

**OIL AND GAS PIPELINE RISK ASSESSMENT MODEL BY FUZZY
INFERENCE SYSTEM AND NEURAL NETWORK**

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Wentao Wu, candidate for the degree of Master of Applied Science in Industrial Systems Engineering, has presented a thesis titled, ***Oil and Gas Pipeline Risk Assessment Model by Fuzzy Inference Systems and Artificial Neural Network***, in an oral examination held on December 5, 2014. The following committee members have found the thesis acceptable in form and content, and that the candidate demonstrated satisfactory knowledge of the subject material.

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Abstract

Pipeline transportation has been widely used and recognized as the best way to transport oil and gas in energy industry, because of its excellent safety features and significant economic advantages. However, the failure accident of pipelines is one of the most frustrating issues, as its significant adverse impact on people, environment and public safety; it can also cause severe economic loss. Due to pipelines mostly being installed underground, information limitation and data uncertainties make it difficult to predict and assess failure risks by a single methodology based model.

Intelligence Systems (IS), in particular Fuzzy Inference System (FIS) and Artificial Neural Networks (ANNs), have been significantly developed in recent years. Besides traditional experts' knowledge risk assessment methods, the IS based assessment methods have been well established to assess risks in many industries, because of their capabilities of dealing with uncertainty and vagueness. In this thesis two hybrid risk assessment systems have been developed which combine the FIS, ANNs, and expert risk assessment methodology to accomplish risk assessment. The FIS based and the ANNs based model are both introduced to give comparable results, which provides experts with a more confident risk score.

The proposed hybrid models have been built and tested by using Fuzzy Logic Toolbox, the Neural Network Toolbox and the GUI (guide) of MATLAB[®]. Each methodology of the two risk assessment models have been tested and analyzed, which proves that these two Pipeline Risk Assessment models can be utilized in pipeline risk assessment areas.

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LIST OF ABBREVIATIONS AND SYMBOLS

Abbreviation and Symbol	Description
IS	Intelligence System
FIS	Fuzzy Inference System
ANN	Artificial Neural Network
PLRA	Pipeline Risk Assessment
GUI	Graphic User Interface
CEPA	Canadian Energy Pipeline Association
AGA	American Gas Association
TPD	Third Party Damage
Party	Damage
C	Corrosion
D	Design
IO	Incorrect Operation
PH	Product Hazard
LV	Leak Volume
DI	Dispersion
RE	Receptor
COA	Centroid of Area
MF	Membership Function
CFD	Computational Fluid Dynamics

CHAPTER ONE: INTRODUCTION

1.1 Overview

Transportation of oil and gas in pipelines is broadly used around the world, since the pipeline transportation method has been generally recognized as safe and economical [20]. Based on the data from the Canadian Energy Pipeline Association (CEPA), approximately 830,000 kilometres of underground natural gas pipelines have been built across Canada. Figure 1.1 [4] and 1.2 [4] provide a quick overall look for current liquid pipeline and natural gas maps from CEPA [4]. In order to manage these pipelines, accurately, and efficiently, while preventing a massive capital loss, an effective risk assessment model is needed by engineers to measure risks among pipelines. Most of the pipelines are settled underground, there are many factors that affect the reliability and safety of pipelines [24]. Muhlbauer introduces eight widely accepted failure factors in his book the *Pipeline risk management manual*; these important determining failure factors include: Third-Party Damage (TPD), Corrosion (C), Design (D), Incorrect Operation (IO), Product Hazard (PH), Leak Volume (LV), Dispersion (DI), and Receptors (RE) [24]. A more detailed explanation of these eight failure factors is mentioned in the following text. However, it is difficult to get accurate numbers for these failure factors and to build a mechanism to determine how they work together to cause a pipeline failure.

There are some typical models purely based on experts' knowledge, quantitative methods and relative risk methods, for example: the AGA PIMAR [17], the integrated Quantitative Risk Analysis method [9], and the Relative Risk Assessment method [24].

Due to physical variability and lack of knowledge, after testing, those models mentioned above are found to be uncomplicated and limited. An appropriate technique requires assessing risks more precisely and more accurately [1]. Fuzzy Logic [12] has received greater attention in a variety of risk management applications, from the manufacturing industry [2] to the pipeline industry [20]. Fuzzy Logic can be utilized as a tool dealing with failure likelihood and consequences that usually combine to assess the rank of risks involved in pipeline transportation. These two parameters' boundaries are not sharp, and reliable data are not available.

Fuzzy Logic has tremendous advantages for overcoming challenges of initial data limitation and mechanism internal uncertainty [12]. However, experts' knowledge and quantitative methods are very useful for determining sub-index of failure factors. the Proposed new hybrid models incorporate experts' knowledge, quantitative methods and Fuzzy Logic to provide experts with a more completed risk score reference.

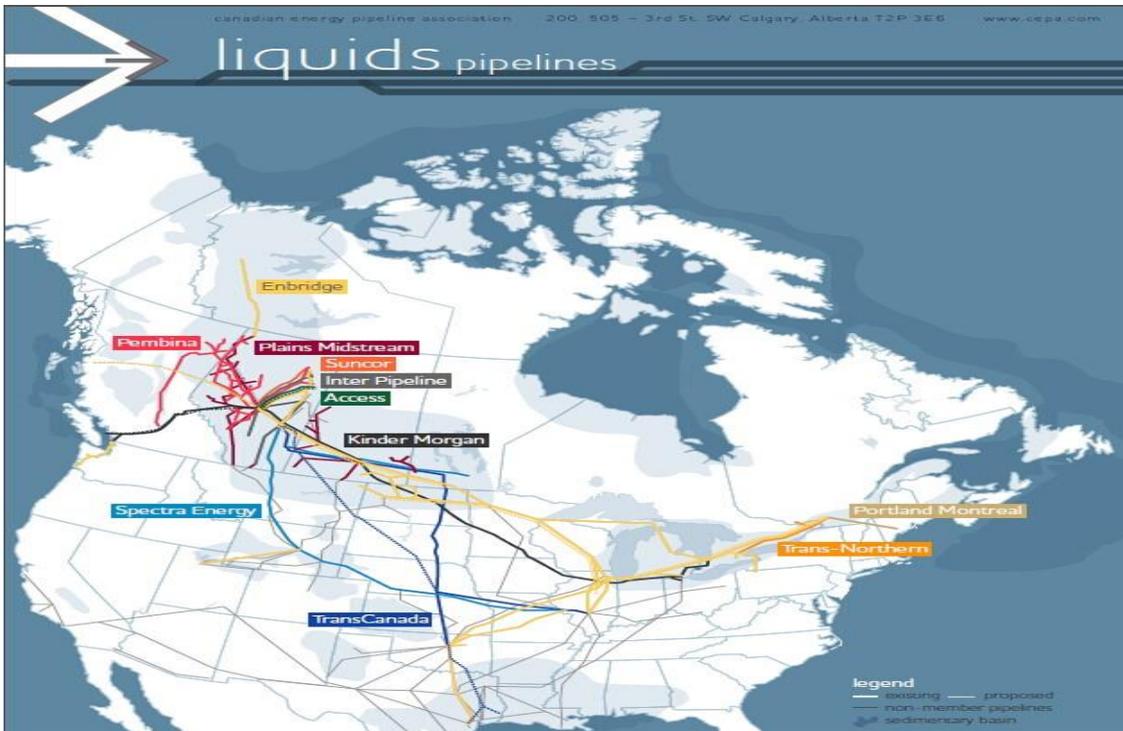


Figure 1.1 Liquid pipeline map [4].

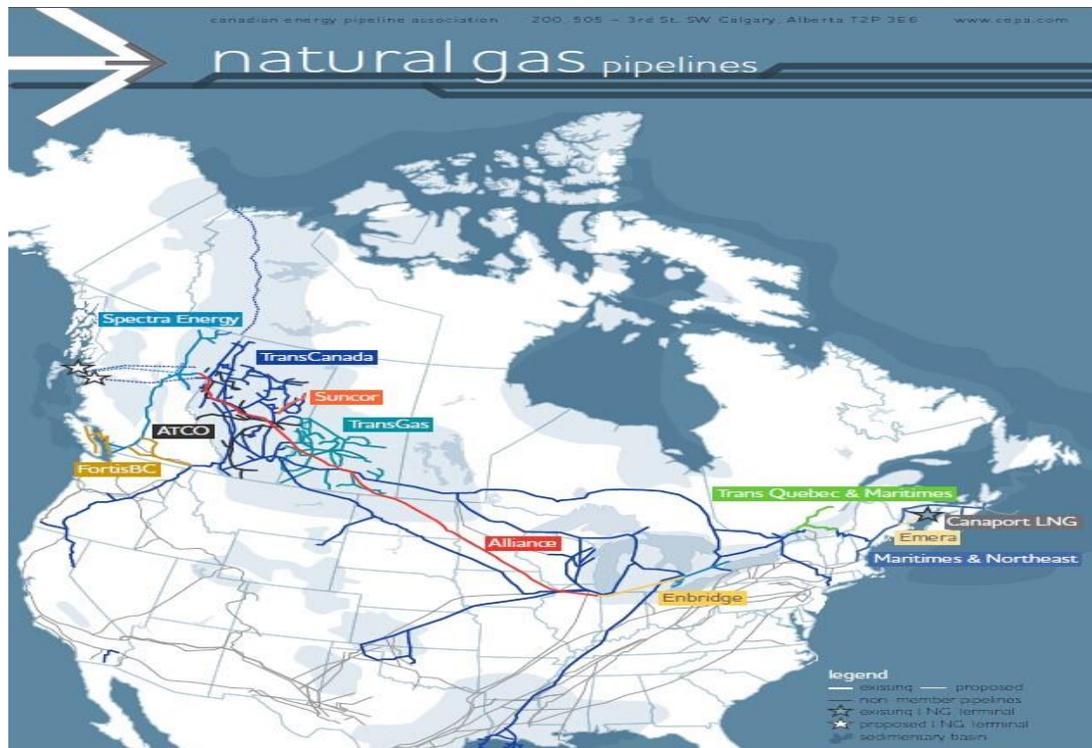


Figure 1.2 Natural gas pipeline map [4].

1.2 Risk Assessment

The main objective of this introduction chapter is to introduce the current definition of risk assessment in the pipeline industry, and its general process.

1.2.1 Risk Assessment

Risk is most commonly defined as the probability of an event that causes a loss and the potential magnitude of that loss [24]; when either of these two components is changed, the risk value will change simultaneously [24]. Failure in oil and gas transportation pipelines can happen due to external or internal reasons.

There are some similar definitions about the ‘risk’ in pipeline industries; the first widely accepted definition of risk can be explained by a mathematical relationship that contains three important concerns: ways of failure; probability of the failure due to these factors; and consequences, which include social, environmental and financial issues [24], [16].

$$\text{Risk} = \text{likelihood} \times \text{Consequence}$$

Although there are many risk indicators, risk assessment models always have to tradeoff system complexity, which is related to the number of inputs, and usability. Therefore, according to the most frequent failures, the failure likelihood mechanisms are grouped into four categories of *Third Party*, *Corrosion*, *Design*, and *Incorrect Operation*; the Consequence can be determined by *Product Hazard*, *Dispersion*, *Leak*, and *Receptors* [24]. More detailed descriptions of these eight categories for likelihood and consequence will be discussed in the following section. In the above equation, likelihood

and consequence are determined by their sub-index factors, which can be scored by quantitative estimation approaches.

The second widely accepted definition can be explained as follows, which is defined in the Risk Analysis and Management for Critical Asset Protection [11].

$$\text{Risk} = \text{Threat} * \text{Vulnerability} * \text{Consequence}$$

According to the definition of eight failure factors (detailed description will be explained in the following chapter), The Vulnerability is grouped into two categories of *Design*, and *Incorrect Operation*. The Threat is determined by *Corrosion*, *Third Party Damage*, and the Consequence can be determined by *Product Hazard*, *Dispersion*, *Leak*, and *Receptors*.

Risk assessment model is widely introduced as a tool for engineers to measure the risk to pipelines; this measuring process means numbers or scores should be assigned to risk to have a clearer and more objective conclusion [14]. Due to the risk failure factors mentioned above, it is always difficult to have a full understanding of the cooperation mechanism of those categories. Many pipelines in Canada are distributed among different provinces, so conditions among these provinces are very different. Therefore, it is impossible to quantify risks by a universally accepted mathematical equation.

Risk assessment efforts by pipeline operating companies are rarely used as a failure prediction; however, these risk assessment efforts are more widely used as a tool to capture information, which can be known or predicted, about the pipeline failure to build a risk context, and then used to make better decisions, instead of predicting a specific pipeline failure section [24]. No risk assessment model can incorporate all failure factors.

It is necessary to determine detectable factors and contributive factors and then use them in the process of risk assessment model building.

1.2.2 General Risk Assessment Process

Based on the *Pipeline Risk Management Manual* by Muhlbauer, the general risk assessment process has the following four steps [24]:

First step - Risk modeling: Building a pipeline risk assessment model is the first step, by using logic ideas to develop systems that consist of algorithms and rules. In this step, it is important to clarify available data and simulate their working mechanism;

Second step – Data collection and preparation: This step involves gathering all the information that is needed in the risk assessment model. There are many data collection methods, such as inspection, original designing and construction information, and historical analysis;

Third step – Segmentation: The pipeline is usually distributed among different provinces or countries, where risks are not constant under all the environmental conditions. It is common to segment the pipeline into segments whose conditions are constant in that section;

Fourth step – Assessing risks: Applying input data to the previously created model for different segments to get a corresponding risk score, commonly displayed as the Relative Score or Absolute Risk Score.

1.3 Summary

This Chapter introduced two common risk definitions in oil and gas pipeline industry, brief introduction of pipeline failure parameters, and general risk model building process.

The following six chapters will cover detailed pipeline risk parameters introduction, literature review, methodology of proposed risk assessment models, experimental results and analysis, and conclusion, respectively.

CHAPTER TWO: PIPELINE RISK PARAMETERS

Generally, there are two ways to build risk assessment models. One is building risk assessment model frames first and then applying this model to a real environment. The other one is collecting data and information first and then analyzing the data to develop a model.

The risk factor is an important parameter that determines the ways to develop a risk assessment model, using either a data first or frame first model. Since pipelines usually go across many provinces or countries whose conditions vary significantly, it is important to have a completed and universally accepted list of factors that can be used to build a risk assessment model. After many years of pipeline accidents research, considering the balance between the accuracy of a risk assessment model and its usability, there are eight widely agreed risk assessment parameter factors. These eight risk assessment model parameters are *Third Party, Corrosion, Design, and Incorrect Operation; Product Hazard, Dispersion, Leak volume, and Receptors* [24]. These eight parameters are determined by their own input indexes. According to the first risk definition, these factors are split into two groups: failure likelihood and consequence; based on the second risk definition, these eight parameters are classified by three groups, which are Vulnerability, Threat, and Consequence [11]. It is necessary to mention that a large part of this pipeline failure factor introduction and analyzing chapter is referenced from the *Pipeline Risk Management Manual - Ideas, Techniques, and Resources* [24].

This chapter is organized as follows:

1. Introduction of eight failure factors.
2. A brief description of the two failure classification methods based on two different risk assessment definitions.

2.1 Failure Factors Introduction

In order to have a better understanding of pipeline risk assessment model building, it is important to spend some efforts on introducing the eight established pipeline risk factors. In this section, a brief introduction of these parameters is presented

2.1.1 Design Likelihood

As mentioned above, there are four failure parameters that determine the failure likelihood. One of these four is the design likelihood which is determined by how pipelines are originally designed. Based on the *Pipeline Risk Management Manual*, there are commonly five variables that need to be calculated by experts, relying on their knowledge and experience. These five parameters include Safety Factor, Fatigue, Surge Potential, Integrity, and Land Movement. The design likelihood can be scored using numerical scale from 1 to 4 which is determined by the effects of material strengths and estimated stresses; the weight percentage of each parameter illustrates its relative importance of this parameter. For example, if the Fatigue parameter's weight percentage is 10%, it means that the Fatigue represents 10% of the total score of Design likelihood. Table 2.1 depicts the weight percentage of these five parameters [24].

It is necessary to acknowledge the weight scores' uncertainty and variance over many years; therefore, it is crucial to incorporate experts' knowledge to get a realistic score

value. Based on their knowledge, experts should analyze the pre-install design documents, actual installation information, and build a risk score level.

1. Safety factors: It is necessary to consider and assess the load, stress, and overall strength. Generally, Safety factor assessment is accomplished by calculating internal pressure (including maximum and normal pressure), external loading, strength of material (pipeline diameter, pipe wall thickness, strength of material components) [24].

Table 2. 1 Design likelihood parameters weight percentage.

Parameter	Weight Percentage	Weight Score
Safety Factor	35%	0.35~1.4
Fatigue	15%	0.15~0.6
Surge Potential	10%	0.1~0.4
Integrity	25%	0.25~1
Land Movement	15%	0.15~0.6

2. Fatigue: Fatigue is a process of structural degradation caused by fluctuation or cycles of stress and strain that are frequently concentrated locally by structural discontinuities, geometric notches, surface irregularities or damage, defects, or metallurgical non-homogeneities [19].

3. Surge Potential: Surge is usually caused by a sudden change in fluid velocity without according surge relief. Surge can damage pipelines, other associated components, and equipment [7].

4. Integrity: Pipeline integrity means a pipeline and all its related components and systems meet their appropriate and designed requirements to make them run properly [21].

5. Land Movement: Underground pipeline installation can result in immediate or long-term stress that can cause failure. There are many typical land movements, including landslides, soil movements, tsunamis, seismic events, seismic faulting, scour and erosion [24].

2.1.2 Incorrect Operation Likelihood

Most forms of pipeline failure, such as leaking and rupture, can be attributed, to some grade, to human factors, which considered as human errors as well. The Human factors is a complex field that aims to understand the various aspects of human characteristics and job experience, job and task design, tool and equipment design, and work environment that can affect operations and overall system performance [29]. Although many factors can cause a pipeline failure or accident, based on statistical records, almost 80% of all accidents are results of human error [24]. It is a valuable effort to identify, measure, assess, and manage potential human error factors that can significantly decrease the risk of pipeline failure.

As one of the most challenging factors to be tracked down, human error factors are always related to many different areas, including engineering and psychology. To build a model to assess human error, engineers need to deal with many elements, such as identifying incorrect operation factors, defining the scope of the model, the methodology, designing, and data collection.

First of all, identifying the human error factors or incorrect operations becomes primary in the risk assessment. These personal, incorrect operation factors go through all the pipeline processes which include designing, constructing, operating and maintaining.

Any small errors, from any phase, can turn out to cause major accident. Any human factors that can increase or decrease pipeline risk need to be incorporated into risk assessment systems.

Considering the tradeoff between usability and accuracy, human factors or incorrect operation factors are determined by four sub-index parameters: Design, construction, operation, maintenance; Table 2.2 informs their weight percentages of determining incorrect operation factors, which are scored by numerical scales between 1 and 4 [24].

1. Operation: Operation is the most important parameter of determining incorrect operation levels. The Operation phase should be very carefully observed and highly controlled as any operational error can cause an immediate pipeline failure. However, it is crucial to examine the operation phase, which can be scored by procedures, records, communication and so on [24].

2. Design: Since documents of design process are often not well defined, the design process becomes a difficult factor to be fully assessed. Therefore, pipeline failure proof information and available documents seeking and checking processes are always necessary. Design assessment can be scored by the level of hazard identification, safety systems, material, and so on [24].

3. Construction: Construction inspection is not necessary if construction is ensured to be well defined, quality, and invariant for new projects. If the construction process does not meet the previous requirements, evaluation and assessment become indispensable. Therefore, Construction is scored by reasonably considering three typical variables, which are inspection, materials, and coating [24].

Table 2. 2 Incorrect operation likelihood parameters weight percentage.

Parameter	Weight Percentage	Weight Score
Design	30%	0.3~1.2
Construction	20%	0.2~0.8
Operation	35%	0.35~1.4
Maintenance	15%	0.15~0.6

4. Maintenance: Lack of attention to maintenance in any phase of pipelines building can result in direct or potential pipeline failures. Maintenance is more a dependent parameter than an immediate failure one. The level of maintenance can be scored by variables, like documentation, schedule, and procedures [24].

2.1.3 Corrosion Likelihood

According to the pipeline failure record, one of the greatest causes of pipeline failure in oil and gas transmission pipelines is corrosion. Corrosion means a loss of metal due to chemical or electrochemical process. Similar to other pipeline failure factors, corrosion can also cause oil and gas leaks or pipeline ruptures. It can happen to either of the internal or external surfaces of pipelines, bases materials, welds, and other associated zones [28]. Corrosions resulting from environmental degradation (including sulfates, acid, and ultraviolet light), can also appear on non-steel pipelines, even if they have good corrosion proof abilities. The deterioration rates of pipelines vary significantly, from a couple of years after being built to decades; this divergent deterioration rate is due to different local environments and time differences [28].

Corrosion has always been regarded as a complicated potential failure factor, which makes it difficult to be assessed and evaluated. In order to evaluate corrosion level, it is

necessary to collect enough documents and other forms of information. Even though, degradation can be prevented by choosing corrosion free materials, considering the mechanical requirements of materials, the balance of mechanical properties and corrosion vulnerabilities need to be well designed.

The general process to evaluate corrosion likelihood typically consists of three steps [24]: (a) Identify the possible forms of corrosion, (b) evaluate the vulnerability of the pipeline material, and (c) evaluate the corrosion failure and prevention measures applied in all phases of the pipeline building process.

There are three classic forms of acknowledged corrosion that can be used to evaluate corrosion likelihood [24]: Atmospheric corrosion, internal corrosion, and buried metal (subsurface) corrosion. Table 2.3 displays their weight percentage of determining corrosion likelihood, which is scored by numerical scales between 1 and 4 [24].

1. Buried metal corrosion: Since corrosion mostly happens when pipelines have some chemical or electrochemical reaction, a pipeline that is built underground can very easily have a corrosion reaction due to a reaction with soil or underground water [28].

Table 2. 3 Corrosion likelihood parameters weight percentage.

Parameter	Weight Percentage	Weight Score
Buried Metal	70%	0.7~2.8
Internal	20%	0.2~0.8
Atmospheric	10%	0.1~0.4

2. Internal corrosion: Internal corrosion normally evaluated by possible corrosion failure originating within the pipeline, which is also pipeline built-in corrosion. Internal

corrosion is scored by two typical assessment parameters, which are Product corrosivity and Preventive actions [24].

3. Atmospheric corrosion: Chemical or electrochemical corrosion processes can happen when pipelines are exposed to the atmosphere, where water, oxygen and acid can react with each other. However, atmospheric corrosion is considered as a relatively lower probability parameter [28].

2.1.4 Third Party Damage Likelihood

Third Party Damage (TPD) is defined as any pipeline failures that result from human errors which are not related to the pipeline itself [24]; According to failure records, TPD is now considered as the biggest threat to the reliability and safety of pipelines; TPD can be caused by internal or external forces, which include excavating, earth movement, and other damages caused by people [25]. Nowadays, excavating activities are the lead TPD failure parameters.

Based on CEPA's report, since 2000, twenty deaths in the U.S. involved digging. Fortunately, no reported deaths in Canada have been related to excavating, but quite a few injuries have occurred. However, the potential consequences of damage to pipelines include loss of life, serious injury, and environmental contamination. Pipeline damage caused by TPD, like excavation, is entirely preventable. There are some popular ways to prevent and measure TPD likelihood [25]: (a) marker posted with pipelines, (b) additional attention to most vulnerable joint, (c) routing system, (d) enquiry process, and (e) liaison with landowners and other key stakeholder groups.

By considering the accuracy and usability of the TPD likelihood evaluation system, there are five failure parameters, which are Activity, Depth of Cover, Above-ground Facilities, Patrol Frequency, and Publication Education [24]. The following Table 2.4 is a look at TPD likelihood parameters weight percentage, which are scored using numerical scales between 1 and 4.

1. Depth of cover: The depth of cover plays an important role in third party damages failure assessment, which means protection of pipelines provided by the depth of earth's cover. Nowadays, new pipeline projects are always required to be built underneath ground no less than 3 feet (91.44 centimeters in metric). Experts will evaluate the depth of cover parameter by scoring cover depth, concrete coating, and warning tape [24].

2. Activity: The intensity level of activity and third party damage level are directly related. Higher activity level, higher third party damage failure score. The scope of activity is not only limited to excavation activity but also includes any activities around the pipeline site.

3. Patrol frequency: As there is no effective method that can be recognized as a reliable method to prevent third party damage in advance, patrolling has been widely used as a failure reduction method [13]. There are many accepted patrol frequencies, varied from daily to monthly, depending on the previous failure record.

Table 2. 4 TPD likelihood parameters weight percentage.

Parameter	Weight Percentage	Weight Score
Depth of cover	25%	0.25~1
Activity	25%	0.25~1
Patrol frequency	20%	0.2~0.8
Public education	20%	0.2~0.8
Aboveground facilities	10%	0.1~0.4

4. Public education: Sufficient public education can effectively decrease the personal unintentional and unknown damage which is known to be a typical failure reasons; Contacting workers, contractors, residents and public is a very effective and economical option to reduce third party damage [25], [13].

2.1.5 Production consequence

It is very important to assess the hazard consequence of different products. Generally, production consequence can be grouped into two categories: Acute Hazard and Chronic Hazard; Table 2.5 is a view of weight percentage of these two forms of consequence [24].

1. Acute hazard: Acute hazard should be measured by a complete analyzing of thermal event, reactivity, and toxicity. The thermal event can be assessed by product type, spark generation, and surrounding environment. To deal with the reactivity, substances surrounding the environment need to be analyzed. The toxicity is assessed by immediate toxicity hazard to people or environment.

2. Chronic hazard: Instead of immediate failure consequence, chronic hazard causes a long-term, indirect, far reaching consequence. There are primary criteria and

secondary criteria that need to be considered to assess chronic hazard consequence [24]. Toxicity and ignitability are two typical criteria need to be considered in both primary criteria and secondary criteria.

Table 2. 5 Product consequence parameters weight percentage.

Parameter	Weight Percentage	Weight Score
Acute Hazard	55%	0.55~2.2
Chronic Hazard	45%	0.45~1.8

2.1.6 Leak Volume consequence

If pipelines are not properly maintained or the surrounding area is inappropriately excavated, oil or gas will be able to unintentionally escape from the pipeline; this unintentional process is defined as a leak or a spill, which are interchangeable. According to three general leaking processes [24], leak prior to system isolation, leak after isolation, and mitigated leak, the leak volume is largely determined by leak or spill size.

Volume size can be assessed by leak rate and duration. Among these two volume size indexes, leak rate largely determines the volume size. Material, Stress, and Initiator are considered as main leak volume parameters. Table 2.6 shows their weight percentage [24].

1. **Material:** Different materials have different cracking vulnerability levels. By analyzing material's fracture toughness, material cracking vulnerability can be assessed [24].

Table 2. 6 Leak Volume consequence parameters weight percentage.

Parameter	Weight Percentage	Weight Score
Material	33.4%	0.334~1.36
Stress	33.3%	0.333~1.332
Initiator	33.3%	0.333~1.332

2. Initiator: The definition of initiator is what forms of the initial damage appear on the pipelines. Since there are some direct or known relationships between the damage initiators and certain types of failure consequence, particular failure consequence can be assessed by analyzing its corresponding failure initiator.

2.1.7 Dispersion consequence

Dispersion is used to assess the consequence caused by the spread of product. Dispersion usually is defined as a process that the product is spreading in the air, instead of water or soil. In this thesis, risk assessment focuses on the production dispersion in the air. There are many reasons that can cause the dispersion process when the release failure happens. Types of products and sites are two factors that can influence the spill movement.

For natural gas: As its characteristic of freedom and readiness, individual volumes of gas may cover more area allowing a possible lower concentration. Density of the gas is an important factor to assess its dispersion scale. For liquid oil: Because of its physical density, leaked oil will spread on the ground, forming a pool and has corresponding vaporization [24].

Gas dispersion hazard zone is related to the Jet Fire and Vapour Cloud; Liquid oil dispersion hazard zone resulted from pool fire or contamination scenario [24]. If

pipelines are installed on the ground, Vapour Cloud is commonly established from a partially diluted vent.

According to a characteristic of dispersion, modeling has been accepted to assess dispersion level. By using appropriate formulas, such as Gaussian dispersion, gas build-up in enclosed volumes, pool spreading or subsea releases, and Computational Fluid Dynamics (CFD), it is reasonable to assess the dispersion [24]. In this pipeline risk assessment study, only four parameters have been used to assess dispersion to tradeoff accuracy and usability; they are affected area size, thermal event, thermal event/contamination, and mitigation; Table 2.7 depicts dispersion consequence parameters' weight percentage [24].

1. Affected area size: After leaking, depending on the types of oil and gas, there will be different affected area sizes. In order to estimate this affected area size, leak rate, wind, environment condition and other factors should be taken into account;

2. Thermal event/ Contamination: When flammable gas escaped from pipeline, it may cause fireballs, Vapor clouds, explosion to create significant hazards to surrounding area. Thermal event and contamination can be related to each other and even interchangeable under certain conditions. Thermal event scales can be assessed by cloud size or pool size (radius, and depth). Contamination mainly depends on spill volume and concentration;

3. Mitigation: If leak accidents happen, emergency response will be enacted. Emergency response plan and secondary containment are two main criteria to assess mitigation [24].

Table 2. 7 Dispersion consequence parameters weight percentage.

Parameter	Weight Percentage	Weight Score
Affected Area size	33.4%	0.334~1.36
Thermal Event	33.3%	0.333~1.332
Mitigation	33.3%	0.333~1.332

2.1. 8 Receptors

In the pipeline scope, the definition of leaking receptors is the facilities, environment, people, and other media that will be affected by the failure of pipelines. According to the receptor's definition, there are two kinds of receptor determining parameters: Environment and Population; the receptor score assessment mainly depends on the distance between pipelines and affected receptors; Table 2.8 depicts receptor consequence parameters' weight percentage [24].

Table 2. 8 Receptors consequence parameters weight percentage.

Parameter	Weight Percentage	Weight Score
Environment	50%	0.5~2
Population	50%	0.5~2

1. Environment: The pipeline site's surrounding environments can be very different, as pipelines are distributed along thousands of kilometers. Along the pipeline, the critical buildings (such as schools, hospitals, and so on), natural parks, the high natural value areas, surface and underground water and atmosphere should be carefully considered to have a realistic score;

2. Population: Assessment needs to incorporate concerns, such as pipeline sites' surrounding population density [24].

2.2 Failure Factors Classification:

2.2.1 Failure-likelihood and Consequence

As presented in the previous chapter, the first risk definition is defined by Failure-likelihood and Consequence.

