Y (2018) A review of applications of fuzzy sets to safety and reliability engineering. *International Journal of Approximate Reasoning* 100:29–55. <https://doi.org/10.1016/j.ijar.2018.05.005>

Klir GJ, Yuan B (1995) *Fuzzy sets and fuzzy logic: theory and applications*. Prentice Hall PTR, Upper Saddle River, N.J

Markowski A, Mannan MS, Bigoszezewska A (2009) Fuzzy logic for process safety analysis. *Journal of Loss Prevention in the Process Industries* 22:. <https://doi.org/10.1016/j.jlp.2008.11.011>

Mechri W, Simon C, Bicking F, Ben Othman K (2013) Fuzzy multiphase Markov chains to handle uncertainties in safety systems performance assessment. *Journal of Loss Prevention in the Process Industries* 26:594–604. <https://doi.org/10.1016/j.jlp.2012.12.002>

Mizumoto M (1988) Fuzzy controls under various fuzzy reasoning methods. *Information Sciences* 45:129–151. [https://doi.org/10.1016/0020-0255\(88\)90037-0](https://doi.org/10.1016/0020-0255(88)90037-0)

Mohan C (2019) *An Introduction to Fuzzy Set Theory and Fuzzy Logic, Second Edition*, New

References

edition, Second. MV Learning

Mourad A, Youcef Z, Tolba C (2022) Cost and Risk Prediction in Road Transportation of Hazmat by ANFIS Trained with PSO, FA, HBBO and ICA. *IJSSE* 12:429–439. <https://doi.org/10.18280/ijssse.120403>

Pappis CP, Siettos CI (2014) Fuzzy Reasoning. In: Burke EK, Kendall G (eds) *Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques*. Springer US, Boston, MA, pp 519–556

Pedrycz W (1994) Why triangular membership functions? *Fuzzy Sets and Systems* 64:21–30. [https://doi.org/10.1016/0165-0114\(94\)90003-5](https://doi.org/10.1016/0165-0114(94)90003-5)

Pham DT, Pham PTN (1999a) Artificial intelligence in engineering. *International Journal of Machine Tools & Manufacture* 39:937–949

Pham DT, Pham PTN (1999b) Artificial intelligence in engineering. *International Journal of Machine Tools and Manufacture* 39:937–949. [https://doi.org/10.1016/S0890-6955\(98\)00076-5](https://doi.org/10.1016/S0890-6955(98)00076-5)

Raesivand A, Kasaeyan M (2019) New fuzzy uncertainty assessment approach of target SIL evaluation by risk graph optimization. *Life Cycle Reliab Saf Eng* 8:291–302. <https://doi.org/10.1007/s41872-019-00093-0>

Sal R, Nait-Said R, Bourareche M (2017) Dealing with uncertainty in effect analysis of test strategies on safety instrumented system performance. *Int J Syst Assur Eng Manag* 8:1945–1958. <https://doi.org/10.1007/s13198-017-0636-2>

Sallak M, Simon C, Aubry J-F (2008) A Fuzzy Probabilistic Approach for Determining Safety Integrity Level. *IEEE Trans Fuzzy Syst* 16:239–248. <https://doi.org/10.1109/TFUZZ.2007.903328>

Sarbayev M (2018) APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PROCESS SAFETY ASSESSMENT

Suresh PV, Babar AK, Raj VV (1996) Uncertainty in fault tree analysis: A fuzzy approach. *Fuzzy Sets and Systems* 83:135–141. [https://doi.org/10.1016/0165-0114\(95\)00386-X](https://doi.org/10.1016/0165-0114(95)00386-X)

Trillas E, Eciolaza L (2015) An Introduction to Fuzzy Control. In: Trillas E, Eciolaza L (eds) *Fuzzy Logic: An Introductory Course for Engineering Students*. Springer International Publishing, Cham, pp 175–202

Vohradsky J (2001) Neural network model of gene expression. *FASEB j* 15:846–854. <https://doi.org/10.1096/fj.00-0361com>

Wang G (1999) On the logic foundation of fuzzy reasoning. *Information Sciences* 117:47–88. [https://doi.org/10.1016/S0020-0255\(98\)10103-2](https://doi.org/10.1016/S0020-0255(98)10103-2)

Wang S-C (2003) Artificial Neural Network. In: Wang S-C (ed) *Interdisciplinary Computing in Java Programming*. Springer US, Boston, MA, pp 81–100

Warwick K (1992) Neural networks: an introduction. In: Warwick K, Irwin GW, Hunt KJ (eds). Peter Peregrinus on behalf of IET

References

Wittwehr C, Blomstedt P, Gosling JP, et al (2020a) Artificial Intelligence for chemical risk assessment. *Computational Toxicology* 13:100114. <https://doi.org/10.1016/j.comtox.2019.100114>

Wittwehr C, Blomstedt P, Gosling JP, et al (2020b) Artificial Intelligence for chemical risk assessment. *Computational Toxicology* 13:100114. <https://doi.org/10.1016/j.comtox.2019.100114>

You M, Li S, Li D, Xu S (2021) Applications of artificial intelligence for coal mine gas risk assessment. *Safety Science* 143:105420. <https://doi.org/10.1016/j.ssci.2021.105420>

Zeng J, An M, Smith NJ (2007) Application of a fuzzy based decision making methodology to construction project risk assessment. *International Journal of Project Management* 25:589–600. <https://doi.org/10.1016/j.ijproman.2007.02.006>

Zhang Y, Tiño P, Leonardis A, Tang K (2021) A Survey on Neural Network Interpretability. *IEEE Transactions on Emerging Topics in Computational Intelligence* 5:726–742. <https://doi.org/10.1109/TETCI.2021.3100641>