According to this definition, eight pipeline failure risk parameters are grouped into Failure-likelihood and Consequence.

Failure-likelihood: Failure-likelihood is used to assess or establish how likely or what the probability is of a pipeline accident [27]. It is the *Design, Incorrect Operation, Corrosion, and Third Party Damage* that are included in this classification. The value of Failure-likelihood can be scored from 1 to 4.

Consequence: It is the outcomes of a failure accident, which include immediate and short-term environmental effects, financial losses, and social impacts. As pipeline failure may cause indirect outcomes, it is also necessary to consider its indirect damages. The Consequence is normally constituted by Production Hazard, Dispersion, Leak, and Receptors. The value of Consequence can be scored from 1 to 4.

2.2.2 Vulnerability, Threat and Consequence

This risk definition is derived from *Risk Analysis and Management for Critical Asset Protection*, (RAMCAP) framework [11]. This definition is determined by three classifications: Vulnerability, Threat and Consequence.

Vulnerability: The weakness resulting from the pipeline's design, installation, or operation can be exploited by an adversary [11]. These weaknesses can happen in any phases of the pipeline project, from the beginning, which is project designing, to the last phases, which is operation or maintenance. In this thesis, Vulnerability is measured by Design and Incorrect Operation. The value of Vulnerability can be assigned from 1 to 4.

Threat: Generally, any circumstance, condition, or event with the potential to cause the pipeline failure accident can be regarded as Threat of pipeline risk [11]. It is critical to have a completed analysis of the accident mechanism of these adversaries. Threat can be calculated by Corrosion and Third Party Damage. The value of Threat can be assigned from 1 to 4.

Consequence: Under the "Vulnerability, Threat and Consequence" definition, the Consequence is similar to its description in the "Total-likelihood and Consequence" definition. The value of Consequence can be assigned from 1 to 4.

2.3 Summary

This chapter provides a detailed introduction of pipeline failure risk factors and sub-indexes, and their classification based on two risk definitions. The following chapter will cover the literature part of Fuzzy Inference Systems and Artificial Neural Networks related to the proposed models.

CHAPTER THREE: LITERATURE REVIEW

Since 1943, Artificial Intelligence started growing and has been well established and greatly applied to almost all industries [18]. In this chapter, brief introductions of Artificial Intelligence (AI), Fuzzy Logic (FL), Fuzzy Inference Systems (FIS), and Artificial Neural Networks (ANNs) [12] will be given. These brief introductions will lay the foundation for the proposed Fuzzy Inference Systems models and Artificial Neural Networks risk assessment models proposed in this thesis. It is *NeuraL-Fuzzy and Soft Computing* [12] that contributes most to discussion material, resources, and ideas.

3.1 Introduction of Artificial Intelligence

Since Artificial Intelligence was born in the 1940s, many researchers and projects about Artificial Intelligence have been done, and because of them, now it has become a greatly recognized field. There are many definitions of Artificial Intelligence; one of the most accepted definitions of AI is the capability and process of intelligent agents, which are capable of continuously learning the corresponding environment, perceiving and acting certain activities. Artificial intelligence has an advantage of dealing with the pervasive imprecision [12]. Over the years, Artificial Intelligence has evolved and generated other separate fields such as Intelligent Systems, Computational Intelligence and Artificial Neural Networks [12]. These tools have already gained world-wide recognition.

3.2 Introduction to Fuzzy Logic

Fuzzy Logic has been studied since the 1920s, as infinite-valued logic [8]. However, the term ‘Fuzzy Logic’ was not introduced until 1965, by Lotfi A. Zadeh’s proposal, *Fuzzy Set Theory*.

Fuzzy Logic is in the form of multiple-valued logic; it processes and introduces reasoning that is in approximate and imprecise linguistic terms rather than fixed and precise crisp numbers. Fuzzy Logic has been proven to be very useful in dealing with partial truth concerns. Furthermore, input and output membership functions can be used to manage the linguistic variables. Fuzzy Logic generally consists of Fuzzy Sets, Fuzzy Rules and Fuzzy Reasoning, and Fuzzy Inference Systems [12]. The following sections give a brief introduction of these three components

3.2.1 Fuzzy Sets

Basically, the Fuzzy Set is defined as a set with a flexible linguistic boundary instead of a crisp number boundary. Each variable of the Fuzzy Logic commonly consists of a truth value that ranges in a degree between 0 and 1. Based on this advanced characteristic of the Fuzzy Logic, it has been expanded to deal with the partial truth concept. Their truth values typically range between completely true and completely false [26].

In *Neural-Fuzzy and Soft Computing* [12], Jang describes the mathematical Fuzzy Logic definition function:

If X represents the collection of objects designated in general by x , then a fuzzy set 'A' in X is defined as a set of ordered pairs:

$A = \{(x, \mu_A(x)) | x \in X\}$, where $\mu_A(x)$ is the membership function, which gives X a membership grade between 0 and 1, for the fuzzy set 'A' [12].

The following example is provided to illustrate this mathematical function: Generally, people describe weather using linguistic words such as hot, comfortable, and cold. In this case, X is defined as 'weather'. Depending on people's personal feelings, 'hot', 'comfortable', and 'cold' are used by people to describe the weather, along with their own membership, μ_A , μ_B , μ_C , respectively. The membership function allow each element x to be mapped to a membership grade, which is between 0 and 1. Then we have the following cases:

1. Under 10 centigrade, people usually use the word 'cold' to describe the weather.
2. Between 15 centigrade and 25 centigrade, people may tend to use the word 'comfortable' to describe the weather.
3. Above 25 centigrade, people may use the word 'hot' to describe the weather.

Figure 3.1 demonstrates the membership function for 'hot', 'comfortable', and 'cold', where 'X' is smooth and gradual.

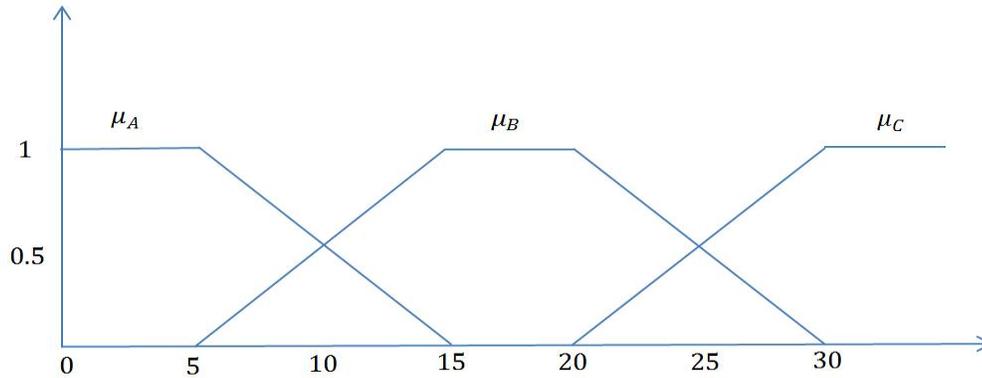


Figure 3. 1 Membership functions of ‘cold’, ‘comfortable’, and ‘hot’.

The membership function is used to characterize its corresponding fuzzy set. There are many widely used membership functions. Based on the condition of the proposed pipeline risk assessment model, only the Gaussian membership function is discussed here. The shape of Gaussian membership is attached in Appendix 2.

The Gaussian membership function has two parameters, c and σ , to characterize it.

$$\text{Gaussian}(x; c, \sigma) = e^{-1/2\left(\frac{x-c}{\sigma}\right)^2}$$

The parameter c represents the center of the membership function, and the σ represents its width. The Gaussian membership function has a smooth transition between risk levels, and it enables the maximum number of fuzzy rules, which is essential for an accurate result [10]. Due to its advantages, The Gaussian membership function is very widespread and broadly introduced in the Fuzzy Logic or Fuzzy Inference System.

It should be mentioned here that fuzzy operation is also very important for designing fuzzy. There are three kinds of operations: intersection, union, and complement.

3.2.2 Fuzzy Rules and Fuzzy Reasoning

Fuzzy Rules and Fuzzy Reasoning, which are emerged from Fuzzy Set Theory, are the core of Fuzzy Inference System, most essential modeling tool [12].

Fuzzy Set is usually used to deal with linguistic inputs, which has the advantage of summarizing information in a complex system. It is the fuzzy rule that manages these linguistic input mechanisms.

Fuzzy Rule is usually defined and described as ‘If-then’, which is in the form of ‘if X is A then Y is B’. This mechanism describes the relationship between Antecedent A and Consequence B [12]. Here is a simple example of fuzzy if-then rules: If the pipeline material quality is low, then failure risk is high. Through fuzzy input membership functions, compatibility between each input and its corresponding membership function is determined. Then the fuzzy rule system, which is fuzzy rules combined with ‘AND’ or ‘OR’ operators, is introduced to process these inputs with their compatibility condition, in this process all rules are evaluated in parallel. Results derived from different rules are combined and taken into consideration together, and then get a consequent output.

3.2.3 Fuzzy Inference Systems

Fuzzy Inference Systems (FIS) are also widely named and known as fuzzy-rule-based-system and it consists of three essential components [12].

There are three typical kinds of Fuzzy Inference Systems, all of these three systems have the same basic frame structure: (1). Fuzzification unit, (2) Knowledge base (consists of database and rule base), (3) Reasoning mechanism, and (4) Defuzzification.

Knowledge base is the central element of the Fuzzy Inference System:

(1) Rule base contains a reasonable and careful selection of fuzzy rules. The Rule base accomplishes the procedure of mapping fuzzy rules of the inputs to fuzzy values of the outputs; the control relationship between these two types of fuzzy values, which represents the decision-making policy, is defined by the combination of all different rules [5].

(2) Data base, which defines the membership function, including input membership function and output membership function, is used in the fuzzy rules [5].

The basic FIS structure and mechanism is depicted by Figure 3.2.

Generally, a complete fuzzy inference system can be described by the following steps:

Step-1-Fuzzification: Crisp inputs are converted into fuzzy values, which are continuous values.

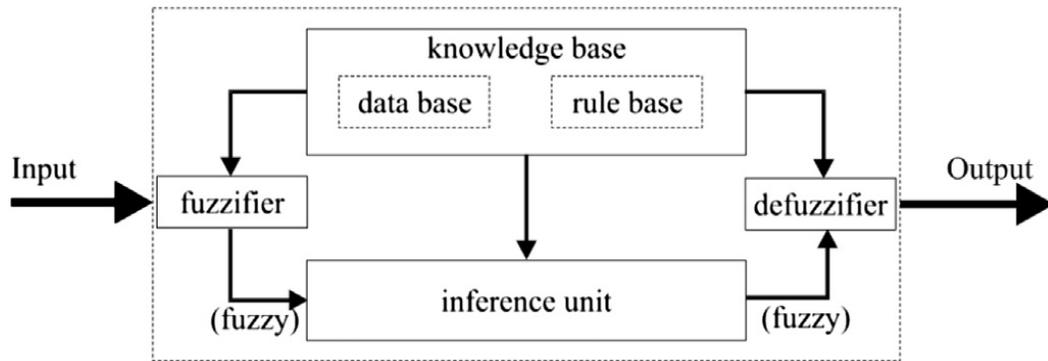


Figure 3. 2 Fuzzy Inference Systems [12].

Step-2-Fuzzy Reasoning: Fuzzy values, produced by step-1, are being considered in the fuzzy engine to produce appropriate consequents (including rules evaluation and conditions evaluation processes). This reasoning mechanism executes the fuzzy

inference procedure upon the pre-determined rule base and given facts to obtain a reasonable output or conclusion.

Step-3-Defuzzification: Consequents given by step-2 are converted into crisp values.

There are mainly three kinds of FIS [12]: (1) Mamdani Fuzzy Inference System, (2) Sugeno Fuzzy Inference System, and (3) Tsukamoto Fuzzy Inference System. All proposed FIS risk assessment models in this thesis are based on the Mamdani fuzzy inference system; the following part is a basic explanation of the Mamdani fuzzy inference system.

3.2.4 Mamdani Fuzzy Inference System:

The Mamdani Fuzzy Inference System is chosen to build proposed fuzzy inference models.

Figure 3.3 [12] demonstrates how a simple two-rule Mamdani FIS works. In this Mamdani FIS, Min and Max have been selected for T-norm and T-conorm, respectively.

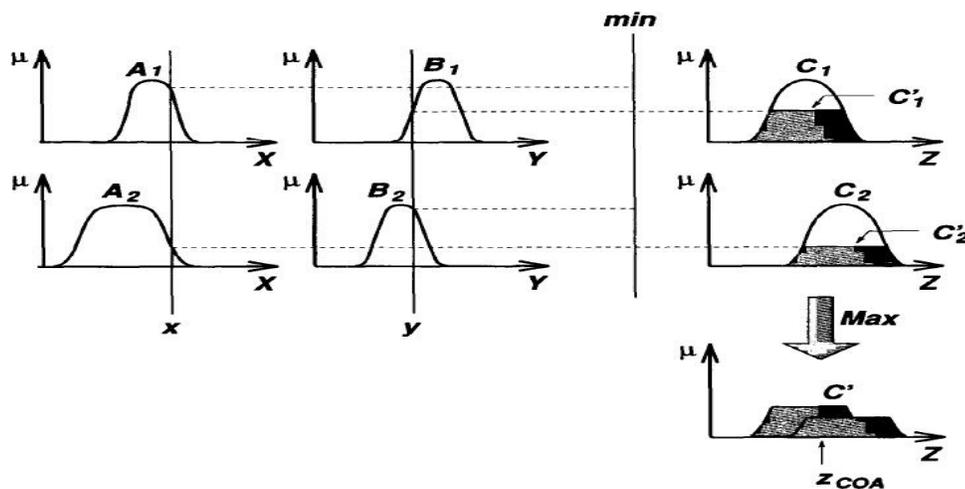


Figure 3.3 Mamdani Fuzzy Inference System [12].

T-norm: T-norm is defined as an intersection operator to implement the aggregation of memberships of two fuzzy sets, which can also be illustrated by the equation as follows [12].

$$\mu_{A \cap B} = \mu_A(x) * \mu_B(x)$$
 , where * defines the binary operator for this intersection operator.

There are generally four types of T-norm operators, which are Minimum, Algebraic product, Bounded product, and Drastic product [12].

T-conorm: T-conorm is defined as a two-place function, which implements the union process of fuzzy sets. This fuzzy union operator can be illustrated as follows:

$$\mu_{A \cup B} = \mu_A(x) + \mu_B(x)$$
 , where + is the binary operator.

Similar to the T-norm, T-conorm has four kinds of operators, which are Maximum, Algebraic sum, Bounded sum, and Drastic sum.

Defuzzification usually is defined as a process weighing and combining numbers of fuzzy sets resulting from the fuzzy inference, which converts fuzzy outputs into crisp values [5]. According to Jiang's description, there are five defuzzification methods, which are Centroid of area (Z_{COA}), Bisector of area (Z_{BOA}), Mean of maximum (Z_{MOM}), Smallest of maximum (Z_{SOM}), and Largest of maximum (Z_{LOM}); Figure 3.4 shows these five defuzzification methods [12].

In this proposed Mamdani FIS, Centroid of Area, Z_{COA} , has been used as a defuzzification method. The following equation is a mathematical definition of the defuzzification method, centroid of area.

$$Z_{COA} = \frac{\int_Z^{\pm} \mu_A(z) z dz}{\int_Z^{\pm} \mu_A(z) dz}, \quad \text{where } \mu_A(z) \text{ is the aggregated output MF.}$$

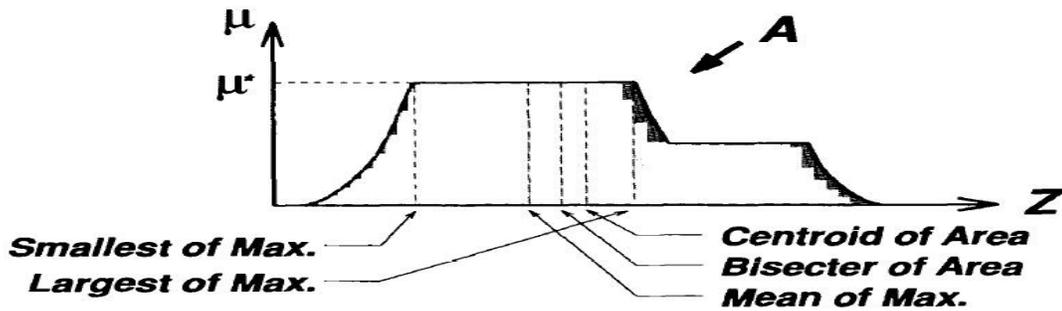


Figure 3. 4 Illustration of five kinds of defuzzification methods [12].

3.3 Introduction of Artificial Neural Network

Emerging from the biological nervous system, Artificial Neural Network (ANN) is an information-processing paradigm. It is the highly interconnected neurons that enable this paradigm to deal with abstract or poorly defined problems [15]. Since 1943, when the neuron was introduced, a large number of ANN models, which all have the same basically neuron sets and interconnection structure, have been proposed. According to the relationship between pipeline failure risk inputs and output risk scores, an adaptive model, which contains built-in adjustable parameters of internal neurons that achieve the goal of desired input-output data sets, is introduced [12]. The basic structure of ANN is shown in Fig.3.5 [15].

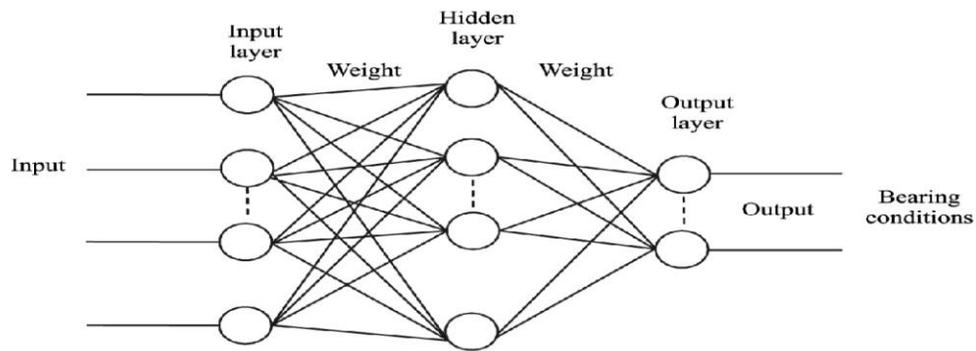


Figure 3. 5 Structure of Artificial Intelligence System [15].

The layers in this structure are constituted by many computational neurons. Every node in this system can produce a specific output according to its input signal, which means the collection of modifiable parameters determines the directly forward relationship between model input and output. There are three groups of layers: input layers, hidden layers, and output layers.

1. Input layer: Each neuron of the input layer receives its own data input signal, and then produces multiple outputs.
2. Hidden layer: Hidden neurons take inputs, which are outputs of the input layer. A weighted sum of outputs, $W_1, W_2, W_3, \dots, W_m$, given from the input layer, is considered as input to every hidden unit, intelligent neuron. These weighted inputs are calculated by function, $u = \sum_{j=1}^m w_j x_j$. The higher weights of artificial neurons will be multiplied by the stronger input. In order to get desired outputs from particular inputs, neurons can utilize the weight adjusting process by algorithms. There are linear and nonlinear neuron functions that can produce different output ranges.
3. Output layer: Each neuron in the output layers is linked by hidden neurons. Weighted outputs, which are calculated by hidden layers, are inputs for the output layer.

Basically, the ANN can be described as a black box which is utilized as an information process tool. A well-trained black box can be used to process input data sets to get desired output data sets. According to the application area, there are a number of different ANN models. However, the most essential and time consuming process of building the ANN model is the network learning or training process to accomplish study and control tasks.

3.4 Summary

A description about two widely recognized Intelligent Systems tools, Fuzzy Inference Systems and Artificial Neural Networks is presented in the chapter. This chapter explains fuzzy sets, fuzzy rules and fuzzy reasoning, Mamdani Fuzzy Inference System, and Artificial Neural Networks, which are the foundation of proposed models. Next chapter presents a completed introduction of the methodology of proposed models.

CHAPTER FOUR: METHODOLOGY

This Chapter presents two risk assessment models for pipeline risk assessment. Each one of these two risk assessment models considers two typical Intelligent Systems techniques: Fuzzy Inference System (FIS) as a sub-model, and also an Artificial Neural Network (ANN) as sub-model. The traditional quantitative relative risk assessment is merely based on a mathematical function, which lacks of experts' knowledge and less practical. Although, the two proposed risk assessment models emerged from traditional pipeline risk relative assessment; here two Intelligent Systems (IS) tools are built in to present an easy-to-use and analytical interface and give a more appropriate result. These two proposed new models combine the mathematical function, experts' knowledge and experience, and intelligence methods, have the following advantages:

1. These sophisticated system methods incorporate the mathematical advantage of calculating inputs by weight, which is based on experts' experience and knowledge [16].
2. This sophisticated system fits the pipeline risk area, which has difficulties of information limitation and internal failure mechanism complexity [24].
3. This sophisticated system also provides comparison results by the Artificial Neural Network, which is trained by given data sets [23].

4.1 First Pipeline Risk Assessment Model

First the Pipeline Risk Assessment (PLRA) model consists of two sub-models, a FIS based risk assessment model and an ANN based model. According to the first definition of risk, $\text{Risk} = \text{Likelihood} * \text{Consequence}$, the FIS based risk assessment model is constituted by Total-likelihood Mamdani FIS model, Consequence Mamdani FIS model,

and PLRA Mamdani FIS model [20], [1], [12]. The ANN based risk assessment model consists of one ANN model. Following sections will give a detailed introduction of these models.

4.1.1 Approach with Fuzzy Inference Systems (FIS)

The first approach proposed here is a mechanism which is not only based on FIS but also incorporates a weighted mathematical process. This approach is built and performed by computer language, Fuzzy Logic Toolbox and GUI on the platform of Matlab [3], [2], [32]. This system also provides an easy-to-use interface, makes it easy to type in different sets of input and display corresponding outputs based on built-in methodology, mathematical weighted process and fuzzy logic. Although it is Matlab that is selected as the platform, it is also important to clarify that this fuzzy logic and mathematical weighted process can be performed and implemented using other computer languages and interfaces.

In order to achieve the goal of the best result, the core of this method, the Fuzzy Inference System, is described as follows:

- 1. Objective:** Different users' goals, such as risk assessment, distributing system design, and activities scheduling, can be reached by completing the system process.
- 2. Environment and condition:** In this step, environment and condition consists of considering all available inputs and parameters. For example, in this proposed model, total-likelihood is calculated by 4 inputs, such as design, incorrect operation, corrosion, and third party damage.

3. System rules setting: As mentioned above, the core of this approach is fuzzy logic, which is based on the if-then rules base. If-then rules setting demonstrates and emerges from the experts' understanding of the pipeline risk assessment

4. Proper weighted function and FIS selection: Proper selection of weighted function and FIS can simulate a more accurate real environmental system.

5. Performing actions: In previous steps, proper inputs, parameters, rules are determined and feed specific inputs to get consequent outputs to achieve desired objectives.

In this proposed model, The Mamdani Fuzzy Inference System [12] is selected to build this FIS base model. The detailed structure building and rules base is attached in Appendix 3 (Rules, Operation methods, Defuzzification and so on).

4.1.1.1 Mamdani FIS based pipeline risk assessment model

Mamdani FIS based pipeline risk assessment model is presented firstly. This FIS model introduces the same input parameters as the parameter in the traditional relative risk score [24]. The Mamdani Fuzzy tool box and GUI programming of Matlab are used to simulate and build this FIS risk assessment model [31], [30].

In the following sections, two mathematical processes and three Mamdani FIS processes of this PLRA model will be presented. The 27 first stage inputs, which are sub-indexes, and subsequent 8 fuzzy inputs constitute a loop system; former stages' outputs are also the next stages' inputs. The overall system can be visually described by Figure 4.1.

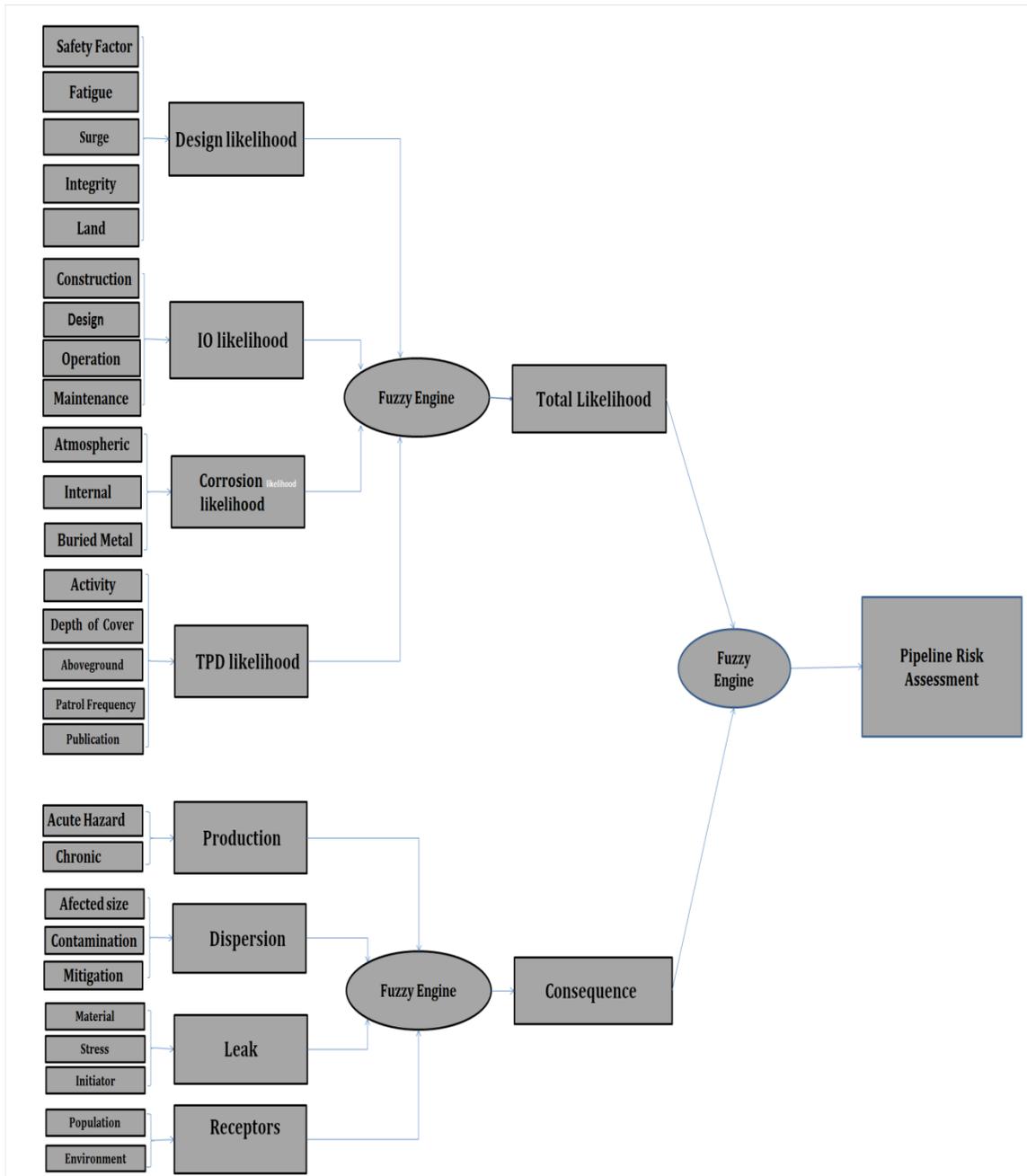


Figure 4. 1 Visual architecture of overall Mamdani FIS PLRA model.

As previously mentioned, this Mamdani Fuzzy Inference System model consists of three sub-Mamdani fuzzy inference models: Total-likelihood model, Consequence model, and Pipeline Risk Assessment model (PLRA). The mechanism of these three Mamdani FIS models is presented as in Figure 4.2, Figure 4.3, and Figure 4.4.

4.1.1.2 Total-likelihood Mamdani FIS model

The Mamdani FIS based model for Total-likelihood consists of two phases: weighted mathematical phase and Mamdani FIS phase. As mentioned in Chapter 2, Total-likelihood Mamdani model has 17 first stage inputs and 4 fuzzy inputs to the fuzzy engine for Total-likelihood.

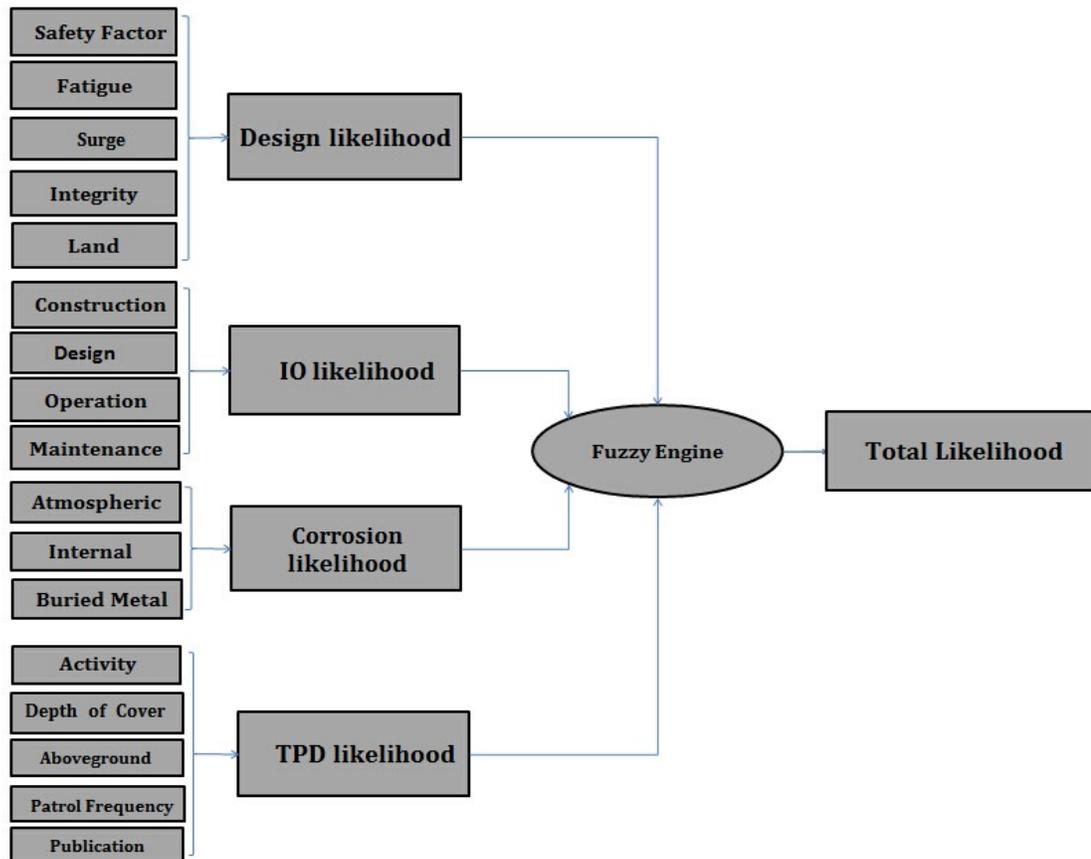


Figure 4. 2 Visual architecture of Total-likelihood Mamdani FIS model.

1. **First stage inputs:** *Safety factor, Fatigue, Surge potential, Integrity, Land movement, Construction, Design, Operation, Maintenance, Atmospheric corrosion, internal corrosion, buried metal (subsurface) corrosion, Activity, Depth of cover, Aboveground facilities, Patrol frequency, and Publication Education* [24]. These 17 first

inputs are scored from 1 to 4 by experts' estimation which comes from their knowledge and experience.

2. Fuzzy Inputs: *Design likelihood, Incorrect Operation likelihood, Corrosion likelihood, and Third Party Damage.*

This Total-likelihood model consists of two phases as follows:

Phase-1- Mathematical process:

There are 17 first stage inputs that are fed to the mathematical phase. As mentioned above, these inputs have their weight in this process. According to experts' experience and knowledge, estimated scores are assigned to the 17 first stage inputs

As explained in chapter 2.1.1, estimated scores of Safety Factor, Fatigue, Surge Potential, Integrity, and Land Movement are fed by weight, 35%, 15%, 10%, 25%, and 15%, respectively, to mathematical function to get fuzzy inputs, Design likelihood. This process can be described as mathematical function: $\text{Safety Factor} \times 0.35\% + \text{Fatigue} \times 0.15\% + \text{Surge Potential} \times 10\% + \text{Integrity} \times 25\% + \text{Land Movement} \times 15\% = \text{Design likelihood}$ [24]. It is important to mention that this numerical score gives experts an initial brief score for Design likelihood, which can be adjusted by experts according to specific conditions to which this model is applied. Other three fuzzy inputs, Incorrect Operation likelihood, Corrosion likelihood, and TPD likelihood, can be calculated by their weighted inputs like the method to get Design likelihood. The other 12 first stage inputs for the Total-likelihood model's weight have been described in Chapter 2.

Phase-2- Mamdani FIS:

The four fuzzy inputs, which are calculated from mathematical phase 1 (outputs of phase-1), have four attributes: Very Low, Low, High, and Very High, considering the

model's sensitivity and complexity. These four inputs will be calculated using built-in fuzzy if-then rules to get output Total-likelihood, which has values of Very Low, Low, High, and Very High as well. It has been introduced that Gaussian membership function is selected as the membership function due to its smooth and gradual transition. The rule based in built by 256 fuzzy rules. The Matlab Mamdani FIS model and if-then rules are provided in Appendix.

4.1.1.3 Consequence Mamdani FIS model

In this Consequence Mamdani FIS based model, similar to Total-likelihood FIS model, it consists of two phases, weighted mathematical phase and Mamdani FIS phase. As mentioned in Chapter 2, Consequence Mamdani model has 10 first stage inputs and 4 fuzzy inputs [24]. The rule base is built by 256 fuzzy rules as well. This Consequence model has a same working mechanism and structure as the Total-likelihood model. The overall system of Consequence Mamdani FIS model can be visually described by Figure 4.3

1. First stage Inputs: *Acute Hazard, Chronic Hazard, Affected Size, Contamination, Mitigation, Material, Stress, Initiator, Population, and Environment* [24]. Similar to previously presented in the Total-Likelihood model, these 10 first stage inputs, sub-indexes, are scored from 1 to 4 by experts, whose estimations based on their knowledge and experience.

2. Fuzzy Inputs: *Production Hazard, Dispersion, Leak, Receptors* [24]. This Consequence FIS model has the same two phases as the previous Total-likelihood FIS model.

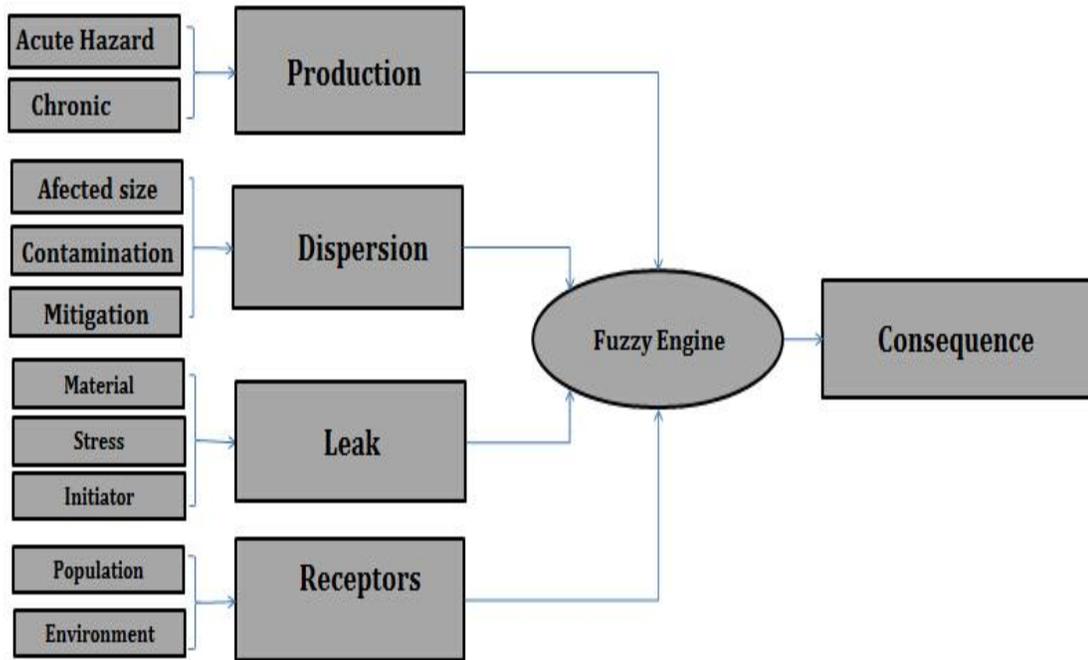


Figure 4. 3 Visual architecture of Consequence Mamdani FIS model.

4.1.1.4 Pipeline Risk Assessment (PLRA) Mamdani FIS model

This PLRA Mamdani FIS model is the last step of this FIS based risk assessment system. This model has two fuzzy inputs, Total-likelihood and Consequence, which are outputs of the Total-likelihood FIS model and the Consequence FIS model, respectively.

Similar to the previously explained FIS models, these two fuzzy inputs are adjustable. Expert knowledge and experience can be applied to get some inputs, which can better represent the real environment, for the PLRA FIS model. This PLRA Mamdani FIS model has only a fuzzy phase, which is different from the previous two FIS models which have a mathematical phase and fuzzy phase. The output, PLRA score, is the result of this PLRA mode, and also the final risk score of this whole pipeline risk rank.

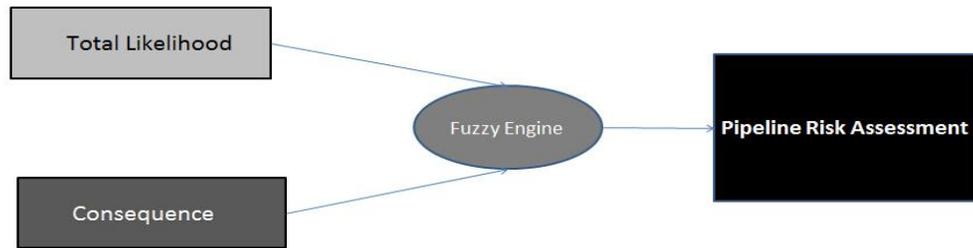


Figure 4. 4 Visual architecture of PLRA Mamdani FIS model.

In the above sections, two mathematical processes and three Mamdani FIS processes of this PLRA model have been presented. The 27 first stage inputs, sub-indexes, and subsequent 8 fuzzy inputs constitute an information forward system; the outputs of former stages are fed into the next stages as inputs. The overall system can be visually described by Figure 4.4

4.1.2 Approach with Artificial Neural Network

The second pipeline risk assessment methodology is based on the Artificial Neural Network (ANN). Matlab Neural Network Toolbox is used to program this ANN based pipeline risk assessment model. The ANN model will consider only eight inputs instead of 27 first stage inputs, which it will be useful as a simpler mode; and the Artificial Neural Network's black box characteristic can effectively deal with complicated inner working mechanism which can provide experts with a completed risk reference [12], [18]. Programming and the Matlab interface are provided in Appendix 6. Generally, there are four steps involved in building an ANN model:

Step 1- Neural Network Design

In this step, ANN factors need to be designed, which include determining number of layers, nodes in each layer, and node structure.

Step 2 – Neural Network Training

In order to have an accurate model to produce a meaningful result, this ANN model needs to be trained to have a mature black box process that creates reliable outputs. In this step, specific input and output data are created by the previously built Mamdani model. After enough training, this ANN based pipeline risk assessment model is eligible to provide experts with a reliable risk score, which is also a comparison of Mamdani based output.

Step 3 –Performing Actions

In step 1 and step 2, the architecture of ANN has been determined, and it has been well trained. It is ready to simulate the risk assessment process: to feed specific inputs to get consequent outputs.

4.1.2.1 Artificial Neural Network based pipeline risk assessment model

It has been widely acknowledged that the ANN model has the advantage of calculating inputs without a clear defined internal working mechanism. As the difficulty of pipeline risk assessment is described in previous chapters, the ability of solving the lack of an internal risk working mechanism is the core of any pipeline risk assessment model. The ANN based pipeline risk assessment model is eligible to get accurate outputs through a black box process. Therefore, it is a necessary step to feed existing inputs and outputs to train existing ANN model to get a mature ANN model.

Based on previously presented pipeline risk assessment parameters in Chapter 2, this ANN based PLRA model has eight inputs: *Design likelihood*, *Incorrect Operation*

likelihood, Corrosion likelihood, Third Party Damage likelihood, Production Hazard, Dispersion, Leak, and Receptors. In this proposed ANN model, each of these eight input sets has 50 scores, in the format X_{ij} and Y_{ij} , and one set of output. X_{ij} and Y_{ij} , stand for likelihood model and consequence model, respectively, where i is the number of these eight inputs and j is the number of data in each set.

$$\text{Design likelihood} = \{X_{11}, X_{12}, X_{13}, \dots, X_{150}\}$$

$$\text{Incorrect Operation likelihood} = \{X_{21}, X_{22}, X_{23}, \dots, X_{250}\}$$

$$\text{Corrosion likelihood} = \{X_{31}, X_{32}, X_{33}, \dots, X_{350}\}$$

$$\text{Third Party Damage likelihood} = \{X_{41}, X_{42}, X_{43}, \dots, X_{450}\}$$

$$\text{Production Hazard} = \{Y_{11}, Y_{12}, Y_{13}, \dots, Y_{150}\}$$

$$\text{Dispersion} = \{Y_{21}, Y_{22}, Y_{23}, \dots, Y_{250}\}$$

$$\text{Leak} = \{Y_{31}, Y_{32}, Y_{33}, \dots, Y_{350}\}$$

$$\text{Receptors} = \{Y_{41}, Y_{42}, Y_{43}, \dots, Y_{450}\}$$

The visual architecture of this ANN based pipeline risk assessment model is presented as follows in Figure 4.5. The programming process and architecture, which include a number of layers and neurons, training function, are also provided in Appendix 6. It is important to mention that this ANN based PLRA model is different from the previously presented Mamdani FIS model. The difference is that the ANN model shares the same values of these eight inputs as the previous Mamdani FIS model fuzzy inputs, in order to reduce the complexity of this ANN model.

Considering the internal complexity of pipeline failure, the Feedforward back-propagation is introduced to simulate the pipeline risk process. If neurons of the neural network are not connected in the form of a directed cycle, which means information only moves forward, the neural network is defined as a Feedforward neural network [12]. The procedure of finding a gradient vector in a network structure is generally referred to as back-propagation, where derivatives of output layers and hidden layers can be calculated recurrently. The Network learning process is implemented by the back-propagation process [12]. Therefore, the Feedforward back-propagation network is a Feedforward neural network, being trained by the back-propagation method. In this Feedforward Backpropagation system, each layer has weights coming from previous layers. The proposed ANN model in this thesis contains 4 layers: 1 input layer, 2 hidden layers, and 1 output layer. The “purelin” is selected as the transfer function. In order to achieve the goal of the training process, the “trainlm” function, Levenberg-Marquardt algorithm, is selected as the training function in Neural Network Toolbox in Matlab [3]. The “Min and Max” method is introduced to scale the inputs and targets to determine the certain specified range of these values to make the training process efficient.

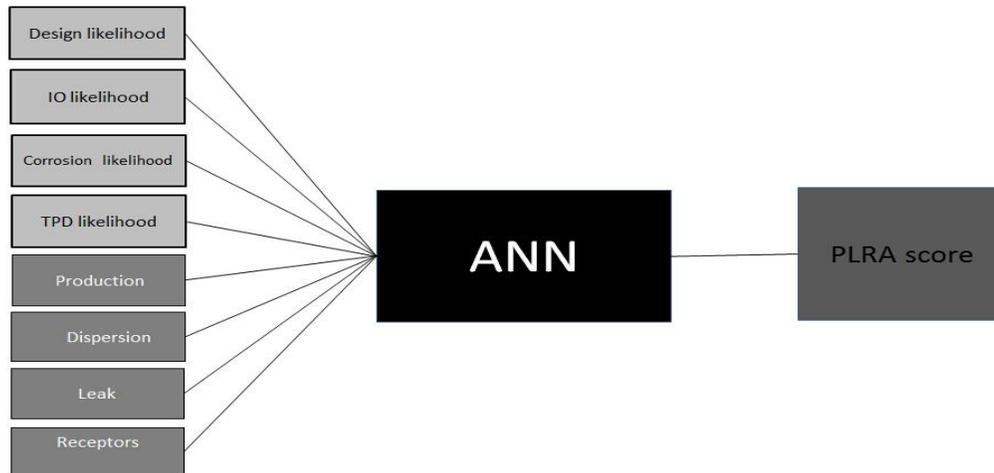


Figure 4. 5 ANN based PLRA model.

4.2 Second Pipeline Risk Assessment Model

Based on the second definition of risk, Risk= Vulnerability* Threat* Consequence, the second Pipeline Risk Assessment Model is built in this section. Similar to the first pipeline risk assessment model, the structure of the second Pipeline Risk Assessment Model is constituted by two sub-models, the FIS based risk assessment model, and the ANN based model. In order to have a better simulation of pipeline risk assessment process and provide experts with a more reliable and confident risk score, the FIS based risk assessment model is constituted by the Vulnerability Mamdani FIS model, the Threat Mamdani FIS model, the Consequence Mamdani FIS model, and the PLRA-2 Mamdani FIS model. The ANN based risk assessment model has a similar structure to the first ANN model.

4.2.1 Approach with Fuzzy Inference Systems (FIS)

The first approach proposed here for the Second Pipeline Risk Assessment Model is a mechanism, which is based on FIS and a weighted mathematical process, similar to the

first model. In this second Pipeline Risk Assessment Model, the Fuzzy Logic Toolbox [31] and GUI of Matlab [30] are introduced to build this model.

The second FIS model is described by the following sequences: Objective, Environment and condition, System rules setting, Proper weighted function and FIS selection, and Performing actions.

In this second proposed model, The Mamdani Fuzzy Inference System is selected to build this FIS based model as well. The detailed structure building and rules base are attached in Appendix 3 (Rules, Operation methods, Defuzzification and so on).

4.2.1.1 Mamdani FIS based Pipeline Risk Assessment model

Similar to the first Pipeline Risk Assessment model (PLRA), the Mamdani FIS based pipeline risk assessment model is presented first.

Three mathematical processes and four Mamdani FIS models constitute the second PLRA model, as Figure 4.6. There are 27 first stage inputs and subsequent fuzzy inputs that constitute a forward system; former stages' outputs are fed to the next stages as inputs. The structure of this second PLRA model can generally be described: the 27 first stage inputs are fed into the mathematical calculation processes, and then the outputs of the mathematical process are translated into fuzzy linguistic terms, which will be fed to the Vulnerability Mamdani model, the Threat Mamdani model, and the Consequence Mamdani model as fuzzy inputs. After these first three fuzzy processes, each Mamdani FIS model, mentioned above, generates one fuzzy output, which will be fed to the last PLRA-2 Mamdani FIS model as inputs. The last step involves the PLRA-2 Mamdani FIS

model generating the final pipeline risk score, which ranges from 1 to 64. The PLRA-2's structure can be illustrated by Figure 4.6.

4.2.1.2 Vulnerability Mamdani FIS model

This Vulnerability Mamdani FIS model consists of two phases: weighted mathematical phase and Mamdani FIS phase. As mentioned in the previous chapter, the Vulnerability Mamdani model has 9 first stage inputs, sub-indexes, which will be fed to the weighted mathematical calculation process; 2 fuzzy inputs, which are outputs of the former weighted mathematical process. Figure 4.7 shows the general structure and process of this Vulnerability Mamdani FIS model.

1. First stage inputs: The *Safety factor, Fatigue, Surge potential, Integrity, and Land movement* are fed into the Design weighted mathematical process; The *Construction, Design, Operation, and Maintenance* are fed into the Incorrect Operation mathematical process; these 9 first stage inputs are scored from 1 to 4 by experts, whose estimation comes from their knowledge and experience.

2. Fuzzy Inputs: There are two fuzzy inputs: *Design and Incorrect Operation*.

This Vulnerability Mamdani FIS model consists of two phases as follows:

Phase-1- Mathematical process:

Those 9 first stage inputs are fed into the mathematical phase. As mentioned above, these inputs have their own weight percentage, in this process, as explained in Chapter 2. According to experts' experience and knowledge, estimated scores are assigned to the 9 first stage inputs

In the Design mathematical process, estimated scores of Safety Factor, Fatigue, Surge Potential, Integrity, and Land Movement are fed by weight percentage, 35%, 15%, 10%, 25%, and 15%, respectively, to get fuzzy input, Design [24]. This process can be described by the following mathematical function: $\text{Safety Factor} \times 0.35\% + \text{Fatigue} \times 0.15\% + \text{Surge Potential} \times 10\% + \text{Integrity} \times 25\% + \text{Land Movement} \times 15\% = \text{Design}$, the Incorrect Operation = $\text{Construction} \times 20\% + \text{Design} \times 30\% + \text{Operation} \times 35\% + \text{Maintenance} \times 15\%$, [24]. Fuzzy inputs, Design and Incorrect Operation, can be adjusted by considering different situations.

Phase-2- Mamdani FIS:

The four fuzzy inputs, which are calculated by the mathematical phase (outputs of phase-1), have four ranges: Very Low, Low, High, and Very High, considering the model's sensitivity. These two inputs will be measured using built-in fuzzy if-then rules to get output Vulnerability, which has values of Very Low, Low, High, and Very High as well. The Gaussian membership function is selected as the membership function. The rule base is built using 16 fuzzy rules. The Matlab Vulnerability Mamdani FIS model and if-then rules are provided in Appendix 3.

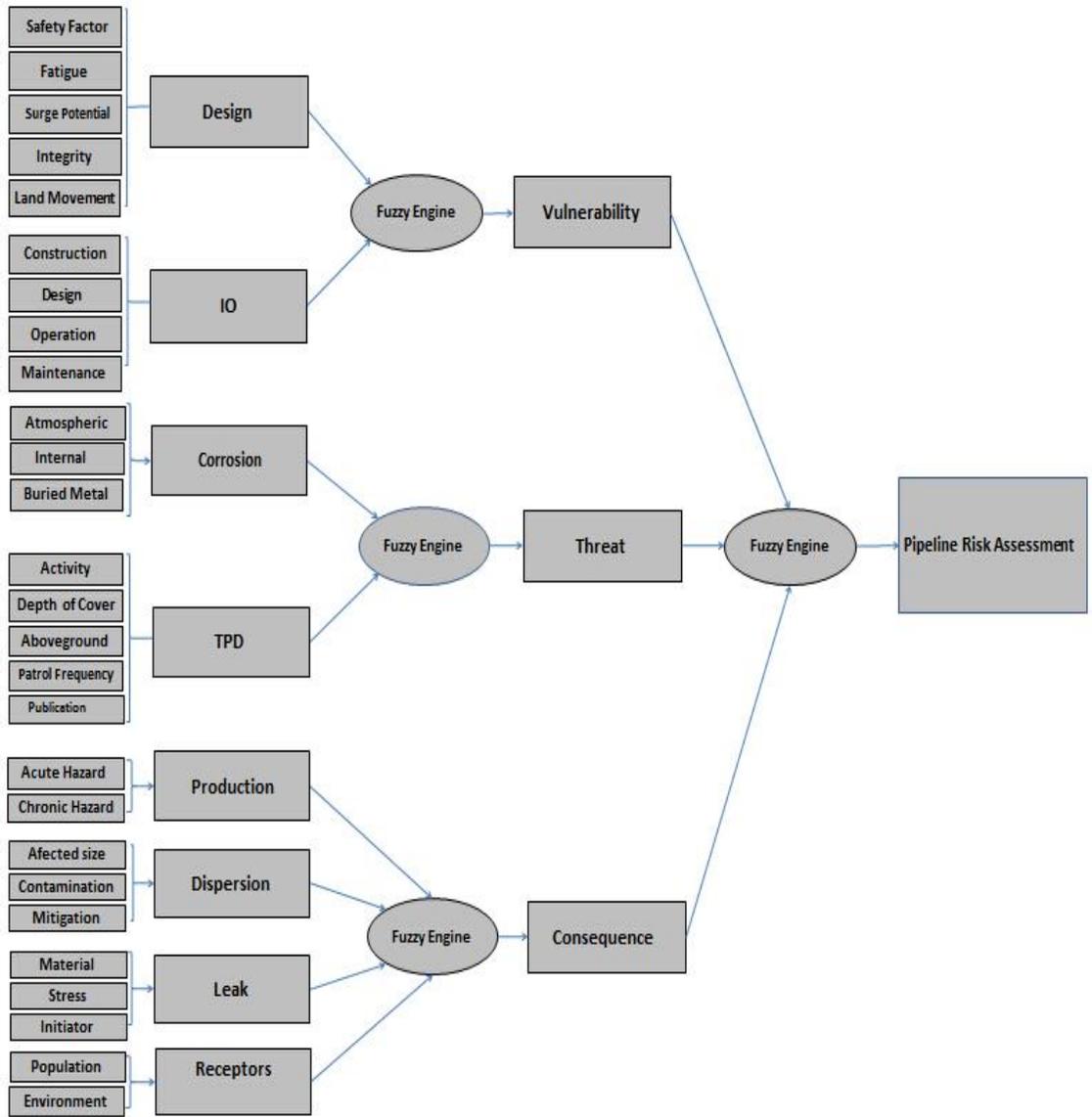


Figure 4. 6 Visual architecture of overall Mamdani FIS PLRA-2 model.

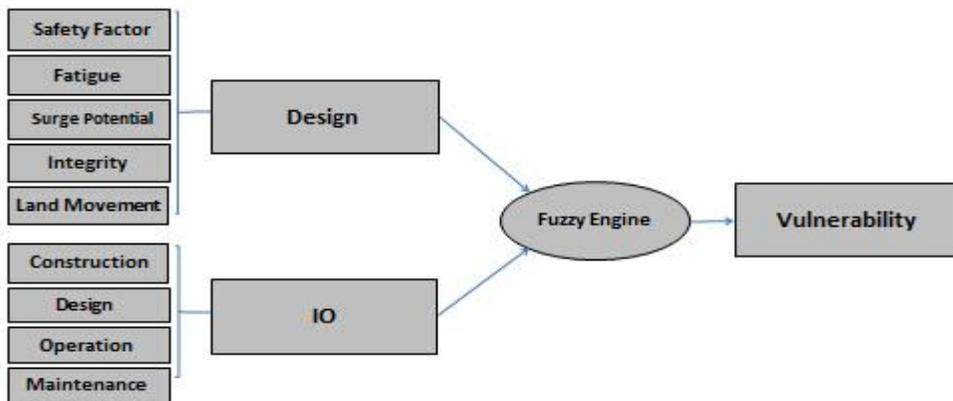


Figure 4. 7 Vulnerability Mamdani FIS model.

4.2.1.3 Threat Mamdani FIS model

This Threat Mamdani FIS based model consists of two phases: weighted mathematical phase and Mamdani FIS phase. As mentioned in Chapter 2, the Threat Mamdani FIS model has 8 first inputs and 2 fuzzy inputs. The rule base is built using 16 fuzzy rules. As the Threat model has a similar working mechanism and structure to the Vulnerability model, detailed introduction of the architecture is not presented here. Figure 4.7 gives a brief illustration of the Threat Mamdani FIS model.

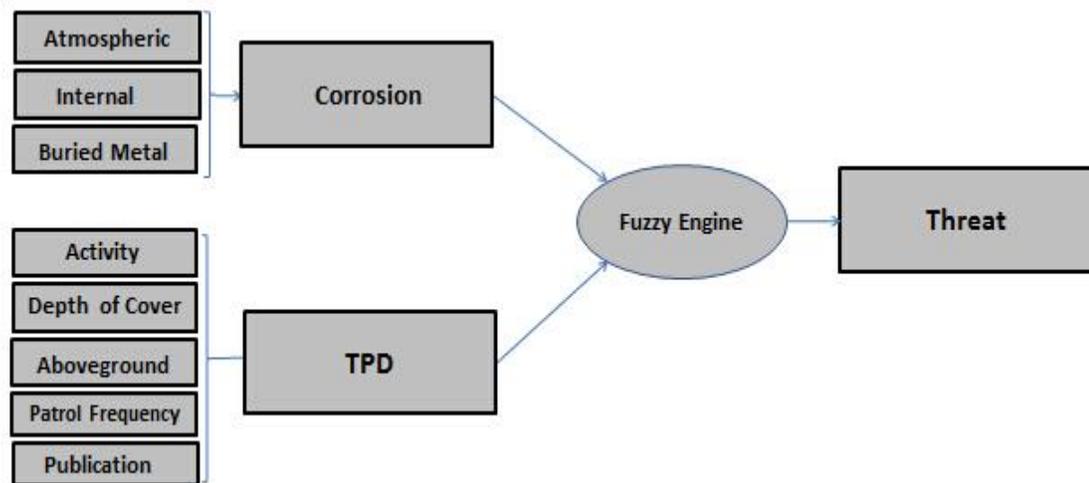


Figure 4. 8 Threat Mamdani FIS model.

1. First Inputs: The *Atmospheric Corrosion*, *Internal Corrosion*, and *Buried Metal (Subsurface) Corrosion* are fed into the Corrosion mathematical process. The *Activity*, *Depth of Cover*, *Aboveground Facilities*, *Patrol Frequency*, and *Publication Education* are fed into the following Third Party Damage mathematical process. These 8 first inputs are scored from 1 to 4 by experts, whose estimation comes from their knowledge and experience.

2. Fuzzy Inputs: There are two fuzzy inputs, *Corrosion and Third Party Damage*, which are scored from 1 to 4. Similar to the Vulnerability Mamdani FIS model, the fuzzy

inputs, Corrosion and Third Party Damage values, can be adjusted by experts' personal experience to better represent specific situations.

This Threat Mamdani FIS model is constituted by two phases: mathematical process phase and Mamdani FIS phase. These two phases are similar to previously built phases in the Vulnerability Mamdani FIS model. In the weighted mathematical process, $\text{Corrosion} = \text{Atmospheric Corrosion} * 10\% + \text{Internal Corrosion} * 20\% + \text{Buried Metal Corrosion} * 70\%$; $\text{Third Party Damage} = \text{Activity} * 25\% + \text{Depth of Cover} * 25\% + \text{Aboveground Facilities} * 10\% + \text{Patrol Frequency} * 20\% + \text{Publication Education} * 20\%$ [24]. In the FIS phase, fuzzy inputs, Corrosion and Third Party Damage, and fuzzy outputs Threat can be represented by linguistic terms, Very Low, Low, High, and Very High. The Matlab Threat Mamdani FIS model and if-then rules are provided in Appendix.

4.2.1.4 Consequence Mamdani FIS model

In this second Pipeline Risk Assessment model, the Consequence phase has the same structure as in the first Pipeline Risk Assessment model. Detailed introduction is not presented here to avoid unnecessary narration. The Matlab Consequence Mamdani FIS model and if-then rules are provided in Appendix.

4.2.1.5 Pipeline Risk Assessment (PLRA)-2 Mamdani FIS model

This PLRA-2 Mamdani FIS model is the last FIS model in the second Pipeline Risk Assessment model. The PLRA-2 includes three fuzzy inputs, Vulnerability, Threat, and Consequence, which are outputs of their corresponding FIS models, the Vulnerability Mamdani FIS model, the Threat Mamdani FIS model, and the Consequence Mamdani FIS model, respectively. In this model, only the fuzzy phase is introduced, and the rule

base is built using 256 fuzzy if-then rules. The detailed rule base and operation is attached in appendix. Figure 4.8 shows the basic structure of PLRA-2 model.

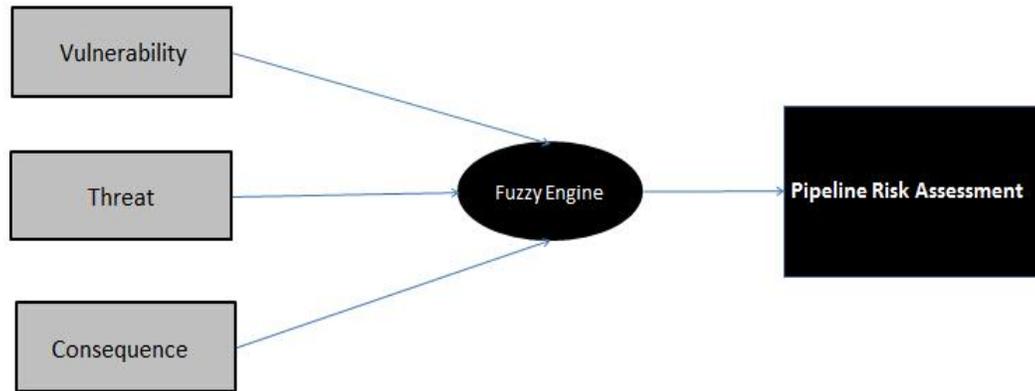


Figure 4. 9 PLRA-2 Mamdani FIS model.

These three fuzzy inputs, Vulnerability, Threat, and Consequence can also be adjusted by experts' knowledge and experience to get more real environment inputs for PLRA FIS model. The output, PLRA score, is the result of this PLRA-2 model and also the final risk score of this whole pipeline risk rank.

4.2.2 Approach with Artificial Neural Network

In order to provide a more reliable risk score, the Artificial Neural Network (ANN) based pipeline risk assessment model is built in the second Pipeline Risk Assessment model. The ANN model will consider only eight inputs instead of 27 first stage inputs, which it will be useful as a simpler mode. However, these eight different are different from the inputs in the first ANN model; and Artificial Neural Network's black box characteristic can effectively deal with unclear inner working mechanism which can provide experts with a completed risk reference The Matlab Neural Network Toolbox is

used to program this ANN based pipeline risk assessment model. Detailed Programming and Matlab interface are provided in Appendix 6. Building an ANN model consists of four basic steps: Neural Network Design, Neural Network Training, and Performing Actions. Detailed introduction of these four steps have been proposed in Chapter 4.1.2.

4.2.2.1 Artificial Neural Network based pipeline risk assessment model

The advantage of building an ANN based pipeline risk assessment model has been explained before. Based on the previously built second Mamdani FIS based Pipeline Risk Assessment model, this ANN based PLRA model incorporates eight inputs: *Design, Incorrect Operation, Corrosion, Third Party Damage, Production Hazard, Dispersion, Leak, and Receptors*. In this proposed ANN model, as Fig. 4.10, each of these eight input sets has 50 scores, in the format X_{ij} and Y_{ij} , and one set of output. X_{ij} and Y_{ij} , stand for likelihood model and consequence model, respectively, where i is the number of these eight inputs and j is the number of data in each set.

$$\text{Design} = \{X_{11}, X_{12}, X_{13}, \dots, X_{150}\}$$

$$\text{Incorrect Operation} = \{X_{21}, X_{22}, X_{23}, \dots, X_{250}\}$$

$$\text{Corrosion} = \{Y_{11}, Y_{12}, Y_{13}, \dots, Y_{150}\}$$

$$\text{Third Party Damage} = \{Y_{21}, Y_{22}, Y_{23}, \dots, Y_{250}\}$$

$$\text{Production Hazard} = \{Z_{11}, Z_{12}, Z_{13}, \dots, Z_{150}\}$$

$$\text{Dispersion} = \{Z_{21}, Z_{22}, Z_{23}, \dots, Z_{250}\}$$

$$\text{Leak} = \{Z_{31}, Z_{32}, Z_{33}, \dots, Z_{350}\}$$

$$\text{Receptors} = \{Z_{41}, Z_{42}, Z_{43}, \dots, Z_{450}\}$$

This ANN based pipeline risk assessment model has a similar structure to the ANN model in the first pipeline risk assessment model. The Feedforward Backpropagation, which has been explained before, is introduced to simulate the pipeline risk process. In this Feedforward Backpropagation system, each layer has weights coming from previous layers. The proposed ANN model in this thesis contains 4 layers: 1 input layer, 2 hidden layers, and 1 output layer. There are 8 neurons in the input layer; there are 3 neurons in the first hidden layer and 2 neurons in the second; there is also 1 neuron in the output layer. The “purelin” is selected as the transfer function. In order to achieve the goal of the training process, the “trainlm” function, Levenberg- Marquardt algorithm, is selected as the training function in Neural Network Toolbox in Matlab. The “Min and Max” method is introduced to scale the inputs and targets to determine the certain specified range of these values to make the training process efficient. The training data sets are produced by the previously built FIS model.

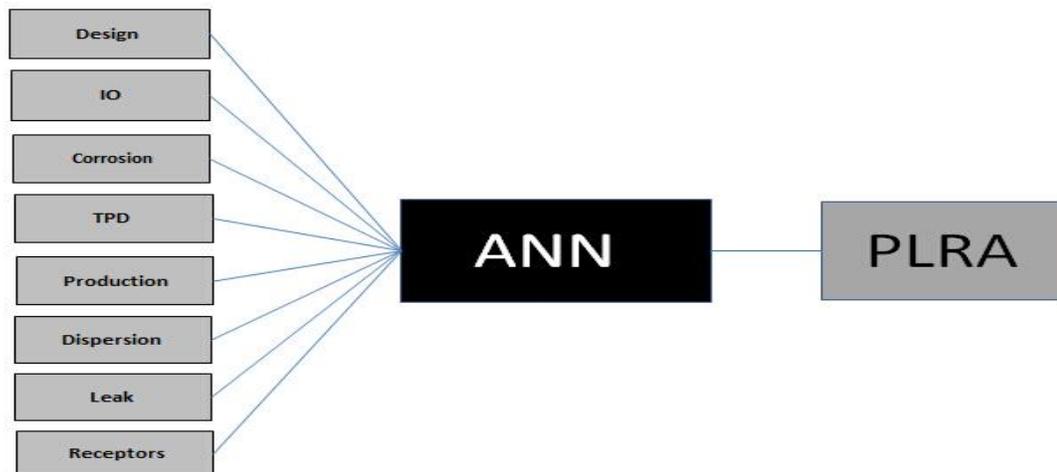


Figure 4. 10 Second ANN based model.

4.3 Summary

In this Chapter, two pipeline risk assessment models, first Pipeline Risk Assessment model and second Pipeline Risk Assessment model, have been presented to represent two risk definitions, “Likelihood and Consequence” and “Vulnerability, Threat, and Consequence”.

In the first Pipeline Risk Assessment model, two sub-models are considered: Mamdani FIS based Pipeline Risk Assessment model and Artificial Neural Network based Pipeline Risk Assessment model. The Mamdani FIS based Pipeline Risk Assessment model is constituted by Total-likelihood, Consequence, and PLRA FIS models.

The second Pipeline Risk Assessment model also considers two sub-models: Mamdani FIS based Pipeline Risk Assessment model and the Artificial Neural Network based Pipeline Risk Assessment model. The Mamdani FIS based Pipeline Risk Assessment model is constituted by Vulnerability, Threat, Consequence, and PLRA-2 FIS models.

It is necessary to mention that each one of the two proposed Pipeline Risk Assessment models is based on the Fuzzy Inference System methodology and the Artificial Neural Networks methodology. Different results measured by these two methodologies are used to provide a reliable risk rating for experts. Different simulation results are presented in the next chapter.

Next chapter presents and analyzes the different scenarios of experimental results from proposed two Mamdani FIS Pipeline Risk Assessment and two ANN Pipeline Risk Assessment models.

CHAPTER FIVE: RESULTS AND ANALYSIS

This chapter presents the experimental results obtained from the previously proposed two Mamdani FIS Pipeline Risk Assessment and the two ANN Pipeline Risk Assessment models. Results from different scenarios for each model are measured and analyzed. The chapter is presented by the sequence of scenarios' implementing sequence of two Pipeline Risk Assessment models. In each of these two models, their inner scenarios are implemented as follows:

For the first Pipeline Risk Assessment model, firstly, the Mamdani Fuzzy Inference System (FIS) based pipeline risk assessment model simulates the pipeline risk assessment process and presents four scenarios of results, which are analyzed to test the accuracy of this method. Different sets of first stage inputs are fed into the system and then obtain corresponding outputs of Total-likelihood and Consequence, which are fed into the PLRA fuzzy process to get a final PLRA score; Secondly, the Artificial Neural Network (ANN) based Pipeline risk assessment procedure is fed directly with different input sets of Total-likelihood and Consequence to get the final PLRA score. The ANN based model's results are compared with results, which are obtained from the FIS based model, to prove the accuracy of the proposed methodology and give experts more reliable results.

For the second Pipeline Risk Assessment model, the Mamdani FIS based pipeline risk assessment model is implemented to simulate two scenarios. Then, the Artificial Neural Network based model is trained by feeding training data sets, which are calculated by the

FIS based model. The results from the ANN based model are compared with results obtained from the FIS based model are also presented.

This Chapter is organized as follows:

1. Application of proposed methodology, presented in Chapter 4, to different scenarios to obtain different risk score results.
2. According to different results' sets created by various pipeline failure risk situations, observation and analysis of results from different scenarios are presented.
3. Summary of experimental results analysis.

5.1 Mamdani FIS model of the first Pipeline Risk Assessment model

The Matlab software and its Fuzzy Logic Toolbox [31] are selected as the platform to implement the proposed Mamdani FIS pipeline risk assessment model presented in Chapter 4. Further detailed Fuzzy Logic Toolbox operation, including rules base, and implementation are provided in Appendix 3, 4 and 5.

As described in Chapter 4, the four mathematical input mechanisms, Design Likelihood, IO likelihood, Corrosion, and TPD likelihood, of the first Mamdani FIS model are described in Figure 5.1. The Total-likelihood Mamdani FIS model (Matlab Fuzzy Toolbox) is presented in Figure 5.2, which gets output Total-likelihood for the third Mamdani FIS model. The Total-likelihood fuzzy phase is built in GUI as explained in last Chapter. Figure 5.3 shows the GUI Total-likelihood fuzzy phase. The estimated values, range from 1 to 5, of 27 first stage inputs can be typed in manually; Pre-adjusted Fuzzy inputs which obtained from previous mathematical and their risk attributes are displayed on the left sides of the fuzzy bars; in order to get more realistic risk scores, pre-adjusted fuzzy inputs can be adjusted by

sliders and displayed on the right side of the fuzzy bars

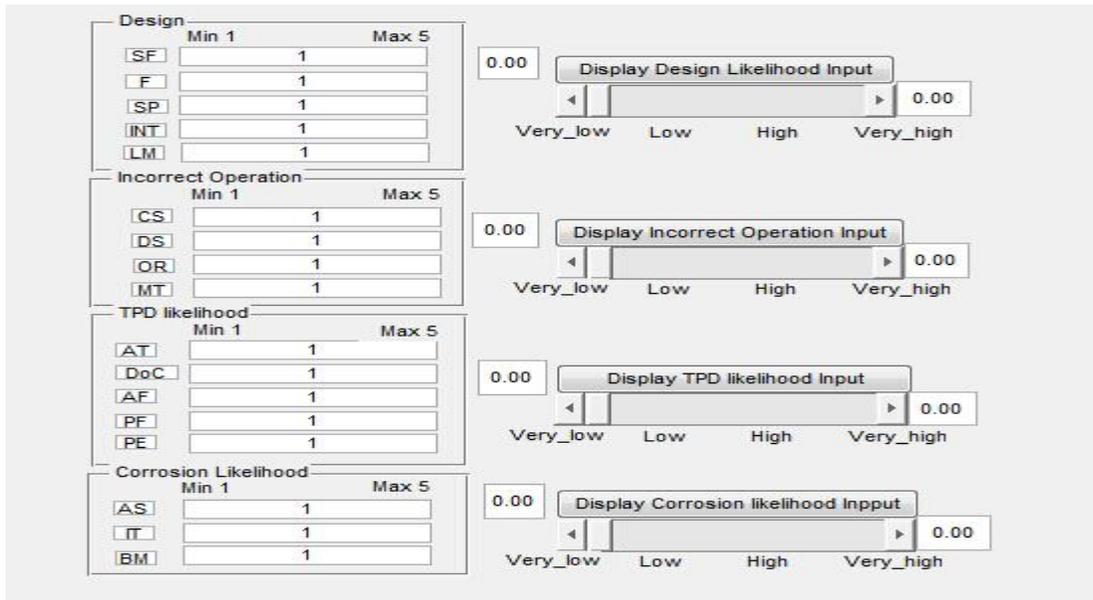


Figure 5. 1 First Mathematical Inputs Mechanism (GUI).

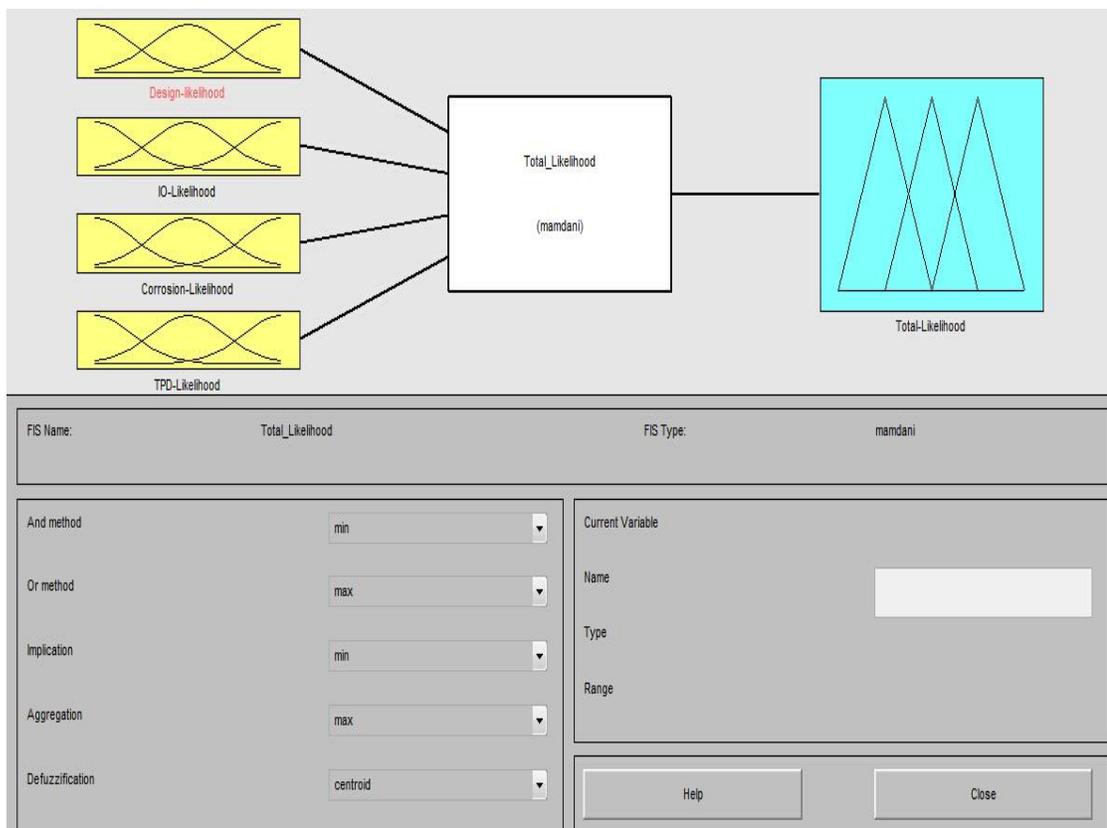


Figure 5. 2 Total-likelihood Mamdani FIS model.

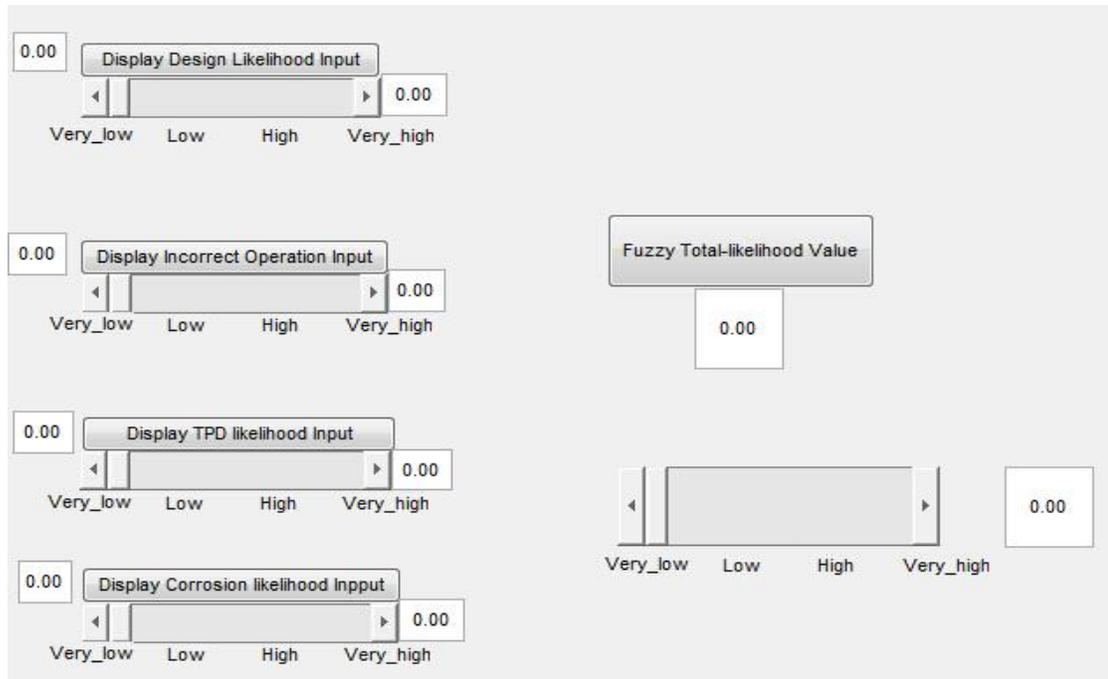


Figure 5. 3 Total-likelihood FIS process GUI implementation.

As proposed in Chapter 4, the second Mamdani FIS model is the Consequence Model. In this model, it also consists of four mathematical input mechanisms, Product Hazard, Dispersion, Leak, and Receptors, of the second Mamdani FIS model is described in Figure 5.4. The mathematical given inputs are fed into the next FIS process. The Consequence Mamdani FIS model (Matlab Fuzzy Toolbox) is presented in Figure 5.5, which produces Consequence as an output for the third Mamdani FIS model. Similar to the previous Total-likelihood model, The Consequence fuzzy phase is also built using the GUI of Matlab, Figure 5.6 shows the GUI Consequence fuzzy phase.

The last presented Mamdani FIS model, in this FIS based pipeline risk assessment system, is the PLRA model that incorporates two inputs, Total-likelihood and Consequence, to calculate the final PLRA score. In this last step, it does not have the mathematical input process; only the Mamdani FIS process is implemented. PLRA inputs can also be adjusted by sliders. This PLRA Mamdani FIS is illustrated in Figure 5.7 and 5.8.

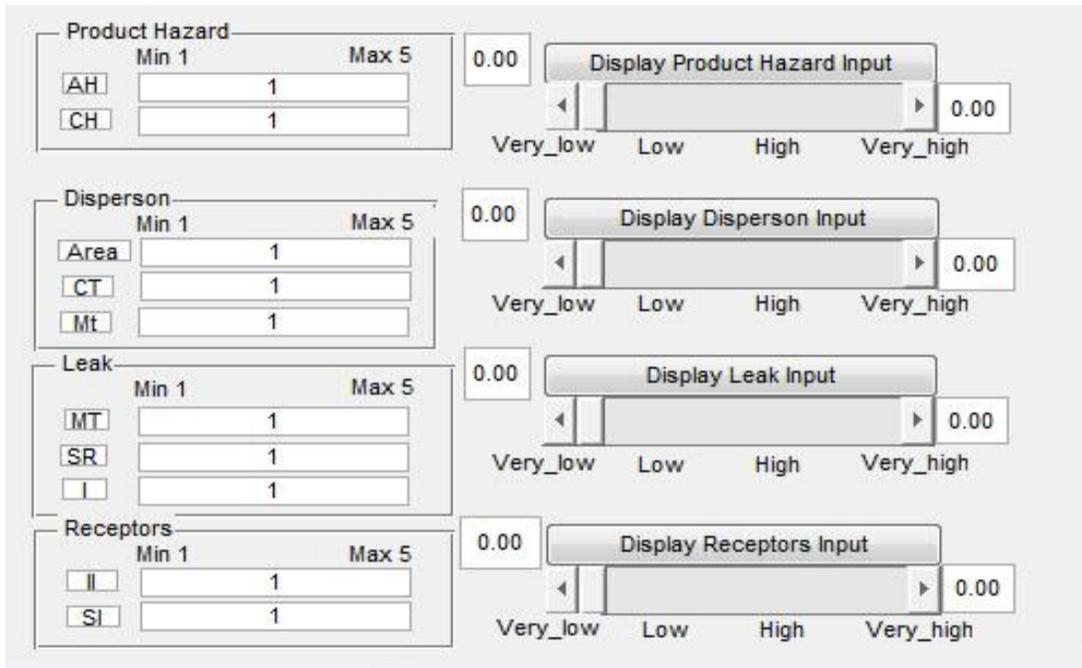


Figure 5. 4 Second Mathematical Inputs Mechanism (GUI).

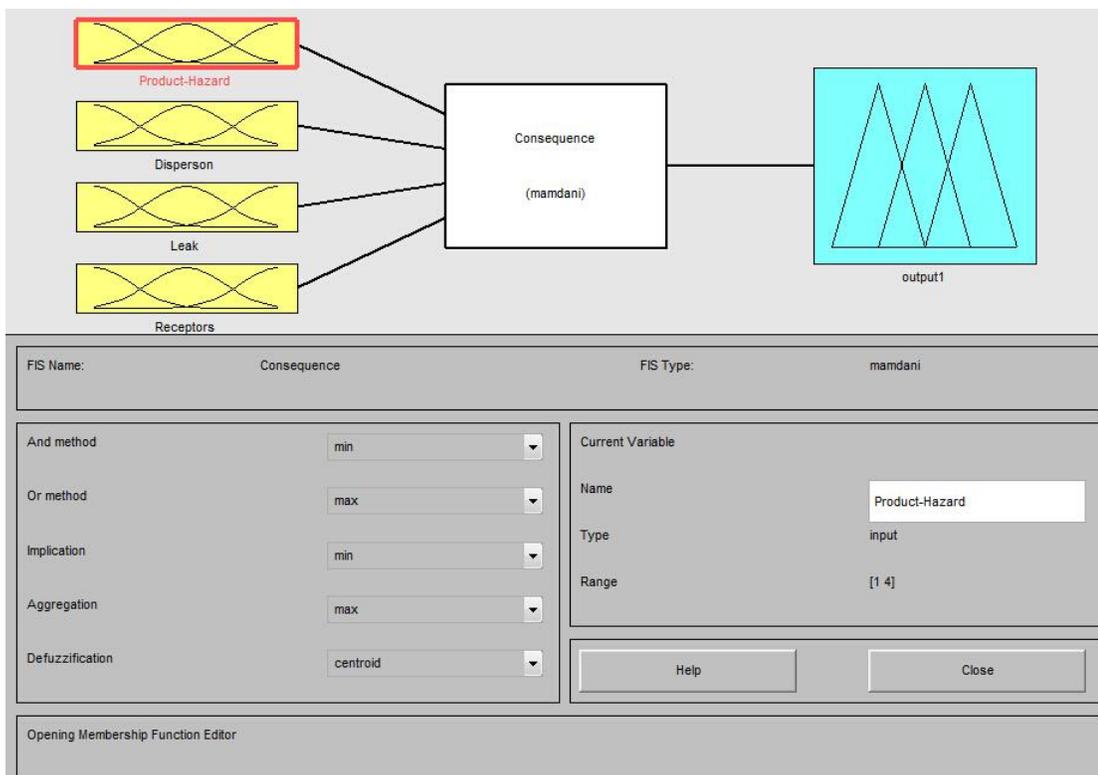


Figure 5. 5 Consequence Mamdani FIS model.

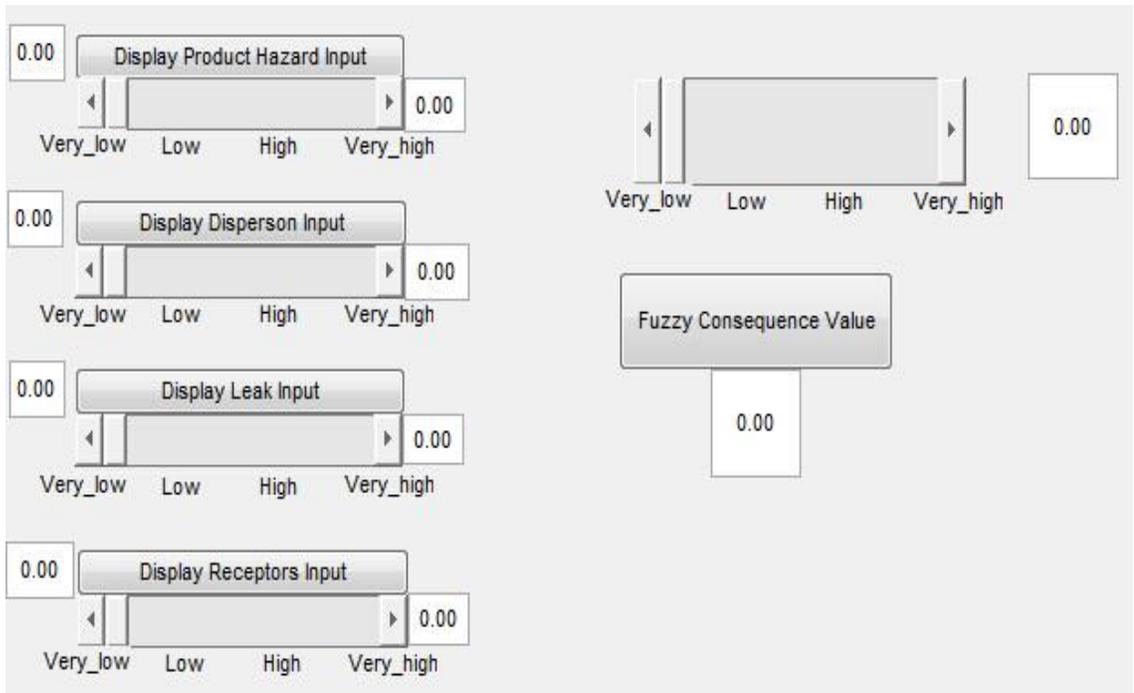


Figure 5. 6 Consequence FIS process GUI implementation.

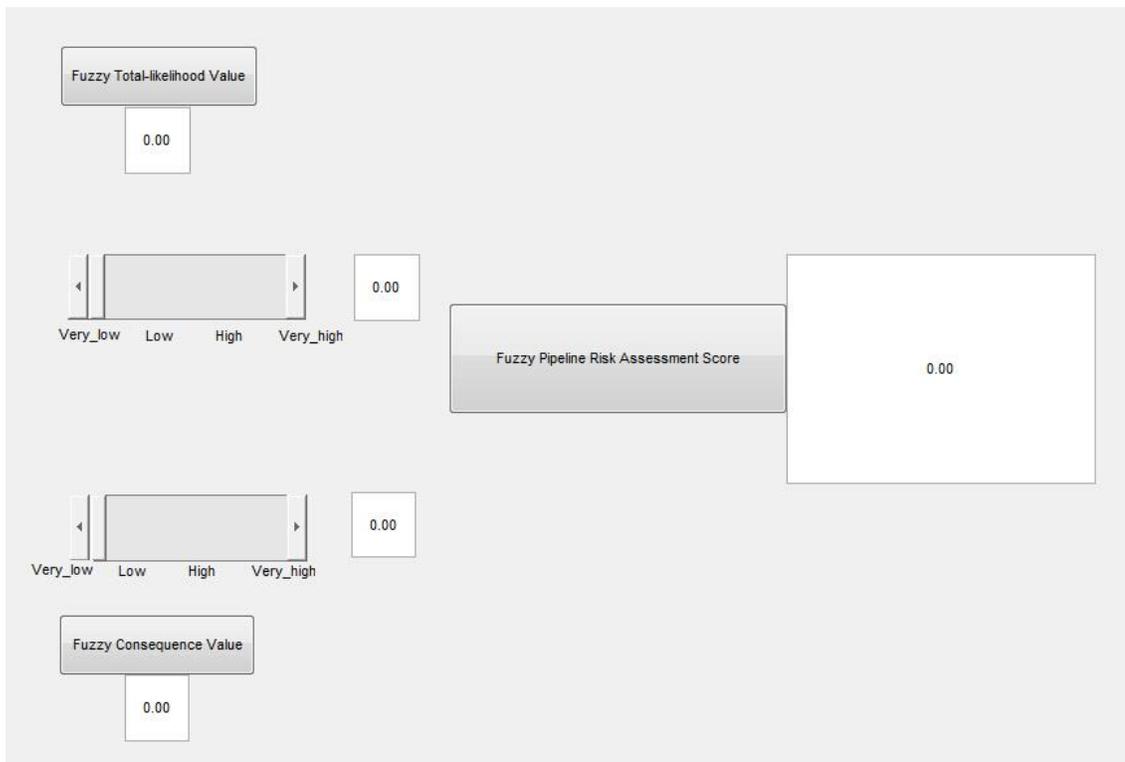


Figure 5. 7 PLRA Mamdani FIS model (GUI).

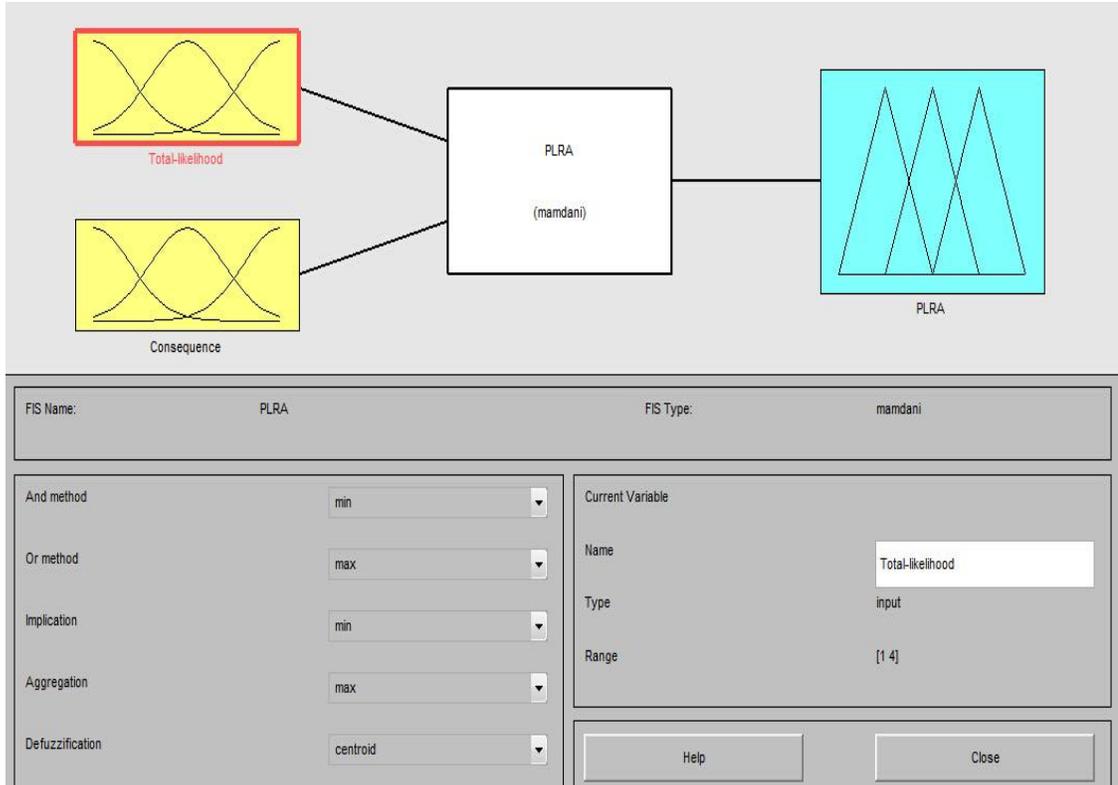


Figure 5. 8 PLRA Mamdani FIS model.

5.2 Artificial Neural Network of the first Pipeline Risk Assessment model

The Artificial Neural Network Toolbox from Matlab [31] is used to apply the proposed Artificial Neural Network technique to pipeline risk assessment methodology. The input and output given from the previously built Mamdani FIS based model is used to train this ANN to achieve its black box characteristic, which is used to measure the PLRA score by fuzzy inputs of Total- likelihood and Consequence. In Figure 4.4, the ANN based pipeline risk assessment model demonstrates the Artificial Neural Network process to measure the PLRA score. In order to implement this artificial neural calculation process, a Matlab program has been built to achieve this goal. The basic architecture of this ANN model is shown in Figure 5.9. Detailed coding is provided in Appendix 6.

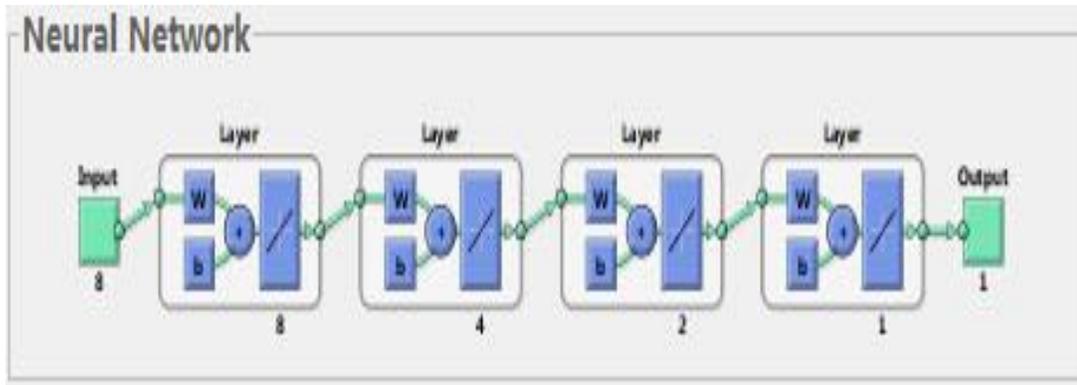


Figure 5. 9 Architecture of ANN based PLRA model.

5.3 Experimental Results of the first Pipeline Risk Assessment model.

As in the previously mentioned description, the FIS model and the ANN model are implemented by using different scenarios. For different scenarios, different sets of input values are based on common pipeline risk assessment situations in the pipeline industry. Each scenario includes a brief description of the situation, along with a table of linguistic and crisp inputs and outputs values. In order to get an easy-to-use process, the Graphical User Interface (GUI) of Matlab has been developed to get the final output PLRA score instantaneously by typing in inputs of different scenarios. Users or experts can change sliders to adjust inputs, which are also the outputs that are created by the previous mathematical process or fuzzy process, to get linguistic inputs. It is also important to mention that experts' experience is relied upon to adjust sliders to have a more reliable and realistic result.

5.3.1 Experimental Results of Mamdani FIS Based Model

Scenario – 1

Considering the risk factors that have been explained in Chapter 2, pipeline failure accidents do not happen that often. The pipeline failure is still considered to be an infrequent accident. Therefore, the following conditions are assumed and implemented:

- All Human issues have been largely controlled, which according linguistic inputs are valued as Very_Low.
- All Material and environmental issues have been largely reduced, which according linguistic inputs are valued as Very_Low.
- All Consequence factors are well estimated as Very_Low.
- All output values are not adjusted by experts to feed to the next stage.

As mentioned above, Mathematical process, and Total-likelihood, Consequence, and the PLRA FIS model are connected together. The outputs of the corresponding Mathematical process are inputs for the Total-likelihood model and the Consequence FIS model, and then the outputs of the Total-likelihood model and the Consequence FIS model are fed into the last PLRA FIS model. The relationship of the previous stage outputs and current stage inputs make this system into a form of a loop process. Hence, the following Tables 5-1, 5-2, 5-3, 5-4, and 5-5 present the inputs and outputs of each model and its loop system. According to the score range of final PLRA, 1~16, risk score 5.5 is regarded as “Low”.

Table 5. 1 Total-likelihood Mathematical process inputs and outputs (scenario #1).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Safety Factor	Very Low	1.1	Design Likelihood	1.1	Very Low
Fatigue	Very Low	1.1			
Surge Potential	Very Low	1.1			
Integrity	Very Low	1.1			
Land Movement	Very Low	1.1			
Design	Very Low	1.1	IO likelihood	1.1	Very Low
Construction	Very Low	1.1			
Operation	Very Low	1.1			
Maintenance	Very Low	1.1			
Buried Metal	Very Low	1.1	Corrosion likelihood	1.1	Very Low
Internal	Very Low	1.1			
Atmospheric	Very Low	1.1			
Depth of cover	Very Low	1.1	TPD likelihood	1.1	Very Low
Activity	Very Low	1.1			
Patrol frequency	Very Low	1.1			
Public education	Very Low	1.1			
Aboveground facilities	Very Low	1.1			

Table 5. 2 Total-likelihood FIS model inputs and outputs (scenario #1).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Design Likelihood	Very Low	1.1	Total- Likelihood	1.53	Very Low
IO likelihood	Very Low	1.1			
Corrosion likelihood	Very Low	1.1			
TPD likelihood	Very Low	1.1			

Table 5. 3 Consequence Mathematical process inputs and outputs (scenario #1).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Acute Hazard	Very Low	1.1	Product Hazard	1.1	Very Low
Chronic Hazard	Very Low	1.1			
Material	Very Low	1.1	Leak	1.1	Very Low
Stress	Very Low	1.1			
Initiator	Very Low	1.1			
Affected Area size	Very Low	1.1	Dispersion	1.1	Very Low
Thermal Event or Contamination	Very Low	1.1			
Mitigation	Very Low	1.1			
Environment	Very Low	1.1	Receptors	1.1	Very Low
Population	Very Low	1.1			

Table 5. 4 Consequence FIS model inputs and outputs (scenario #1).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Product Hazard	Very Low	1.1	Consequence	1.53	Very Low
Leak	Very Low	1.1			
Dispersion	Very Low	1.1			
Receptor	Very Low	1.1			

Table 5. 5 PLRA FIS model inputs and outputs (scenario #1).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Total-likelihood	Very Low	1.53	PLRA	5.53	Low
Consequence	Very Low	1.53			

Scenario -2

Even the pipeline failure is considered as an infrequent accident; its accident consequence can always cause big negative impacts on environment, safety, and financial concerns. Therefore, it is important to consider a high risk assumed situation:

- All human issues have not been effectively controlled, which according linguistic inputs are valued as Very_High.

- All material and environmental issues have not been reduced, which according linguistic inputs are valued as Very_Low.

- Consequence factors are well estimated as Very_High.

- All output values are not adjusted by experts to feed to the next stage.

According to previously described situations, pipeline failure is very likely to happen, which means the pipeline risk score will be at a high range. In this situation, a more careful resource allocation and risk score analysis should be performed. The following Tables 5-6, 5-7, 5-8, 5-9, and 5-10 present the inputs and outputs of each model and its loop system. According to the score range of final PLRA, 1~16, risk score 11.24 is regarded as “High”. This result matches real-situation records, failure accidents are not highly frequent.

Table 5. 6 Total-likelihood Mathematical process inputs and outputs (scenario #2).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Safety Factor	Very High	3.8	Design Likelihood	3.8	Very High
Fatigue	Very High	3.8			
Surge Potential	Very High	3.8			
Integrity	Very High	3.8			
Land Movement	Very High	3.8			
Design	Very High	3.8	IO likelihood	3.8	Very High
Construction	Very High	3.8			
Operation	Very High	3.8			
Maintenance	Very High	3.8			
Buried Metal	Very High	3.8	Corrosion likelihood	3.8	Very High
Internal	Very High	3.8			
Atmospheric	Very High	3.8			
Depth of cover	Very High	3.8	TPD likelihood	3.8	Very High
Activity	Very High	3.8			
Patrol frequency	Very High	3.8			
Public education	Very High	3.8			
Aboveground facilities	Very High	3.8			

Table 5. 7 Total-likelihood FIS model inputs and outputs (scenario #2).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Design Likelihood	Very High	3.8	Total- Likelihood	3.38	High
IO likelihood	Very High	3.8			
Corrosion likelihood	Very High	3.8			
TPD likelihood	Very High	3.8			

Table 5. 8 Consequence Mathematical process inputs and outputs (scenario #2).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Acute Hazard	Very High	3.8	Product Hazard	3.8	Very High
Chronic Hazard	Very High	3.8			
Material	Very High	3.8	Leak	3.8	Very High
Stress	Very High	3.8			
Initiator	Very High	3.8			
Affected Area size	Very High	3.8	Dispersion	3.8	Very High
Thermal Event or Contamination	Very High	3.8			
Mitigation	Very High	3.8			
Environment	Very High	3.8	Receptors	3.8	Very High
Population	Very High	3.8			

Table 5. 9 Consequence FIS model inputs and outputs (scenario #2).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Product Hazard	Very High	3.8	Consequence	3.38	High
Leak	Very High	3.8			
Dispersion	Very High	3.8			
Receptor	Very High	3.8			

Table 5. 10 PLRA FIS model inputs and outputs (scenario #2).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Total-likelihood	Very High	3.38	PLRA	11.24	High
Consequence	Very High	3.38			

Scenario -3

In the two previously proposed scenarios, two extreme conditions have been simulated and tested. However, the real environment conditions are more complicated and variable. It is commonly a complex combination of different values of each failure risk factors, instead of all factors being at the same extreme point. Therefore, these pipeline failure risk factors have different crisp values or linguistic values, which can be described by the following conditions:

- Human issues have been only partially controlled.
- Material and environmental issues have not been optimally reduced due to complicated environmental conditions.
- Consequence factors are well estimated.
- All output values are not adjusted by experts to be fed to the next stage.

Tables 5-11, 5-12, 5-13, 5-14, and 5-15 present the inputs and outputs of each model and its loop system. According to the numerical ranges of Likelihood and Consequence parameters, eight failure factors are regarded as Low, Low, High, High, High, High, Low, Low, High, respectively. The final PLRA score, Low, is given by systems executing FIS process of “Low” consequence and “High” Total-likelihood inputs.

Table 5. 11 Total-likelihood Mathematical process inputs and outputs (scenario #3).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Safety Factor	Low	2	Design Likelihood	2	Low
Fatigue	Low	2			
Surge Potential	Low	2			
Integrity	Low	2			
Land Movement	Low	2			
Design	Low	2	IO likelihood	2	Low
Construction	Low	2			
Operation	Low	2			
Maintenance	Low	2			
Buried Metal	High	3	Corrosion likelihood	3	High
Internal	High	3			
Atmospheric	High	3			
Depth of cover	High	3	TPD likelihood	3	High
Activity	High	3			
Patrol frequency	High	3			
Public education	High	3			
Aboveground facilities	High	3			

Table 5. 12 Total-likelihood FIS model inputs and outputs (scenario #3).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Design Likelihood	Low	2	Total- Likelihood	2.9	High
IO likelihood	Low	2			
Corrosion likelihood	High	3			
TPD likelihood	High	3			

Table 5. 13 Consequence Mathematical process inputs and outputs (scenario #3).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Acute Hazard	High	3	Product Hazard	3	High
Chronic Hazard	High	3			
Material	Low	2	Leak	2	Low
Stress	Low	2			
Initiator	Low	2			
Affected Area size	Low	2	Dispersion	2	Low
Thermal Event or Contamination	Low	2			
Mitigation	Low	2			
Environment	High	3	Receptors	3	High
Population	High	3			

Table 5. 14 Consequence FIS model inputs and outputs (scenario #3).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Product Hazard	High	3	Consequence	2.1	Low
Leak	Low	2			
Dispersion	Low	2			
Receptor	High	3			

Table 5. 15 PLRA FIS model inputs and outputs (scenario #3).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Total-likelihood	High	2.9	PLRA	6.64	Low
Consequence	Low	2.1			

Scenario -4

In the three previously proposed scenarios, the fuzzy inputs are directly measured by the first mathematical phase, which lack of experts' control. In order to get a more reliable and confident risk score, it is important and necessary to incorporate experts' knowledge and experience in the risk assessment process to adjust the outputs of first mathematical phase. Therefore, this expert's knowledge and experience cooperation process can be accomplished and simulated by adjusting 8 fuzzy inputs. Through the GUI interface, experts can adjust sliders to create more realistic failure factors to get after-adjustment fuzzy inputs, after the first mathematical process phase has been performed, to simulate the expert cooperation process. The expert knowledge cooperation process can be simulated and performed by this parameters adjustment step. It is necessary to mention that this adjustment is based on scenario-3.

Tables 5-16, 5-17, 5-18, 5-19, and 5-20 present the pre-adjustment inputs and corresponding after-adjustment inputs and outputs of each model. Figure 5.10 and Figure 5.11 show the expert adjustment process, the comparison of fuzzy inputs difference as shown in the number box: The number boxes at the left side of the Fuzzy control button show the results calculated by the weighted mathematical calculation process; the number boxes on the other side show the after-adjustment results.

Table 5. 16 Pre-adjusting and After-adjusting Total-likelihood Parameters (scenario #4).

Input Parameters:	Pre-adjusting Linguistic Term	Crisp Value	After-adjusting Linguistic Term	Crisp Value
Design Likelihood	Low	2	Low	2.3
IO likelihood	Low	2	Low	2.3
Corrosion likelihood	High	3	High	3.2
TPD likelihood	High	3	High	3.2

Table 5. 17 Pre-adjusting and After-adjusting Total-likelihood (scenario #4).

Output Parameter	Pre-adjusting Linguistic Term	Crisp Value	After-adjusting Linguistic Term	Crisp Value
Total-likelihood	High	2.9	High	3.0

Table 5. 18 Pre-adjusting and After-adjusting Consequence Parameters (scenario #4).

Input Parameters:	Pre-adjusting Linguistic Term	Pre-adjusting Crisp Value	After-adjusting Linguistic Term	After-adjusting Crisp Value
Design Likelihood	High	3	High	3.3
IO likelihood	Low	2	Low	1.8
Corrosion likelihood	Low	2	Low	1.8
TPD likelihood	High	3	High	3.3

Table 5. 19 Pre-adjusting and After-adjusting Consequence (scenario #4).

Output Parameter	Pre-adjusting Linguistic Term	Crisp Value	After-adjusting Linguistic Term	Crisp Value
Consequence	Low	2.1	Low	2.3

Table 5. 20 PLRA FIS model inputs and outputs (scenario #4).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Total-likelihood	High	3	PLRA	7.40	Low
Consequence	Low	2.3			

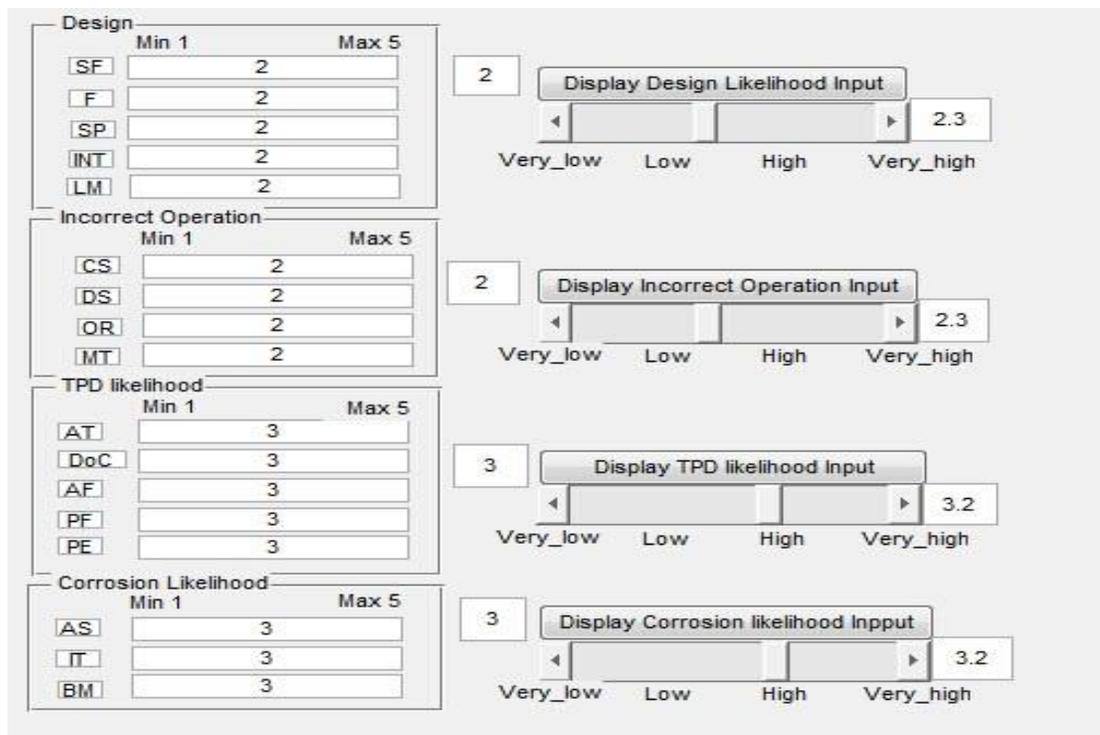


Figure 5. 10 GUI Total-likelihood fuzzy inputs adjustment.

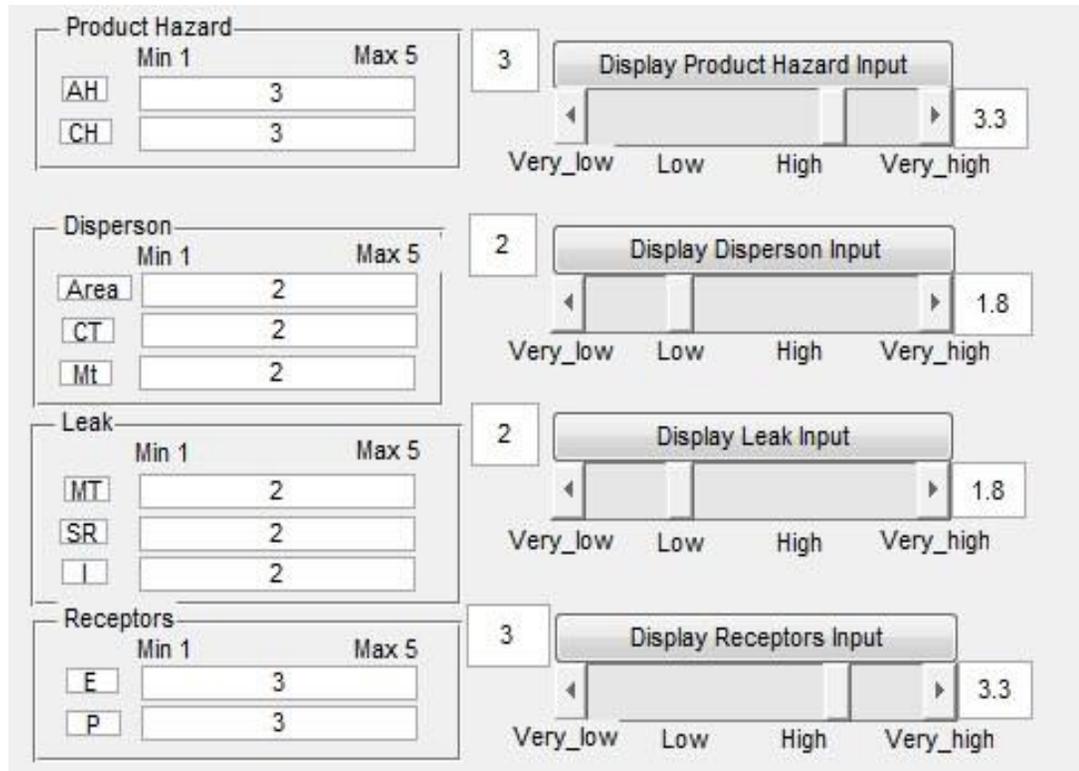


Figure 5. 11 GUI Consequence fuzzy inputs adjustment.

5.3.2 Experimental Results of ANN Based Model

As pipeline risk assessment methodology has been explained in Chapter 3, the ANN based pipeline risk assessment model is introduced in this proposed pipeline risk assessment model. Input data and corresponding output data have been obtained from the Mamdani based PLRA model. This ANN based model can be utilized as a synergistic or an alternative method, which means the ANN is introduced as a new technique to assess pipeline risk, but it is also used to provide experts a comparison result [23]; This ANN model has the advantages that it has fewer inputs than FIS based model, and that it requires less experts' knowledge and less inner mechanism building efforts.

As explained in the previous chapter, a well-trained ANN model, capable of processing input data set to get desired output data set, can be applied to real-environment use; the proposed training process is also named as supervised training [22]. Through computing network simulation outputs against the desired outputs, the Network can produce error sets to adjust inner neuron weights; these error numbers, which are the difference of simulation outputs and desired outputs, need to decrease until they reach an accepted value. This weight adjustment process is known as Network training [22].

There are two common training problems of the ANN model: Less-training and Over-training. If there is not enough training data sets or only no-information data sets, it can result in a less-training problem. If the ANN model is fed with too many data sets, it will result in Over-training, or Over-fitting. This after-trained ANN model is not capable of learning the real underlying trend or mechanism in the data set; therefore, the ANN model is not well generalized for other experimental data sets [22].

In order to get a well-trained Artificial Neural Network, as a black box, this ANN based PLRA model is fed with 50 sets of input data and output data, considering the inner training complexity and efficiency of proposed ANN model. The training and simulation process are performed on the Artificial Neural Network toolbox from Matlab. The training interface is demonstrated in Figure 5.12. The completed training data sets and detailed training coding are included in Appendix 6. After this ANN based model has been well trained, this ANN based model is implemented seven times to simulate extreme and normal risk conditions. Table 5.21 demonstrates the input and output data sets of seven scenarios. Considering the usability of this ANN model, 27 first stage

inputs for mathematical calculation are not built into this ANN model. The mathematical calculation process is also performed in the previous GUI interface. Comparison of experimental results of the ANN based model and the FIS based model is given in the following section. The ANN based model and the FIS based model share the same input data sets.

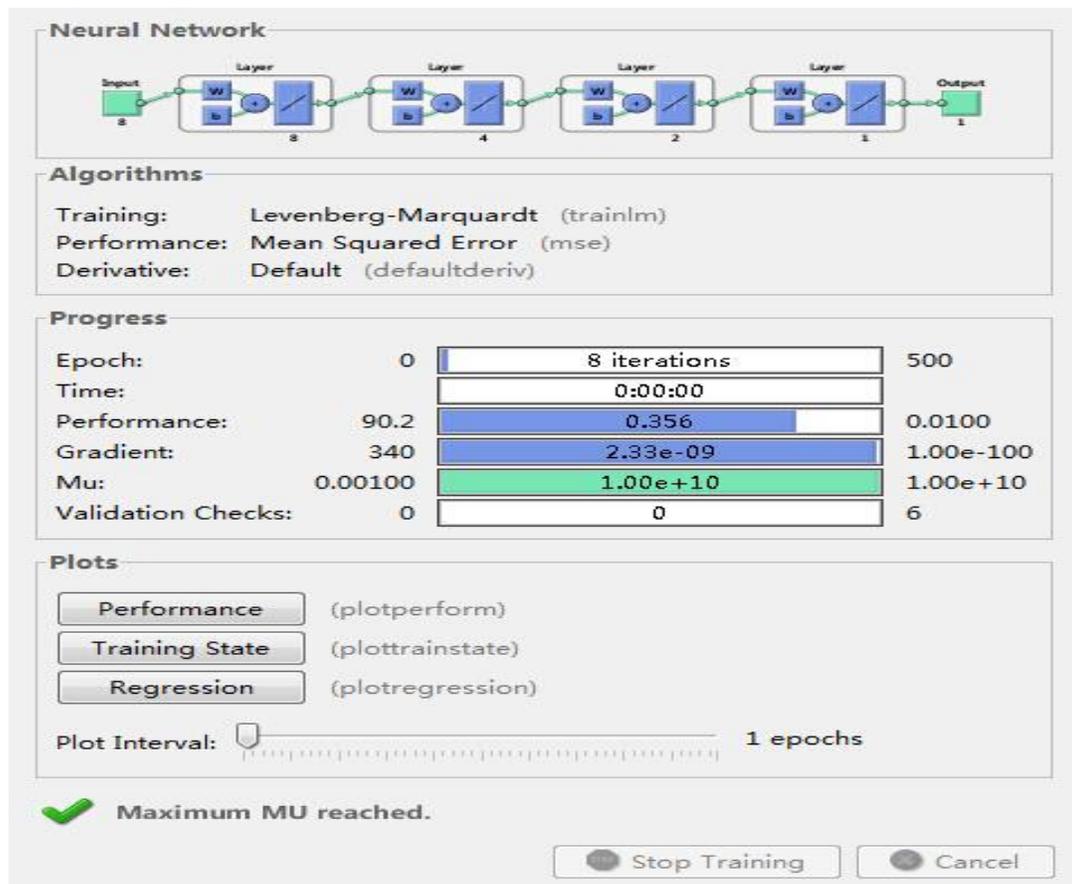


Figure 5. 12 Matlab Neural Network training and simulation interface.

The training progress is constantly shown and updated in the training window, as shown in the figure 5.12. There are three essential training factors: Performance; Gradient; and Validation; the gradient number will be continuously decreased and stop till the training reaches the designed minimum performance, 1e-100 as designed in the

training window; Mu defines the iteration step size; Validation will stop training if its value reach the value 6, which means the number of successive iterations fails to decrease [3].

Table 5. 21 Inputs and outputs of ANN based model (7 scenarios).

Scenario	Design	IO	Corrosion	TPD	Production	Leak	Dispersion	Receptors	PLRA Score
1	1.7	1.7	1.6	1.5	1.6	1.6	1.6	1.6	6.34
2	1.7	2.8	2.8	1.0	2.7	2.7	1.6	4.0	6.71
3	3.9	3.1	1.7	1.5	1.6	1.6	2.8	3.9	8.93
4	3.8	3.8	3.8	3.8	3.8	3.8	3.8	3.8	11.24
5	2.9	3.1	2.9	3.0	3.3	2.7	2.6	2.6	9.11
6	3.1	2.8	3.1	2.9	2.5	2.5	2.5	2.6	8.52
7	1.3	3.3	1.9	2.1	3.3	2.0	2.2	1.6	7.20

The ANN based model provides 7 numerical scores from 6.34 to 11.24, which are termed as low and high respectively. This PLRA score result set matches real-environment risk records, where failure accidents happen at a middle level frequency.

5.4 Results Analysis of first Pipeline Risk Assessment model

In the previous sections, the working mechanism of the Mamdani FIS based pipeline risk assessment model and the ANN based model have been illustrated. Four Mamdani FIS based PLRA scenarios have been implemented in previous sections. These four scenarios are based on different situations, which represent common pipeline conditions.

For the ANN PLRA model, seven scenarios have been simulated for each certain situation to measure pipeline risk score. In order to test the reliability of the proposed Mamdani FIS model and the ANN model, the risk score of the Mamdani FIS model is also measured by feeding the same inputs data. It is important to mention that although the Total-likelihood and Consequence index inputs are the same; their final PLRA score is not exactly the same, which demonstrates the risk sensibility of each model. These different pipeline risk assessment scores provide experts an alternative way to get a more confident and reliable risk score. Table 5.22 shows outputs risk ranking for each model.

Table 5. 22 Results comparison of Mamdani FIS model and ANN model (7 scenarios).

Scenario	ANN based model	FIS based model	Risk Difference
1	6.34	6.21	0.13
2	6.71	6.86	-0.15
3	8.93	9.04	-0.11
4	11.24	11.07	0.17
5	9.11	8.92	0.19
6	8.52	8.71	-0.19
7	7.20	7.15	0.05

As shown in the Table 5.22, the maximum risk score difference is 0.19, and the minimum risk score difference is 0.05; the above risk score differences create an average of 0.14, which is acceptable, considering the PLRA score ranges from 1~16. These 7 scenarios and their corresponding pipeline risk scores shown above demonstrate that the Mamdani FIS based PLRA model and the ANN based PLRA model agreed with each other. The Positive difference and negative difference illustrate different sensibilities of the FIS and ANN based models while considering the same input set of parameters.

These two PLRA based models can be performed as a synergistic model to provide experts reliable and confident alternative results.

5.5 Mamdani FIS model of the second Pipeline Risk Assessment model

The proposed Mamdani FIS pipeline risk assessment model is also implemented by the Matlab Fuzzy Logic Toolbox. Further detailed Fuzzy Logic Toolbox operation, including rules base, and implementation are provided in Appendix 3. The GUI of Matlab is also used to build the measuring process.

In the Vulnerability model, the two mathematical inputs mechanisms, Design and Incorrect Operation, are described in Figure 5.13. The Vulnerability Mamdani FIS model (Matlab Fuzzy Toolbox) is presented in Figure 5.14, which gets as output Vulnerability for the PLRA-2 Mamdani FIS model. The Vulnerability fuzzy phase is built in the GUI. Figure 5.15 shows the GUI Vulnerability fuzzy phase.

In the Threat model, the two mathematical inputs mechanisms, Corrosion and Third Party Damage, are shown by Figure 5.16. After the mathematical process, the fuzzy inputs are fed into the following Threat Mamdani FIS model (Matlab Fuzzy Toolbox), which is illustrated in Figure 5.17. The Threat fuzzy phase is also built in the GUI; the Figure 5.18 shows the GUI Threat fuzzy phase.

In the Consequence FIS model, Figure 5.19, Figure 5.20, and Figure 5.21 represent its mathematical inputs mechanism, the consequence Mamdani FIS model (Matlab Fuzzy Toolbox), and GUI Consequence fuzzy phase.

Similar to the first Pipeline Risk Assessment model, the last phase of the Mamdani FIS model is the PLRA-2 model, which incorporates three fuzzy inputs, Vulnerability, Threat, and Consequence, to obtain the final PLRA score. In this phase only the Mamdani FIS

process is built. Three fuzzy inputs can also be adjusted by sliders. This PLRA-2 Mamdani FIS is illustrated in Figure 5.22 and 5.23.



Figure 5. 13 Mathematical Inputs Mechanism of Vulnerability model (GUI).

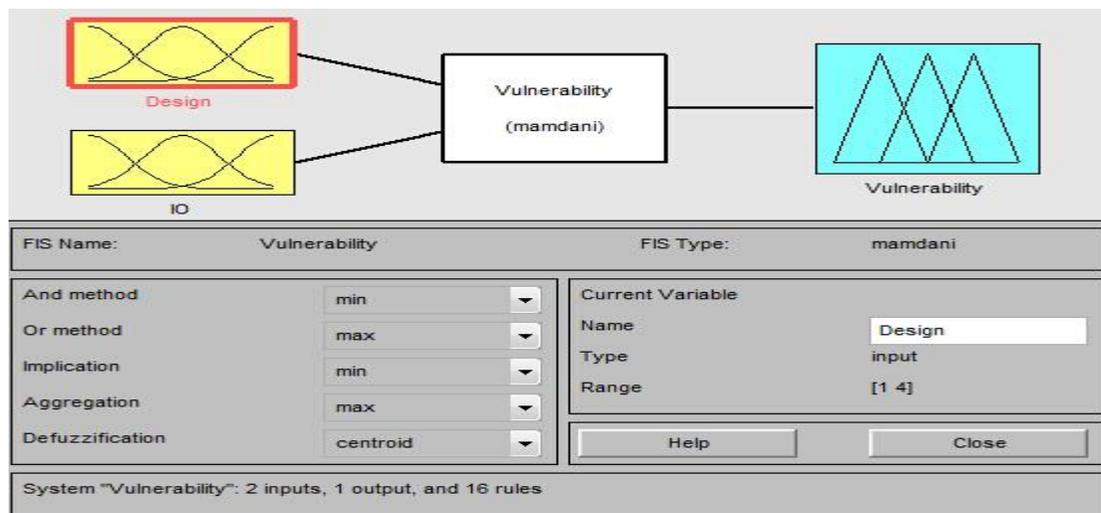


Figure 5. 14 Vulnerability Mamdani FIS model.

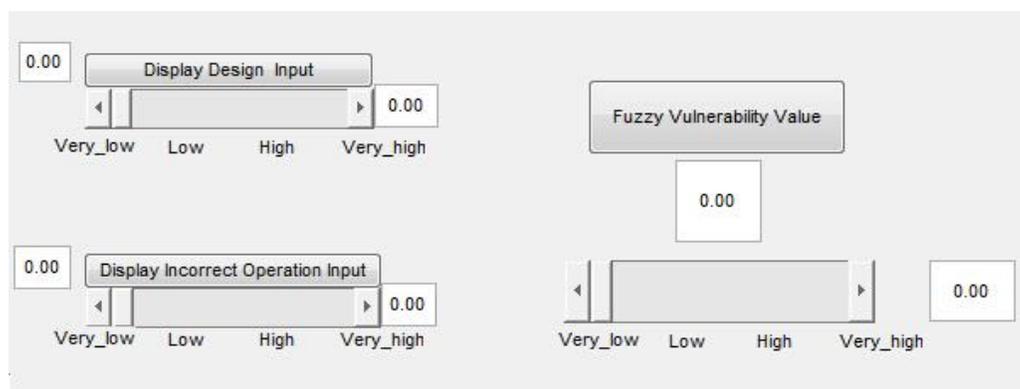


Figure 5. 15 Vulnerability FIS process GUI implementation.

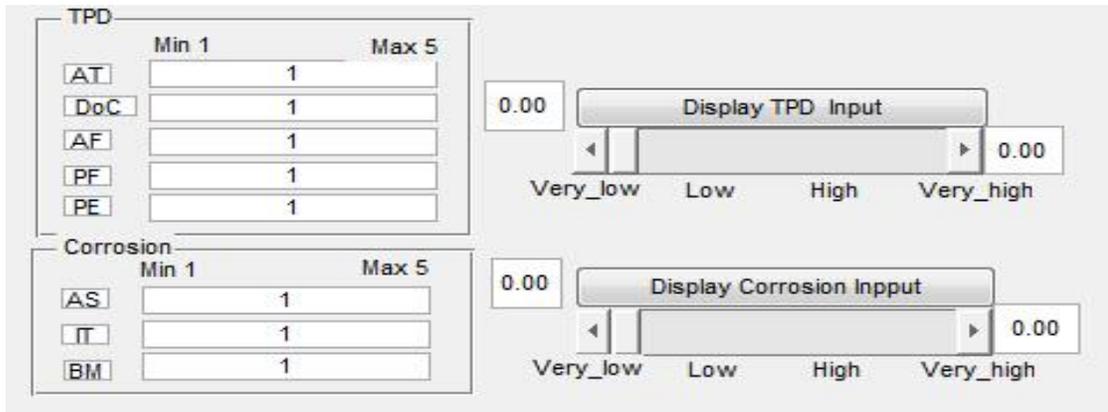


Figure 5. 16 Mathematical Inputs Mechanism of Threat model (GUI).

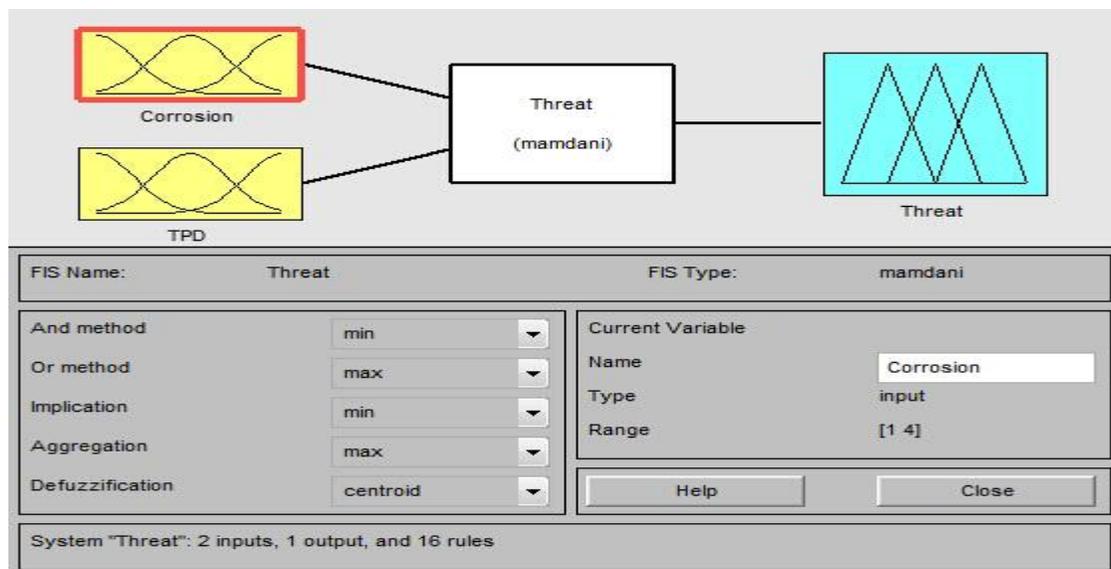


Figure 5. 17 Threat Mamdani FIS model.

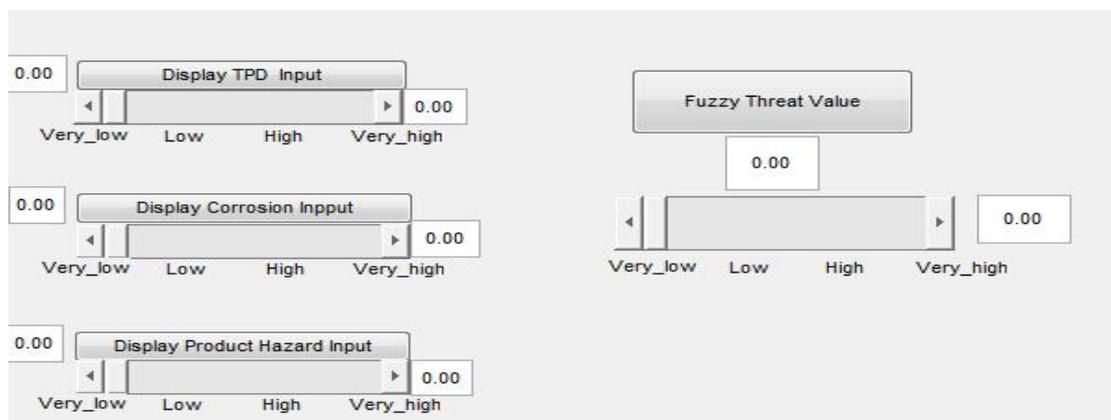


Figure 5. 18 Threat FIS process GUI implementation.

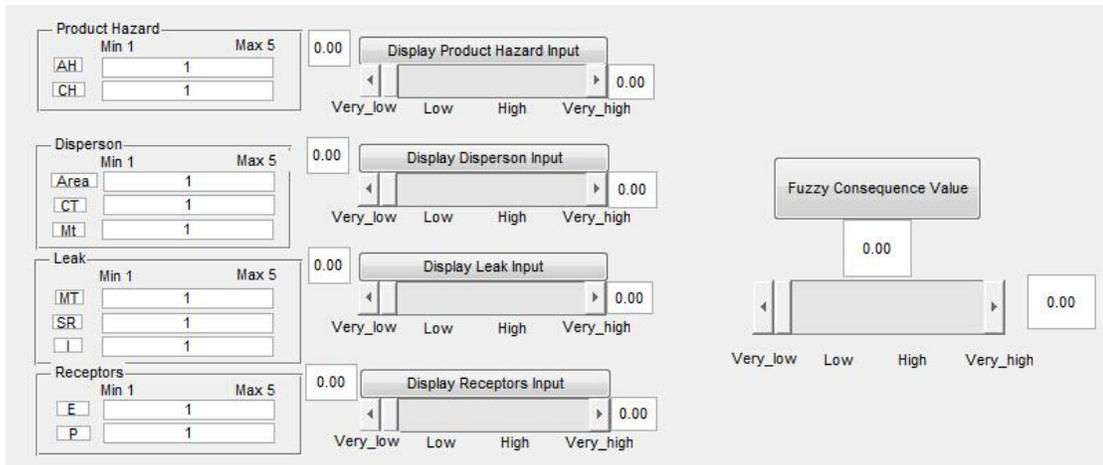


Figure 5. 19 Mathematical Inputs Mechanism of Consequence model (GUI).

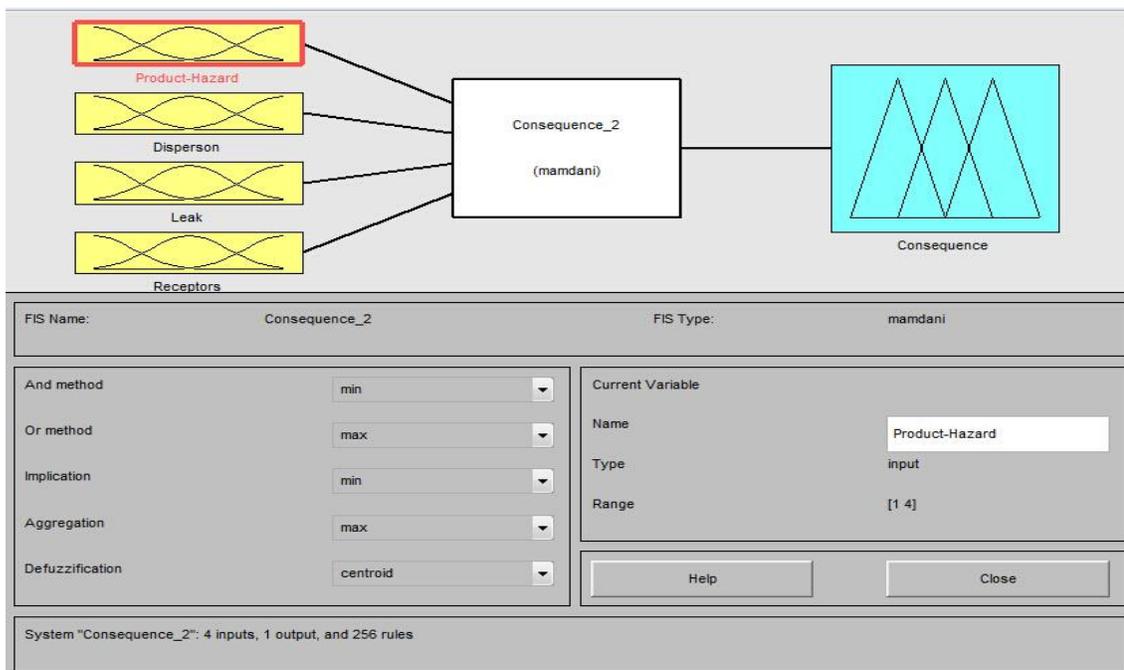


Figure 5. 20 Consequence Mamdani FIS model.

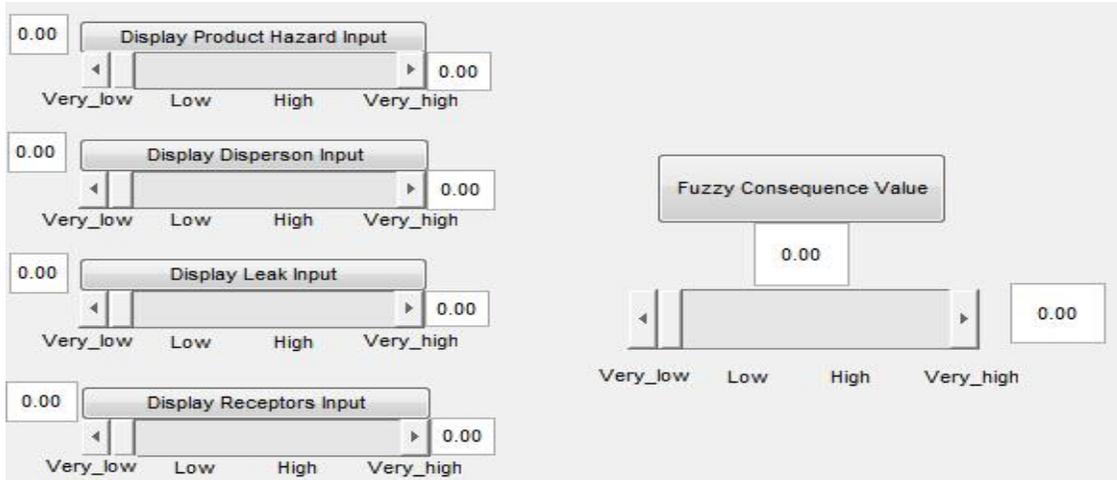


Figure 5. 21 Consequence FIS process GUI implementation.

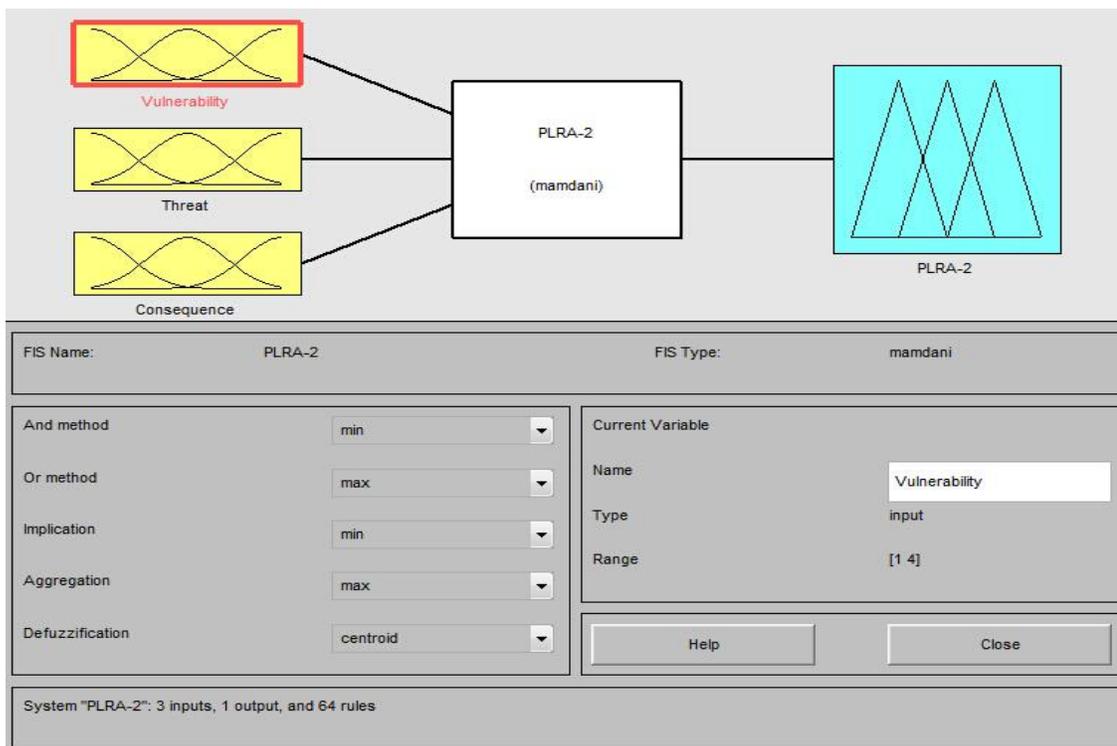


Figure 5. 22 PLRA-2 Mamdani FIS model.

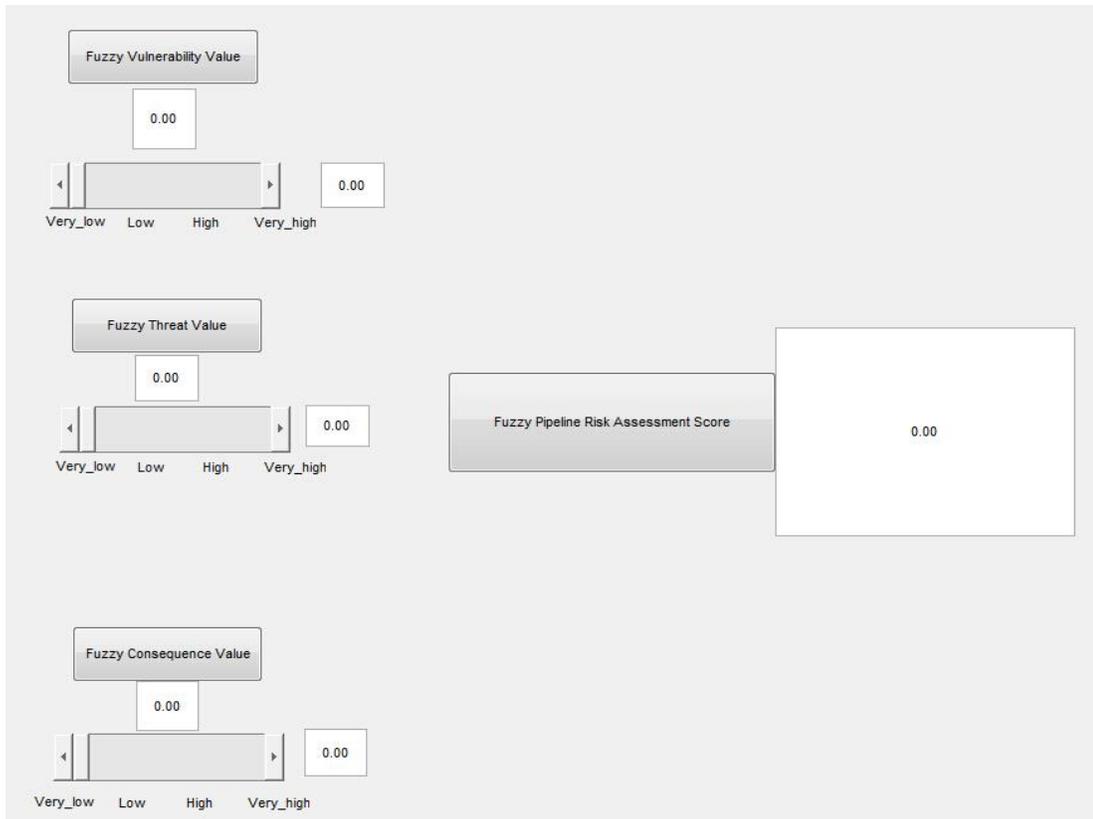


Figure 5. 23 PLRA-2 FIS process GUI implementation.

5.6 Artificial Neural Network for the second Pipeline Risk Assessment model

The Matlab Artificial Neural Network Toolbox is introduced to implement the proposed Artificial Neural Network model, which is based on the second pipeline risk assessment definition. The training input and output data sets are obtained from the previously built Mamdani FIS based model. The eight fuzzy inputs, which belong to the Vulnerability, the Threat, and the Consequence FIS model, are firstly calculated by the same weight mathematical process and then fed directly into the ANN based model. This ANN based model has a similar visual structure to the ANN based model in the first Pipeline Risk Assessment model. Both the Detailed ANN program and the architecture are included in the Appendix 6. This ANN based model can be utilized as a synergistic

or an alternative method to provide experts a comparison result [23]; This ANN model has the advantages that it has fewer inputs than FIS based model, and that it requires less experts' knowledge and less inner mechanism building efforts.

5.7 Experimental Results of the second Pipeline Risk Assessment model.

For the second Pipeline Risk Assessment mode, the FIS model and the ANN model are implemented using different scenarios. The Mamdani FIS model is implemented in two scenarios. Each scenario includes a brief description of the situation, along with a table of linguistic and crisp inputs' and outputs' values. The Graphical User Interface (GUI) from Matlab is built to get the final output PLRA score instantaneously, by typing in inputs of different scenarios. The ANN based model is also utilized as a synergistic or an alternative method. The ANN based model is implemented in 5 scenarios to obtain comparison results of the FIS based model, where the two methodology-based models are fed with the same input sets.

5.7.1 Experimental Results of Mamdani FIS Based Model

Scenario – 1

This scenario is implemented to simulate an infrequent accident condition, which means failure issues have been largely controlled. In this scenario, the 27 first stage inputs are assigned as 1.3. Through feeding the mathematical process with values of 1.3, the corresponding fuzzy inputs and outputs are shown in the following table 5.23, table 5.24, table 5.25, and table 5.26. According to the numerical scales of output parameters

and PLRA, 1~4 and 1~64, respectively, output parameters are termed as Low and PLRA is termed as low

Table 5. 23 Vulnerability FIS model inputs and outputs (scenario #1).

Fuzzy Inputs	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Design	Very Low	1.3	Vulnerability	1.71	Low
Incorrect Operation	Very Low	1.3			

Table 5. 24 Threat FIS model inputs and outputs (scenario #1).

Fuzzy Inputs	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
TPD	Very Low	1.3	Threat	1.71	Low
Corrosion	Very Low	1.3			

Table 5. 25 Consequence FIS model inputs and outputs (scenario #1).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Product Hazard	Very Low	1.3	Consequence	1.71	Low
Leak	Very Low	1.3			
Dispersion	Very Low	1.3			
Receptor	Very Low	1.3			

Table 5. 26 PLRA-2 FIS model inputs and outputs (scenario #1).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Vulnerability	Low	1.71	PLRA-2	9.0	Low
Threat	Low	1.71			
Consequence	Low	1.71			

Scenario -2

In this scenario, all failure factors are at a very high level to simulate pipeline accident high risk conditions. Under these conditions, failure material and environmental issues have not been reduced and consequence is well estimated. In order to simulate these high risk conditions, the 27 first stage inputs are scored as 3.6. Through feeding the mathematical process with values of 3.6, the corresponding fuzzy inputs and outputs are shown in the following table 5.27, table 5.28, table 5.29 and table 5.30. According to the numerical scales of output parameters and PLRA, 1~4 and 1~64, respectively, output parameters are termed as High and PLRA is termed as High

Table 5. 27 Vulnerability FIS model inputs and outputs (scenario #2).

Fuzzy Inputs	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Design	Very High	3.6	Vulnerability	3.20	High
Incorrect Operation	Very High	3.6			

Table 5. 28 Threat FIS model inputs and outputs (scenario #2).

Fuzzy Inputs	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
TPD	Very High	3.6	Threat	3.20	High
Corrosion	Very High	3.6			

Table 5. 29 Consequence FIS model inputs and outputs (scenario #2).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Product Hazard	Very High	3.6	Consequence	3.20	High
Leak	Very High	3.6			
Dispersion	Very High	3.6			
Receptor	Very High	3.6			

Table 5. 30 PLRA-2 FIS model inputs and outputs (scenario #2).

Input Parameters:	Linguistic Term	Crisp Value	Output Parameters	Resulting output	Linguistic Term
Vulnerability	High	3.2	PLRA-2	26.7	High
Threat	High	3.2			
Consequence	High	3.2			

5.7.2 Experimental Result of Second ANN Based Model

This ANN based model is implemented as a synergistic method, which means the ANN is introduced as an alternate technique to assess pipeline risk, but it is also used to provide experts with a comparison result. This ANN based model can be utilized as a synergistic or an alternative method to provide experts a comparison result; This ANN model has fewer inputs than the FIS based model which can achieve faster operation speed. Furthermore, this ANN based model requires less experts' knowledge and less inner mechanism building efforts because of its black box characteristic.

Similarly to the previous ANN based model presented in section 5.3.2, this ANN based PLRA model is fed with 50 sets of input and output data to get a well-trained model. The training and simulation processes are performed using the Artificial Neural

Network toolbox from Matlab. The completed training data sets and detailed training coding are provided in the Appendix 6. After this ANN based model has been well trained, this ANN based model is implemented five times and all results are also properly measured. Table 5.31 demonstrates the input and output data sets of five scenarios.

Table 5. 31 Inputs and outputs of second ANN based model (5 scenarios).

Scenario Number	Design	IO	Corrosion	TPD	Production	Leak	Dispersion	Receptors	PLRA score
1	1.3	1.0	1.4	1.3	1.2	1.1	1.0	1.0	10.7
2	3.8	3.9	3.8	3.8	3.9	3.9	3.9	3.9	31.9
3	1.2	1.1	1.0	1.2	1.2	1.0	1.2	1.1	9.6
4	3.9	3.8	3.5	3.7	3.6	3.8	3.6	3.8	31.1
5	3.3	2.5	2.1	3.2	2.8	3.4	3.1	3.0	24.5

A comparison of the experimental results of the ANN based model and the FIS based model is given in the following section. The ANN based model and the FIS based model share the same input data sets.

5.8 Results Analysis of second Pipeline Risk Assessment model

The risk assessment mechanisms of Mamdani FIS based pipeline risk assessment model and the ANN based model have been illustrated in the above sections. Two Mamdani FIS based PLRA scenarios and five ANN based PLRA scenarios are performed.

In order to test the reliability of the second Pipeline Risk Assessment model, Mamdani FIS model and ANN based model are fed with the same input data to measure

corresponding final risk scores. This testing process is implemented 5 times on previously built FIS based model and ANN based model. Table 5.32 shows outputs risk ranking for each model.

Table 5. 32 Results comparison of Mamdani FIS model and ANN model (5 scenarios).

Scenario	Mamdani FIS model	ANN based model	Risk Difference
1	10.2	10.7	-0.5
2	32.3	31.9	0.4
3	9.5	9.6	-0.1
4	30.2	31.1	-0.9
5	23.6	24.5	-0.9

As shown in the Table 5.32, the maximum risk score difference is 0.9, and the minimum risk score difference is 0.1; the above risk score differences create an average of 0.56 which is acceptable, considering the PLRA score ranges from 1~64. These 5 scenarios and their corresponding pipeline risk scores shown above demonstrate that the Mamdani FIS based PLRA model and the ANN based PLRA model are agreed with each other and jointly validate the reliability of these two models. Further validation of these two models can be accomplished by feeding FIS based model and ANN based model with accidents records given from Pipeline companies. The Positive difference and negative difference illustrate different sensibilities of FIS and ANN based model while calculating same input set of parameters. These two PLRA based model can be performed as a synergistic model to provide experts reliable and confident alternative results.

5.9 Summary

In this chapter, the application of proposed methodology is presented to obtain different risk score results. The proposed two Mamdani FIS Pipeline Risk Assessment and the two ANN Pipeline Risk Assessment models have been implemented and tested in the simulation of different risk environments. Different scenarios can simulate corresponding pipeline risk situations or environments. The results from the different scenarios for each model are measured and analyzed.

CHAPTER SIX: CONCLUSIONS

This thesis focuses on the integrated application of the Fuzzy Inference System and the Artificial Neural Networks techniques in pipeline risk assessment areas. Normally, risk assessment techniques deal with incomplete or vague information and do not have a clear internal failure mechanism to provide experts with a reliable and completed pipeline risk score value. In the other hand, Intelligent Systems techniques are able to deal with vague and unclear information. To achieve the objective of developing effective pipeline risk assessment techniques, this thesis builds two hybrid Intelligent Systems models, in which FIS and ANN techniques can be used as alternative synergetic techniques for each model. The Fuzzy Logic Toolbox, the Artificial Neural Network Toolbox, and the GUI module enable this framework to be an easy-to-use interface to assess risk. After the models are built, different data sets have been implemented as simulations of certain real environmental situations to test this risk assessment model. The general structure of this thesis is organized as follows:

1. In the first part of this thesis, there is a brief introduction of the pipeline risk assessment and its pipeline failure risk factors. This part identifies and studies the limitation and difficulty of pipeline risk assessment. Further, a brief explanation of the general accident mechanism due to these failure risk factors is also given in this part. The pipeline risk factors and their general risk weights, which are built into the proposed PLRA model, are completely clarified in this part as well.
2. Two Intelligent Systems tools, the Fuzzy Inference Systems and the Artificial Neural Networks, are reviewed in this second stage. Based on the pipeline risk

assessment areas, to which the proposed model is applied, the Mamdani FIS has been presented. Besides the introduction of the general ANN model, the more detailed Feedforward Backpropagation ANN model, which is introduced in the proposed risk assessment process, has been explained. In this IS tools introduction stage, advantages of each tool and their synergism effects are also presented to validate proposed models.

3. In the third stage, this thesis implements the previously proposed FIS and ANN techniques. Two completed PLRA models, which both consist of a Mamdani FIS technique and a Feedforward Backpropagation ANN technique, have been built. In this stage, the detailed model structure and the inner mechanism have been explained to demonstrate their working mechanism and synergistic corporation mechanism to provide experts with a more reliable and confident result score.

4. In this last stage, different scenarios are implemented to simulate and assess some common pipeline failure conditions. There are 4 scenarios for FIS based model and 7 scenarios for ANN based model in PLRA model; 2 scenarios for FIS based model and 5 scenarios for ANN based model have been implemented for PLRA-2 in this thesis. Experimental results of different scenarios are measured and analyzed to prove the reliability and usability of these two models.

In general, the synergic combination of the Fuzzy Inference System and the Artificial Neural Network performed by Matlab has the following advantages:

(a) It allows more imprecise inputs and incorporates experts' subjective experience and knowledge instead of only precisely crisp values or pure experts' knowledge due to the characteristic of IS techniques, that have a better tolerance with data limitation and unclear internal mechanism.

(b) The Fuzzy if-then working mechanism and the ANN black box corroborate with each other. Each of these two techniques can not only calculate the PLRA score through their own measuring process, but also verify and compare the other method's risk results.

(c) The ability of solving the lack of an internal risk working mechanism is the core of any pipeline risk assessment model. The ANN based pipeline risk assessment model is eligible to get accurate outputs through a black box process. The ANN based models, which have fewer inputs than the FIS based models and require less inner mechanism building efforts, can be utilized as a synergistic or an alternative method to provide experts a comparison result;

(d) The Matlab Fuzzy Toolbox and GUI provide users with an easy to use interface. Simply typing in different failure risk input data sets, the corresponding risk score output sets can be measured by clicking the built-in push-button.

6.1. Summary of Results.

In summary, this thesis has achieved the following:

(i) The typical pipeline risk assessment factors and sub-indexes have been properly selected and introduced in the proposed risk assessment model.

(ii) The Mamdani FIS models and the Artificial Neural Network models have been properly built and proposed to assess pipeline risk effectively and efficiently compared to traditional methods, for which is normally difficult to get complete and precise data or information, complicated to quantify inner failure mechanism, and incompatible with other complementary methods.

(iii) Different extreme scenarios and general scenarios, simulating real-environment situation, have been discussed for both the Mamdani FIS model and the ANN model, to test functionality of each model. The results Mamdani FIS based PLRA model and the ANN based PLRA model agree with each other, jointly validate the reliability of these two models and work as a synergetic system to provide more completed risk reference.

(iv) The PLRA-2 model is built to get a complete risk score which is based on the second risk definition. The PLRA-2 consists of four FIS models. The PLRA-2 has fewer number of fuzzy if then rules to reduce FIS model building difficulty.

(v) These proposed models are capable to consider and incorporate more or other aspects by introducing new factors in certain environment: updating FIS reasoning mechanism to get new FIS based model; Feed ANN based model with industry data sets to re-run ANN training process to get a new well-trained ANN based model.

6.2. Conclusions

Fuzzy Inference Systems and Artificial Neural Networks can be implemented to lead more reliable and completed risk assessment models. These two Intelligent Systems techniques can improve the reliability of a confident and mature risk assessment model for pipelines. Good compatibility of these models and an ability to deal with uncertain data and mechanism help engineers to incorporate experts' knowledge. In these two models, more potential risk factors from experts' subjective knowledge and experience can be taken into account and easily analyzed.

6.3. Recommendations and Future Work

It has been proposed that the FIS and the ANN based methodology are effective to assess pipeline risk scores. However, these synergistic models can be further considered as follows:

1. The proposed methodologies can be improved by taking into account more failure risk factors in the first mathematical process.
2. The weighted mathematical calculation process can be implemented by the FIS or the ANN techniques.
3. An Inverse ANN methodology can be implemented to have a better understanding of the inputs' weight, which can give a more realistic weight for each input. This implementation can further help experts or companies allocate time, effort, and resources more reasonably.

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APPENDIX

1. Mamdani Fuzzy Inference Models

As presented in previous chapters, it is the Mamdani Fuzzy Inference System model that is selected to build the FIS based PLRA model. Due to its usability and reliability, it is accepted as a universal platform that can be used to study and define non measurable data from users' personal perspectives. Users' control can be accomplished and simulated by Mamdani's fuzzy judgments. The most important characteristic of the Mamdani FIS model is that vague linguistic inputs can be completely effective by being integrated with the system.

2. Gaussian Membership Function

Although there are many types of membership functions, such as Triangular Membership function, Trapezoidal Membership function, Bell Membership function, and Gaussian Membership function, it has been introduced that it is the Gaussian Membership function that is selected in Matlab Fuzzy Toolbox to develop proposed Fuzzy Inference Systems. Figure A2.1 [17] illustrates the general shape of Gaussian Membership function.

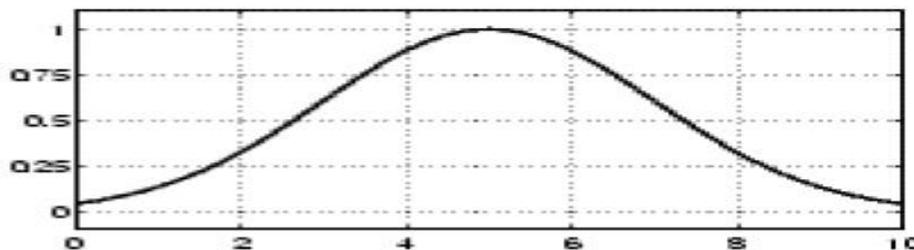


Figure A2. 1 Gaussian Membership function [17].

3. Mamdani FIS model Fuzzy If-Then Rules

It is important to mention that if-then rules can be combined to represent different systems.

The following sections show the three Mamdani FIS IF-Then Rules bases.

Section-1 Total-likelihood Mamdani FIS model:

1. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Very_Low) (1)
2. If (Design-likelihood is Low) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Low) and (TPD-Likelihood is Low) then (Total-Likelihood is Low) (1)
3. If (Design-likelihood is High) and (IO-Likelihood is High) and (Corrosion-Likelihood is High) and (TPD-Likelihood is High) then (Total-Likelihood is High) (1)
4. If (Design-likelihood is Very_High) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_High) and (TPD-Likelihood is Very_High) then (Total-Likelihood is Very_High) (1)
5. If (Design-likelihood is Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Very_Low) (1)
6. If (Design-likelihood is High) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
7. If (Design-likelihood is Very_High) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
8. If (Design-likelihood is Very_Low) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Very_Low) (1)
9. If (Design-likelihood is Very_Low) and (IO-Likelihood is High) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
10. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
11. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Very_Low) (1)
12. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is High) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
13. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_High) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
14. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Low) then (Total-Likelihood is Very_Low) (1)
15. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is High) then (Total-Likelihood is Low) (1)
16. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_High) then (Total-Likelihood is Low) (1)
17. If (Design-likelihood is Low) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
18. If (Design-likelihood is High) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
19. If (Design-likelihood is Very_High) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
20. If (Design-likelihood is Low) and (IO-Likelihood is High) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
21. If (Design-likelihood is High) and (IO-Likelihood is High) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
22. If (Design-likelihood is Very_High) and (IO-Likelihood is High) and (Corrosion-Likelihood is Very_Low) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)

247. If (Design-likelihood is Very_Low) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Low) and (TPD-Likelihood is High) then (Total-Likelihood is Low) (1)
248. If (Design-likelihood is Very_Low) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Low) and (TPD-Likelihood is Very_High) then (Total-Likelihood is Low) (1)
249. If (Design-likelihood is Very_Low) and (IO-Likelihood is Low) and (Corrosion-Likelihood is High) and (TPD-Likelihood is Very_High) then (Total-Likelihood is High) (1)
250. If (Design-likelihood is Very_Low) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Very_High) and (TPD-Likelihood is Low) then (Total-Likelihood is Low) (1)
251. If (Design-likelihood is Very_Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Very_High) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
252. If (Design-likelihood is High) and (IO-Likelihood is High) and (Corrosion-Likelihood is High) and (TPD-Likelihood is Very_Low) then (Total-Likelihood is Low) (1)
253. If (Design-likelihood is High) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is High) and (TPD-Likelihood is High) then (Total-Likelihood is Low) (1)
254. If (Design-likelihood is Very_Low) and (IO-Likelihood is High) and (Corrosion-Likelihood is High) and (TPD-Likelihood is High) then (Total-Likelihood is Low) (1)
255. If (Design-likelihood is Very_High) and (IO-Likelihood is Low) and (Corrosion-Likelihood is Low) and (TPD-Likelihood is Low) then (Total-Likelihood is Low) (1)
256. If (Design-likelihood is Low) and (IO-Likelihood is Very_Low) and (Corrosion-Likelihood is Low) and (TPD-Likelihood is Low) then (Total-Likelihood is Low) (1)

Section-2 Consequence Mamdani FIS model:

1. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_Low) and (Receptors is Very_Low) then (Consequence is Low)
2. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_Low) and (Receptors is Low) then (Consequence is High)
3. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_Low) and (Receptors is High) then (Consequence is High)
4. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_Low) and (Receptors is Very_High) then (Consequence is High)
5. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Low) and (Receptors is Very_Low) then (Consequence is High)
6. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Low) and (Receptors is Low) then (Consequence is High)
7. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Low) and (Receptors is High) then (Consequence is High)
8. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Low) and (Receptors is Very_High) then (Consequence is Very_High)
9. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is High) and (Receptors is Very_Low) then (Consequence is High)
10. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is High) and (Receptors is Low) then (Consequence is High)
11. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is High) and (Receptors is High) then (Consequence is Very_High)
12. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is High) and (Receptors is Very_High) then (Consequence is Very_High)
13. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_High) and (Receptors is Very_Low) then (Consequence is High)
14. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_High) and (Receptors is Low) then (Consequence is Very_High)
15. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_High) and (Receptors is High) then (Consequence is Very_High)
16. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_High) and (Receptors is Very_High) then (Consequence is Very_High)

241. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_Low) and (Receptors is Very_Low) then (Consequence is Very_Low)
242. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_Low) and (Receptors is Low) then (Consequence is Very_Low)
243. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_Low) and (Receptors is High) then (Consequence is Very_Low)
244. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_Low) and (Receptors is Very_High) then (Consequence is Low)
245. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Low) and (Receptors is Very_Low) then (Consequence is Very_Low)
246. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Low) and (Receptors is Low) then (Consequence is Very_Low)
247. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Low) and (Receptors is High) then (Consequence is Low)
248. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Low) and (Receptors is Very_High) then (Consequence is Low)
249. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is High) and (Receptors is Very_Low) then (Consequence is Very_Low)
250. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is High) and (Receptors is Low) then (Consequence is Low)
251. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is High) and (Receptors is High) then (Consequence is Low)
252. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is High) and (Receptors is Very_High) then (Consequence is Low)
253. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_High) and (Receptors is Very_Low) then (Consequence is Low)
254. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_High) and (Receptors is Low) then (Consequence is Low)
255. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_High) and (Receptors is High) then (Consequence is Low)
256. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_High) and (Receptors is Very_High) then (Consequence is Low)

Section-3 PLRA Mamdani FIS model:

1. If (Total-likelihood is Very_Low) and (Consequence is Very_Low) then (PLRA is Very_Low)
2. If (Total-likelihood is Very_Low) and (Consequence is Low) then (PLRA is Very_Low)
3. If (Total-likelihood is Very_Low) and (Consequence is High) then (PLRA is Low)
4. If (Total-likelihood is Very_Low) and (Consequence is Very_Low) then (PLRA is Low)
5. If (Total-likelihood is Low) and (Consequence is Very_Low) then (PLRA is Very_Low)
6. If (Total-likelihood is Low) and (Consequence is Low) then (PLRA is Low)
7. If (Total-likelihood is Low) and (Consequence is High) then (PLRA is Low)
8. If (Total-likelihood is Low) and (Consequence is Very_Low) then (PLRA is High)
9. If (Total-likelihood is High) and (Consequence is Very_Low) then (PLRA is Low)
10. If (Total-likelihood is High) and (Consequence is Low) then (PLRA is Low)
11. If (Total-likelihood is High) and (Consequence is High) then (PLRA is High)
12. If (Total-likelihood is High) and (Consequence is Very_Low) then (PLRA is Very_High)
13. If (Total-likelihood is Very_High) and (Consequence is Very_Low) then (PLRA is Low)
14. If (Total-likelihood is Very_High) and (Consequence is Low) then (PLRA is High)
15. If (Total-likelihood is Very_High) and (Consequence is High) then (PLRA is Very_High)
16. If (Total-likelihood is Very_High) and (Consequence is Very_Low) then (PLRA is Very_High)

Section-4 Vulnerability Mamdani FIS model:

1. If (Design is Very_Low) and (IO is Very_Low) then (Vulnerability is Very_Low) (1)

2. If (Design is Very_Low) and (IO is Low) then (Vulnerability is Low) (1)
3. If (Design is Very_Low) and (IO is High) then (Vulnerability is Low) (1)
4. If (Design is Very_Low) and (IO is Very_High) then (Vulnerability is High) (1)
5. If (Design is Low) and (IO is Very_Low) then (Vulnerability is Low) (1)
6. If (Design is Low) and (IO is Low) then (Vulnerability is Low) (1)
7. If (Design is Low) and (IO is High) then (Vulnerability is High) (1)
8. If (Design is Low) and (IO is Very_High) then (Vulnerability is High) (1)
9. If (Design is High) and (IO is Very_Low) then (Vulnerability is Low) (1)
10. If (Design is High) and (IO is Low) then (Vulnerability is High) (1)
11. If (Design is High) and (IO is High) then (Vulnerability is High) (1)
12. If (Design is High) and (IO is Very_High) then (Vulnerability is Very_High) (1)
13. If (Design is Very_High) and (IO is Very_Low) then (Vulnerability is Low) (1)
14. If (Design is Very_High) and (IO is Low) then (Vulnerability is High) (1)
15. If (Design is Very_High) and (IO is High) then (Vulnerability is High) (1)
16. If (Design is Very_High) and (IO is Very_High) then (Vulnerability is Very_High) (1)

Section-5 Threat Mamdani FIS model:

1. If (Corrosion is Very_Low) and (TPD is Very_Low) then (Threat is Very_Low) (1)
2. If (Corrosion is Very_Low) and (TPD is Low) then (Threat is Low) (1)
3. If (Corrosion is Very_Low) and (TPD is High) then (Threat is Low) (1)
4. If (Corrosion is Very_Low) and (TPD is Very_High) then (Threat is High) (1)
5. If (Corrosion is Low) and (TPD is Very_Low) then (Threat is Very_Low) (1)
6. If (Corrosion is Low) and (TPD is Low) then (Threat is Low) (1)
7. If (Corrosion is Low) and (TPD is High) then (Threat is High) (1)
8. If (Corrosion is Low) and (TPD is Very_High) then (Threat is High) (1)
9. If (Corrosion is High) and (TPD is Very_Low) then (Threat is Low) (1)
10. If (Corrosion is High) and (TPD is Low) then (Threat is Low) (1)
11. If (Corrosion is High) and (TPD is High) then (Threat is High) (1)
12. If (Corrosion is High) and (TPD is Very_High) then (Threat is Very_High) (1)
13. If (Corrosion is Very_High) and (TPD is Very_Low) then (Threat is Low) (1)
14. If (Corrosion is Very_High) and (TPD is Low) then (Threat is High) (1)
15. If (Corrosion is Very_High) and (TPD is High) then (Threat is Very_High) (1)
16. If (Corrosion is Very_High) and (TPD is Very_High) then (Threat is Very_High) (1)

Section-6 Consequence_2 Mamdani FIS model:

1. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_Low) and (Receptors is Very_Low) then (Consequence is Very_Low)
2. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_Low) and (Receptors is Low) then (Consequence is High)
3. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_Low) and (Receptors is High) then (Consequence is High)
4. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Very_Low) and (Receptors is Very_High) then (Consequence is High)
5. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Low) and (Receptors is Very_Low) then (Consequence is High)
6. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Low) and (Receptors is Low) then (Consequence is High)
7. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Low) and (Receptors is High) then (Consequence is High)
8. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is Low) and (Receptors is Very_High) then (Consequence is Very_High)
9. If (Product-Hazard is Very_High) and (Dispersion is Very_High) and (Leak is High) and (Receptors is Very_Low) then (Consequence is High)

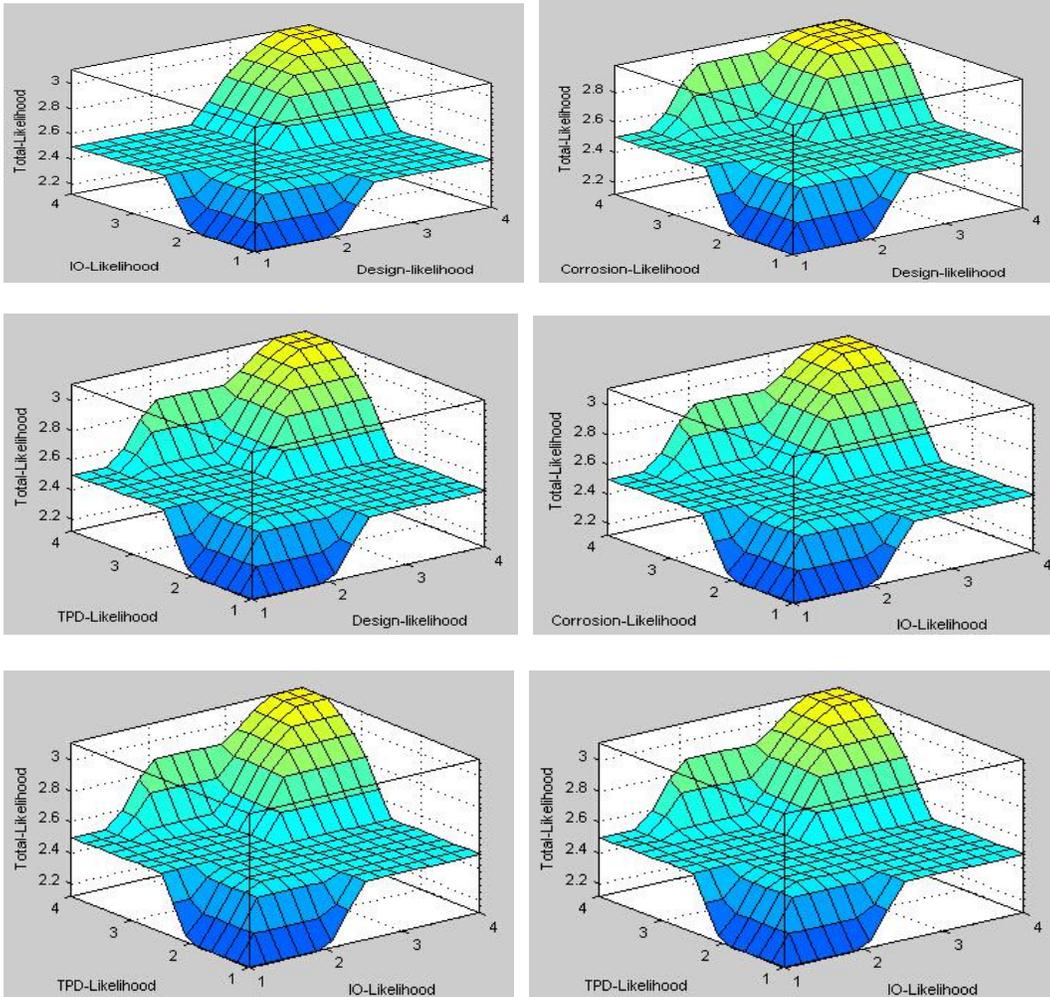
234. If (Product-Hazard is Very_Low) and (Dispersion is Low) and (Leak is High) and (Receptors is Low) then (Consequence is Low)
235. If (Product-Hazard is Very_Low) and (Dispersion is Low) and (Leak is High) and (Receptors is High) then (Consequence is Low)
236. If (Product-Hazard is Very_Low) and (Dispersion is Low) and (Leak is High) and (Receptors is Very_High) then (Consequence is Low)
237. If (Product-Hazard is Very_Low) and (Dispersion is Low) and (Leak is Very_High) and (Receptors is Very_Low) then (Consequence is Low)
238. If (Product-Hazard is Very_Low) and (Dispersion is Low) and (Leak is Very_High) and (Receptors is Low) then (Consequence is Low)
239. If (Product-Hazard is Very_Low) and (Dispersion is Low) and (Leak is Very_High) and (Receptors is High) then (Consequence is Low)
240. If (Product-Hazard is Very_Low) and (Dispersion is Low) and (Leak is Very_High) and (Receptors is Very_High) then (Consequence is High)
241. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_Low) and (Receptors is Very_Low) then (Consequence is Very_Low)
242. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_Low) and (Receptors is Low) then (Consequence is Very_Low)
243. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_Low) and (Receptors is High) then (Consequence is Very_Low)
244. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_Low) and (Receptors is Very_High) then (Consequence is Low)
245. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Low) and (Receptors is Very_Low) then (Consequence is Very_Low)
246. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Low) and (Receptors is Low) then (Consequence is Very_Low)
247. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Low) and (Receptors is High) then (Consequence is Low)
248. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Low) and (Receptors is Very_High) then (Consequence is Low)
249. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is High) and (Receptors is Very_Low) then (Consequence is Very_Low)
250. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is High) and (Receptors is Low) then (Consequence is Low)
251. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is High) and (Receptors is High) then (Consequence is Low)
252. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is High) and (Receptors is Very_High) then (Consequence is Low)
253. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_High) and (Receptors is Very_Low) then (Consequence is Low)
254. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_High) and (Receptors is Low) then (Consequence is Low)
255. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_High) and (Receptors is High) then (Consequence is Low)
256. If (Product-Hazard is Very_Low) and (Dispersion is Very_Low) and (Leak is Very_High) and (Receptors is Very_High) then (Consequence is Low)

4. Mamdani Model Surface Plots

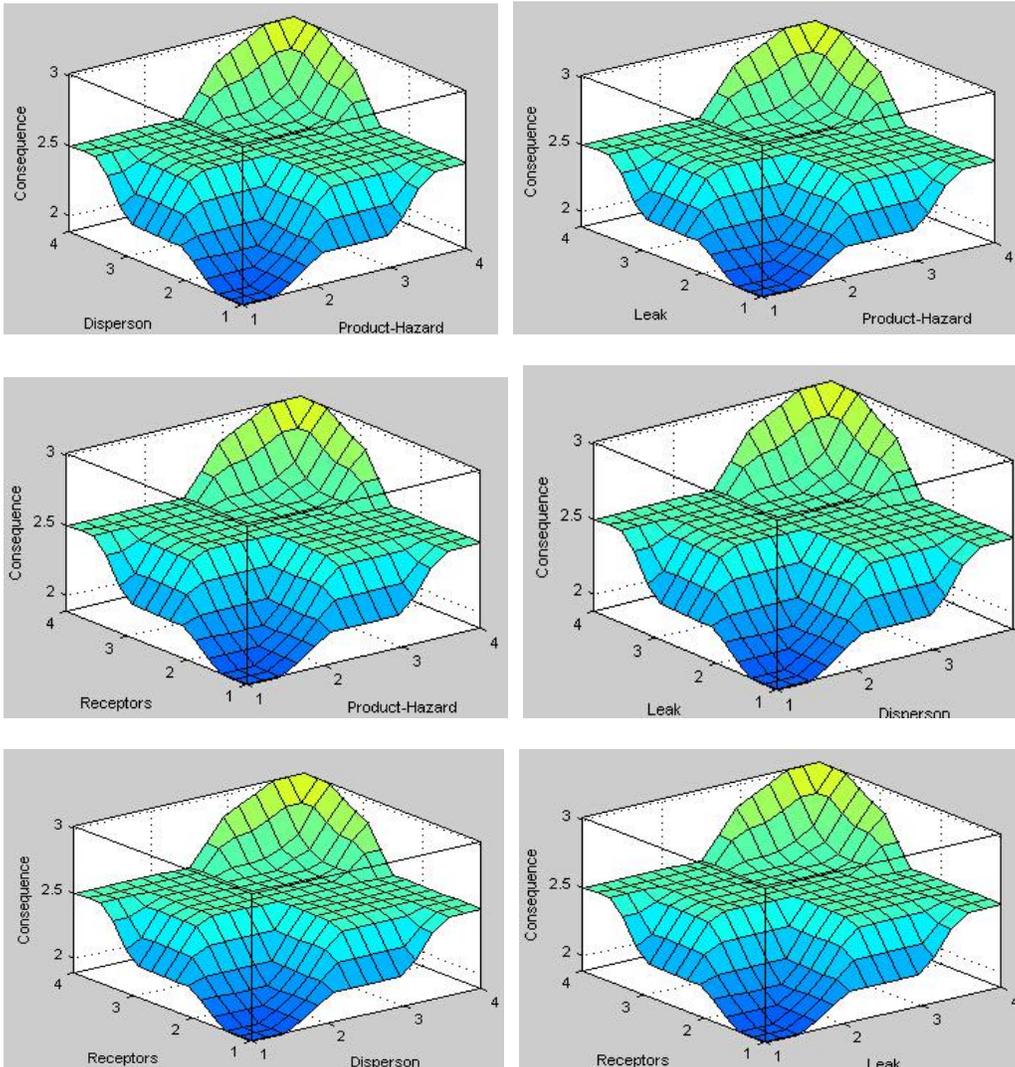
The relationship of various combinations of inputs and the sole output can be represented by surface plot of each FIS model in Matlab. It is necessary to note that each

surface plot can only display two inputs and corresponding outputs in the x, y and z axis, respectively.

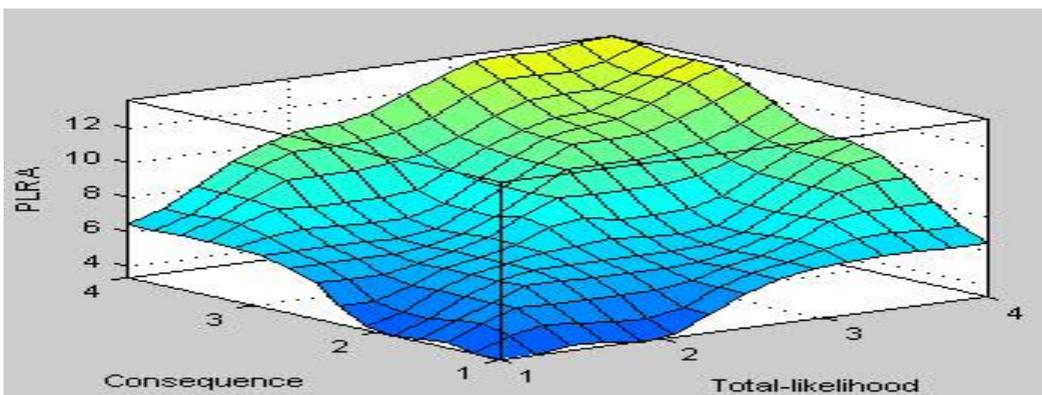
Section-1 Total-likelihood Mamdani Fuzzy Inference System



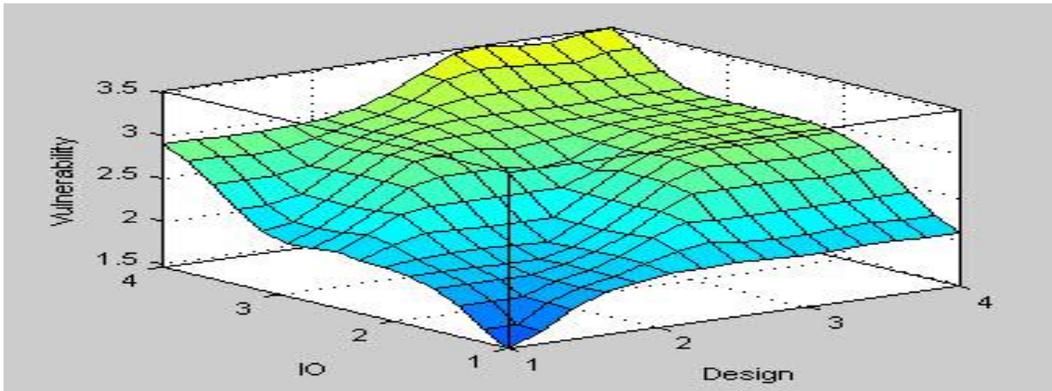
Section-2 Consequence Mamdani Fuzzy Inference System



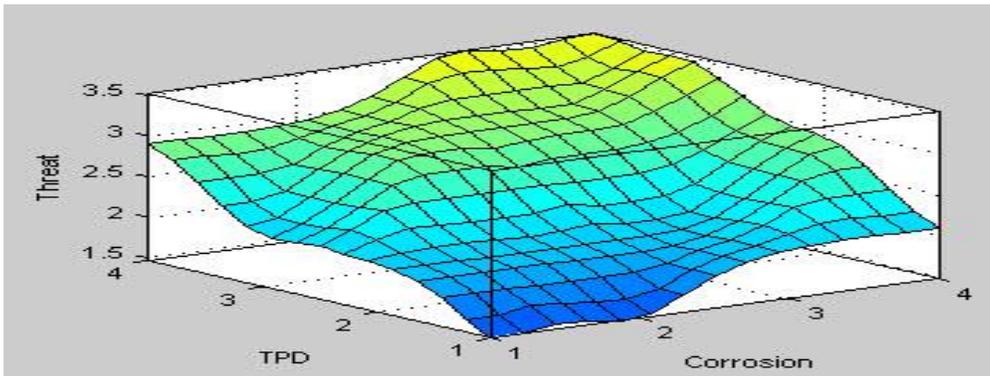
Section-3 PLRA Mamdani Fuzzy Inference System



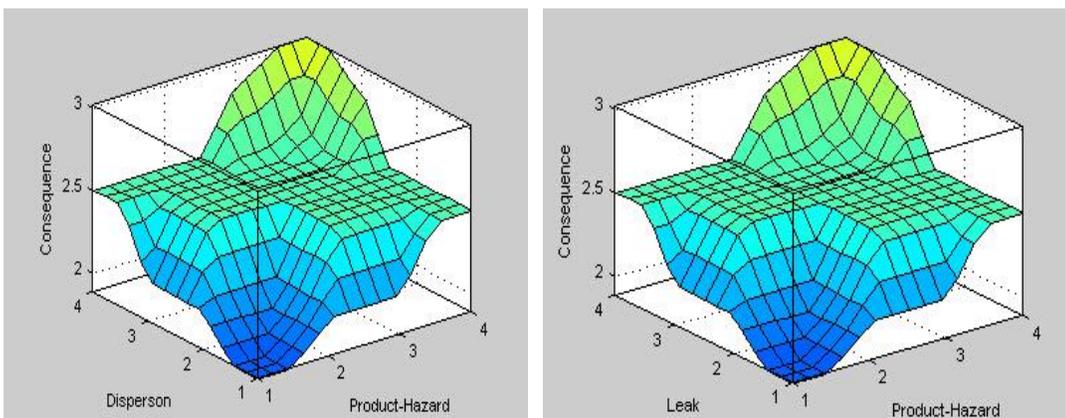
Section-4 Vulnerability Mamdani Fuzzy Inference System

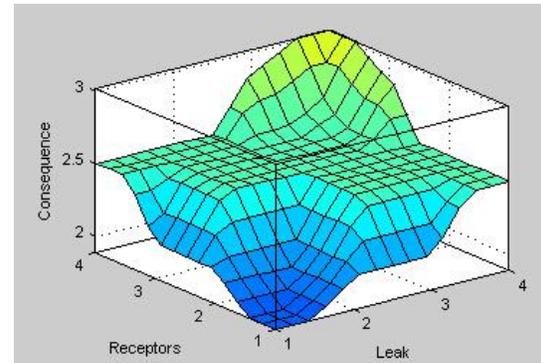
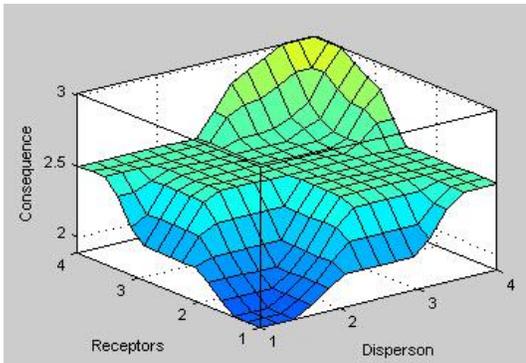
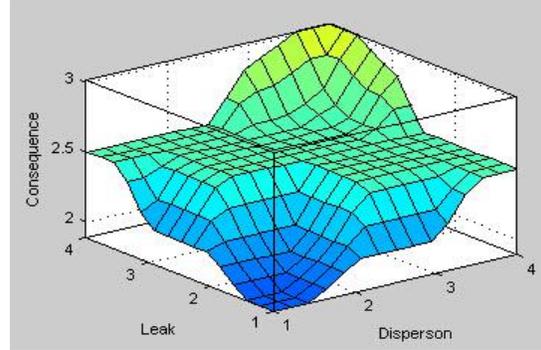
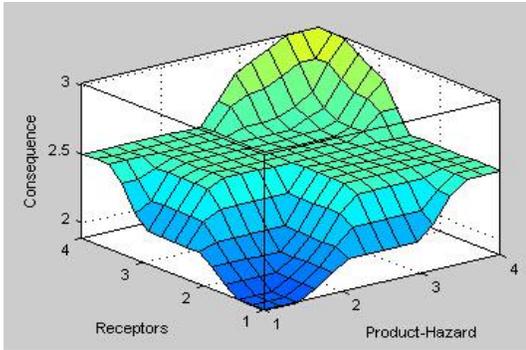


Section-5 Threat Mamdani Fuzzy Inference System

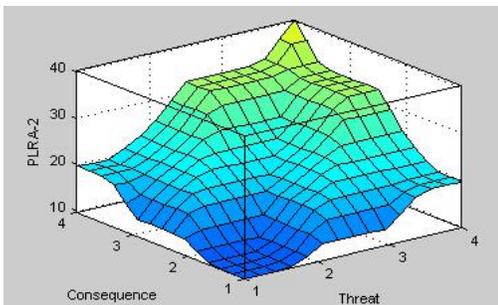
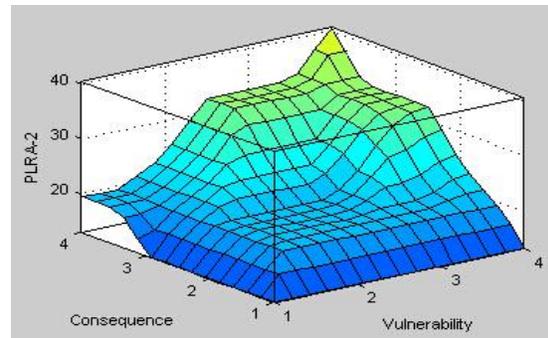
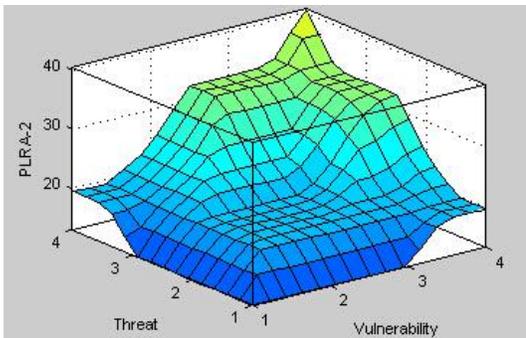


Section-6 Consequence_2 Mamdani Fuzzy Inference System





Section-7 PLRA-2 Mamdani Fuzzy Inference System



5. Mamdani Models If-Then Rules

This section will present the experimental if-then rules viewer for each one of the Mamdani models. If inputs' values are changed, the corresponding outputs will be given simultaneously. This Rules Viewer process is built in the GUI interface as well.

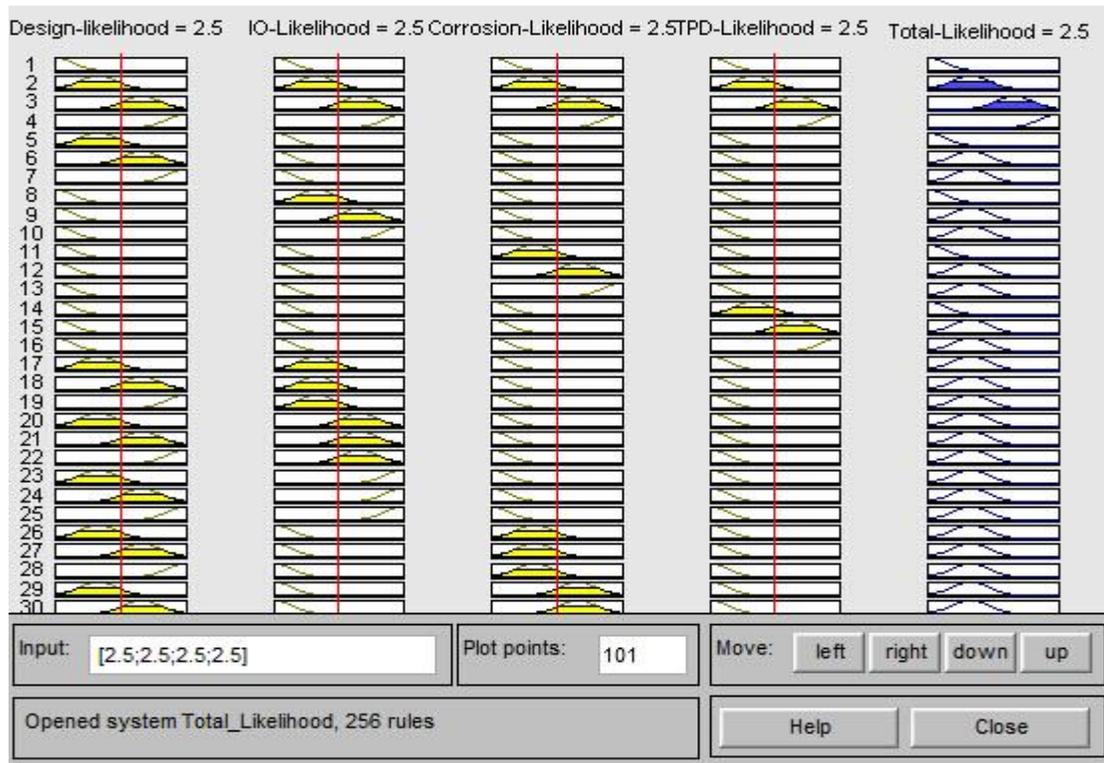


Figure A5. 1 Total-likelihood Rules Viewer.

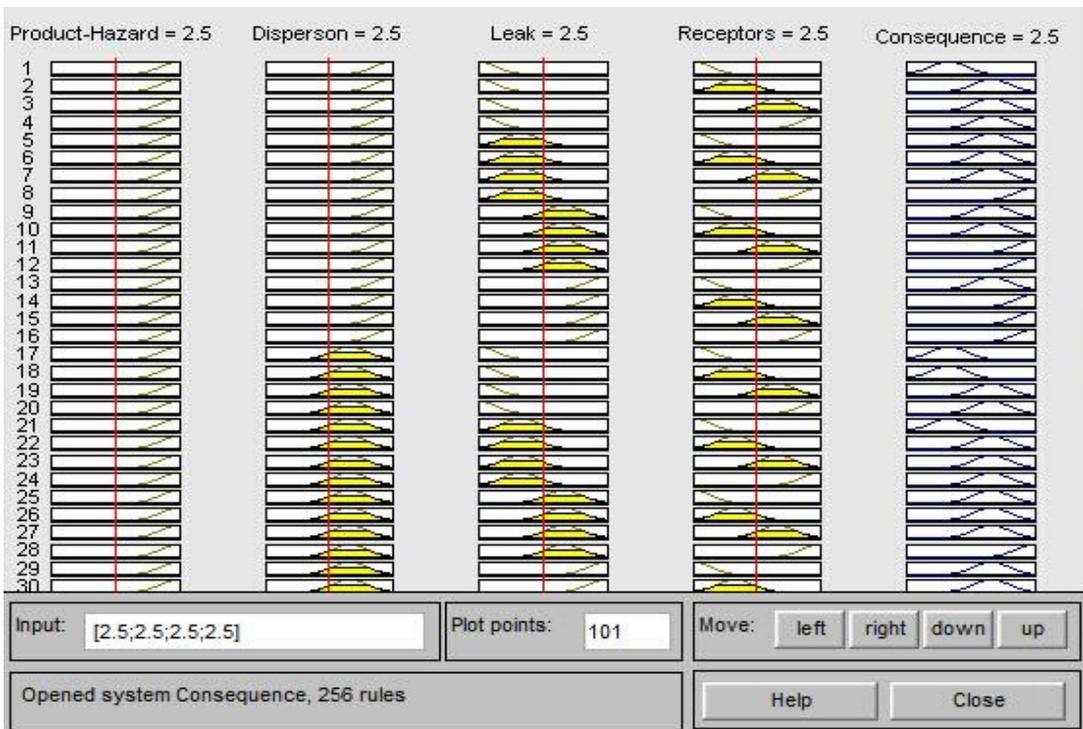


Figure A5. 2 Consequence Rules Viewer.

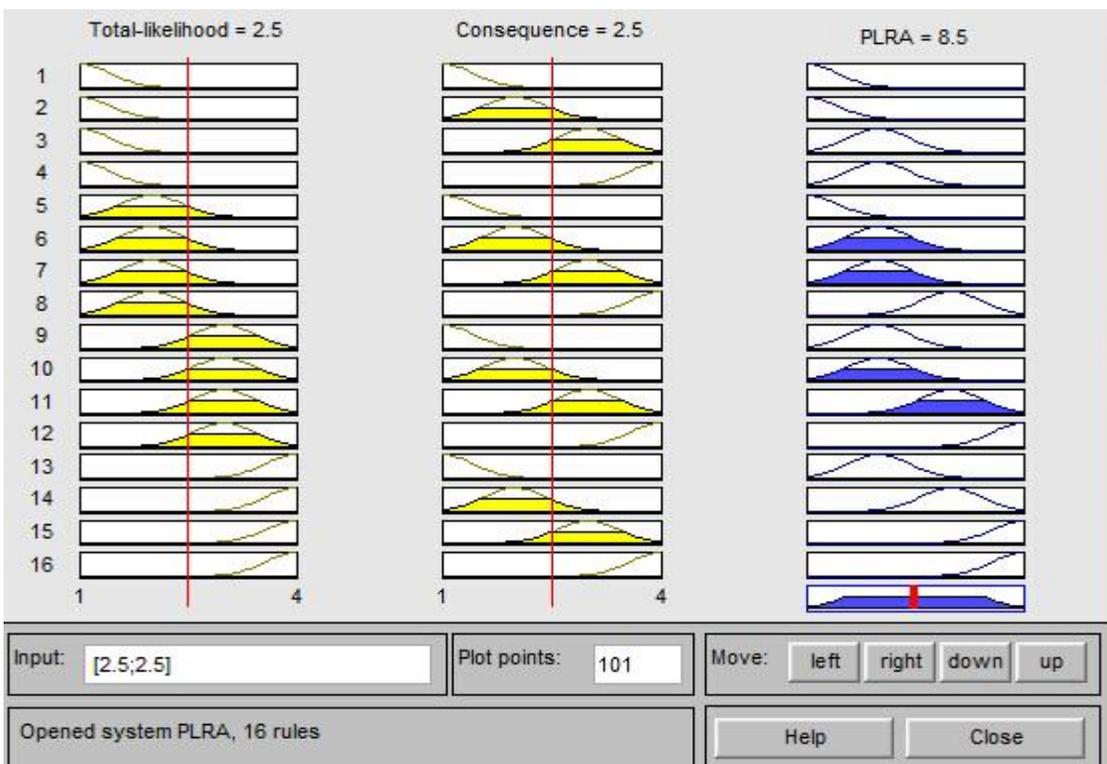


Figure A5. 3 PLRA Rules Viewer.

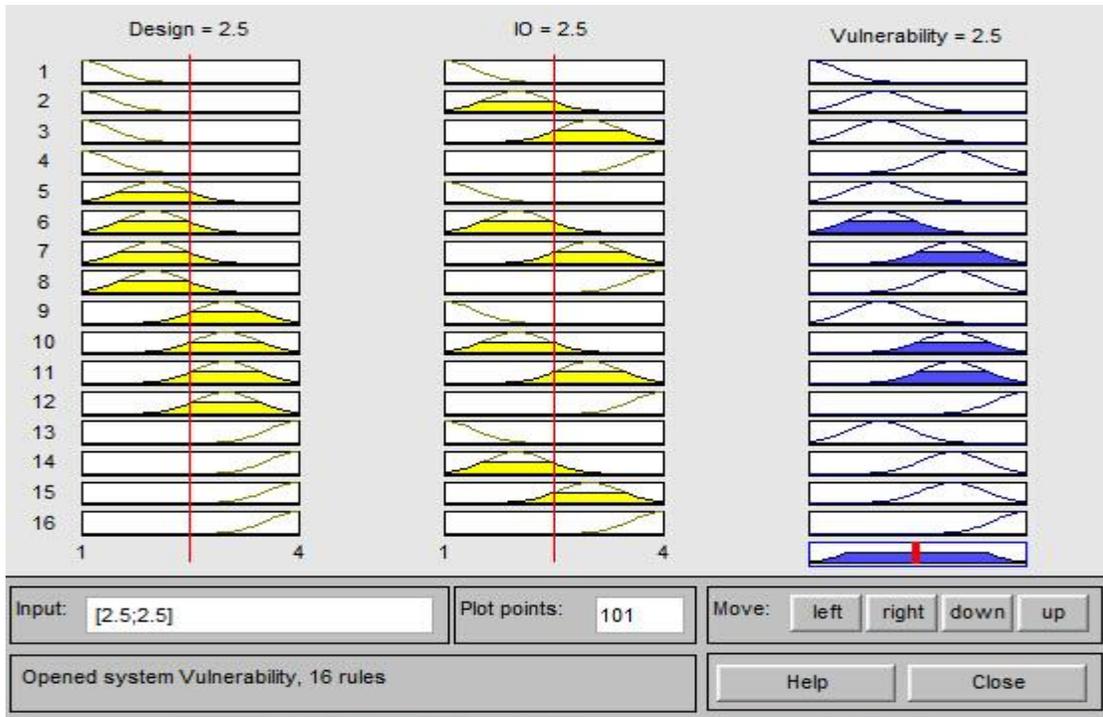


Figure A5. 4 Vulnerability Rules Viewer.

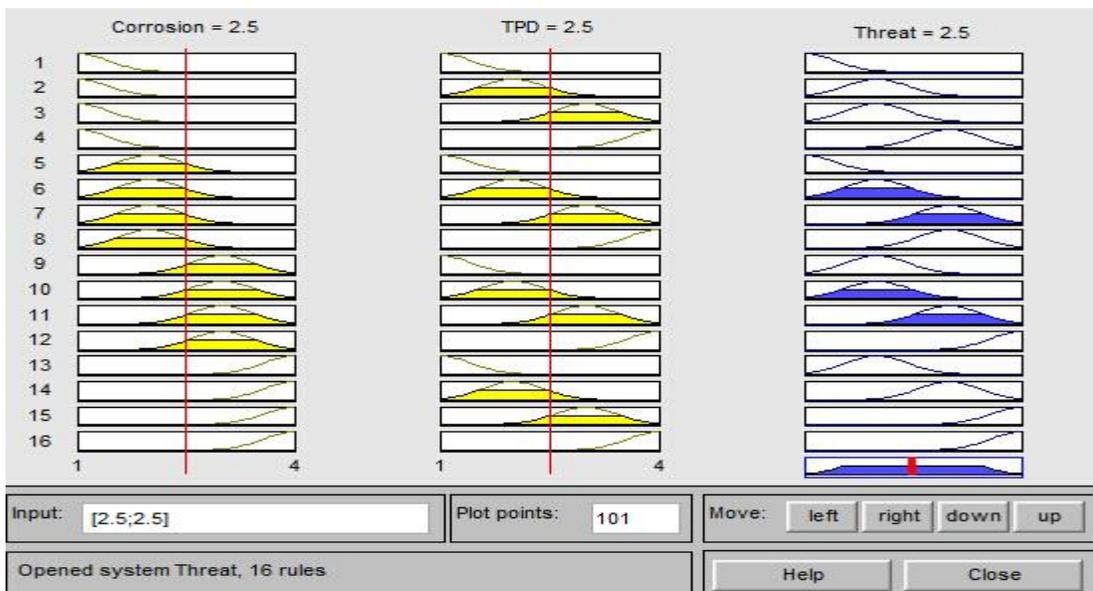


Figure A5. 5 Threat Rules Viewer.

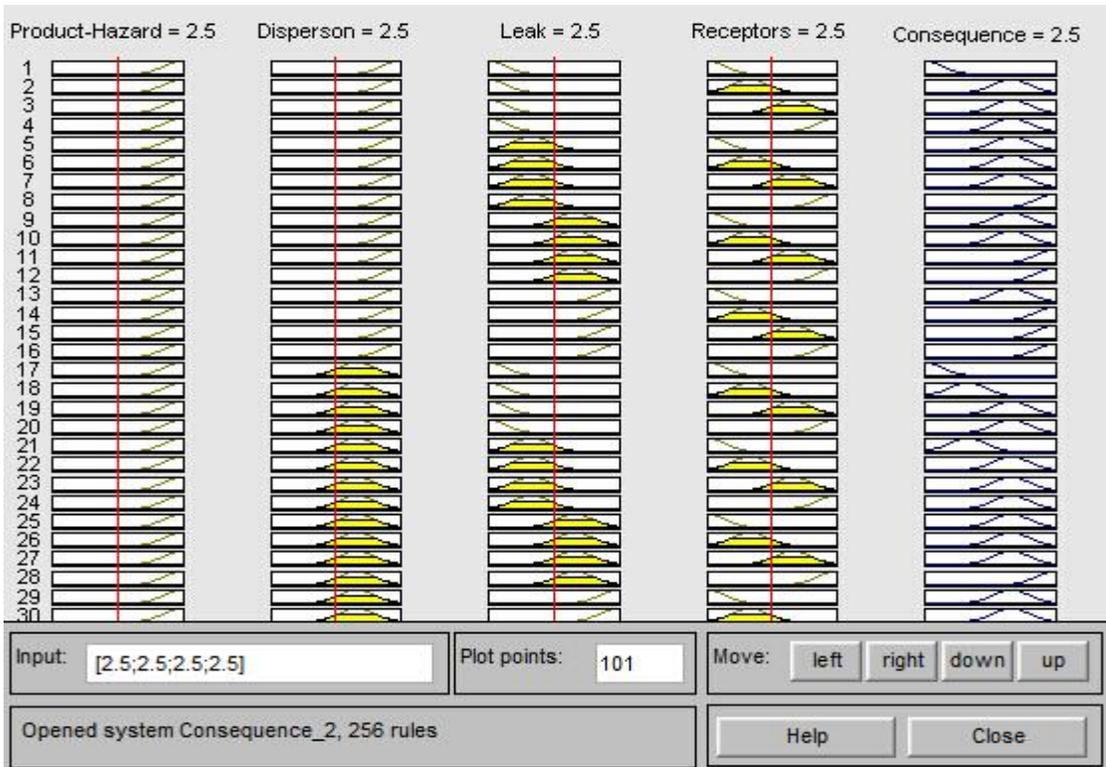


Figure A5. 6 Consequence_2 Rules Viewer.

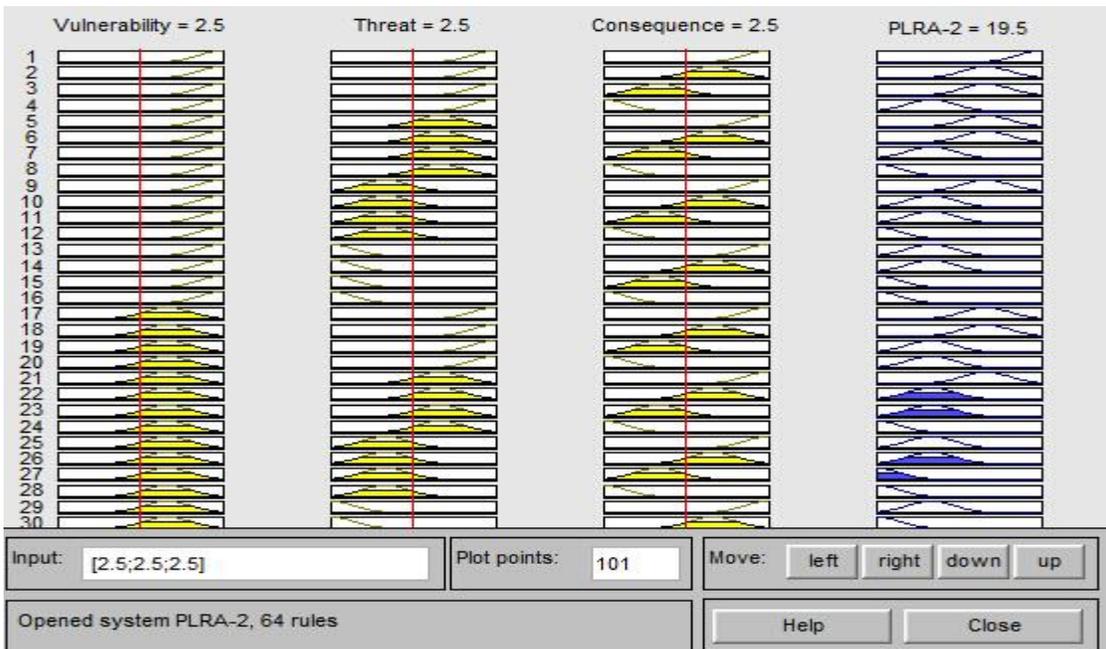


Figure A5. 7 PLRA-2 Rules Viewer.

6. Artificial Neural Networks Matlab Code

6.1 ANN model of first Pipeline Risk Assessment model

```
clear all
clc
% Training input data TI and output data TO
% input TI sequence design, incorrect operation, tpd, corrosion, product hazard, dispersion, leak, receptor,
% Training data given by previous built FIS model.
original_input=[1, 1.1, 1.5, 2, 3, 2.3, 4, 4, 1.7, 1.5, 2.3, 2.5, 1.5, 2.3,2.0, 1.2, 1.3, 3.2, 3.1, 2.9, 2.8, 2.9, 1.1,
1, 1, 1, 3, 3.1, 2.1, 2.2, 2.3, 2.4, 1.5, 1.6, 2.6, 1.9, 2.7, 3.3, 3.5, 3.6, 3.9, 3.9,3.9, 4, 4, 3.2, 2.8, 2.8, 3, 1;

1, 1.0, 1.4, 3, 1, 3.2, 3.1, 2.2, 3.1, 1.5, 2.5, 2.9, 1.5, 2, 3, 1.5,2, 2.6, 2.5, 2.2, 2.2, 2.3, 1.2, 1.2, 1.1, 1, 3.0,
3.1, 2.1, 2.2, 2.3, 2.5,3.2, 3.4, 1.4, 2.3, 3.2, 3.2, 3.4, 3.6, 3.7, 3.7, 4, 4,4, 3.4, 3.0, 3, 3.0, 1.0;

1.0, 1.12, 1.9, 2.5, 2, 3.2, 3.4, 3.4, 2.8, 1.5, 3.5, 3.5, 1.5, 4.2, 1.7, 2.2, 2.2, 2, 1.9, 1.8, 2.2, 1.3, 1.1, 1, 3, 3.1,
2.1, 2.2, 2.3, 2.3, 1.8, 1.9, 3.9, 2.9, 1.7, 3.6, 3.6, 3.7, 3.7, 3.8, 4, 4,4, 3.2, 2.8, 3.0, 2.9, 1.0;

1.1, 1.1, 2.1, 3.3, 4, 3.1, 3.5, 2.2, 3.7, 1.5, 1.3, 1.9, 1.5, 2.0, 1, 2, 1.5, 3.3, 3, 2.8, 2.6, 2, 1.4, 1, 1, 1, 3, 3.1,
2.1, 2.2, 2.3, 2.6, 2.2, 2.3, 3.3, 1.3, 3.9, 3.7, 3.8, 3.9, 3.9, 3.9, 3.9, 4, 4, 2.9, 2.6, 2.8, 3.0, 1;

1, 1.2, 1.3, 3, 2, 2.2, 3.6, 2.7, 2.7, 1.5, 2.7, 2.1, 1.3, 2.2,3, 2, 1.8, 2.8, 2.7, 2.7, 3, 2.9, 1.1, 1, 1, 1, 3, 2.5, 2.4,
2.6, 3, 2.8,3.5, 3.4, 2.6, 2.2, 2.7, 3.4, 3.6, 3.6, 3.7, 3.7, 3.8,3.9, 4, 3.6, 3.2, 3.3, 3.4, 1.0;

1.1, 1.1, 1.1, 2, 2, 1.8, 2.8, 2.7, 2.7, 2, 3.3, 3.6, 1.3, 1.3,3, 1.3, 2.2, 3.6, 3.4, 3.2, 3, 3, 1, 1, 1, 1, 3, 2.5, 2.4,
2.3, 3, 3.2, 2.1,2.3, 2.5, 2.8, 3.1, 3.3, 3.5, 3.8, 3.8, 3.9, 3.9, 4,4, 2.7, 2.0, 2.4, 2.7, 1.0;

1, 1.1, 1.4, 1, 3, 2.7, 3.4, 3.8, 3.5, 2.5, 1.3, 2.0, 2.5, 2.0,1, 2.2, 3, 3, 3.1, 1.9, 2.4, 2.5, 1, 1, 1, 1, 3, 2.5, 2.4,
2.6, 3, 2.0, 1.9,1.9, 1.3, 1.6, 1.8, 3.6, 3.7, 3.6, 3.7, 3.8, 3.8, 3.9,4, 2.6, 2.2, 2.5, 2.6, 1;

1, 1.1, 1.5, 2.5, 3, 2.8, 3.7, 2, 1.6, 3.5, 3.8, 2, 2, 2.6, 4, 3.5, 2.1, 2.9, 2.8, 2.6, 2.8, 2.8, 1.1, 1.1, 1.1, 1, 3, 2.5,
2.4, 2.3,3, 2.8, 1.3, 1.3, 2.1, 2, 3.0, 3.4, 3.6, 3.9, 3.9, 3.9, 4,4, 3.0, 2.9, 2.8, 2.6, 1.0];

original_output=[5.30, 5.45, 6.03, 6.74, 6.64, 7.03, 10.81, 9.82, 8.72, 6.29, 8.36,6.86, 6.21, 6.7, 6.64, 6.41,
6.75, 10.22, 9.85, 9.32, 9.11, 7.4, 5.30, 5.32, 5.29, 4.08, 10.36, 8.5, 6.93, 7.11, 7.4, 8.6, 7.10,7.62, 7.02,
6.74, 9.42, 10.73, 10.87, 10.97, 11.22, 11.34, 11.45,11.65,11.71, 9.44, 7.10, 8.29, 8.96, 5.29];

% Network Design
pr=minmax(original_input);
si=[8,4,2, 1];
tf={'purelin' 'purelin' 'purelin' 'purelin'};

% Net training
net=newff(pr, si, tf,'trainlm');
net.trainparam.epochs= 500;
net.trainparam.goal=1e-2;
net.trainparam.show= 30;
net.trainParam.min_grad=1e-100;
net=train(net,original_input, original_output);

% introduce and simulate new input data & get corresponding output
```

```

% plot output
new_input= [1.7, 1.7,3.9,3.8,2.9,3.1,1.3;
            1.7, 2.8,3.1,3.8,3.1,2.8,3.3;
            1.6, 2.8,1.7,3.8,2.9,3.1,1.9;
            1.5, 1,1.5,3.8,3.0,2.9,2.1;
            1.6, 2.7,1.6,3.8,3.3,2.5,3.3;
            1.6, 2.7, 1.6,3.8,2.7,2.5,2.0;
            1.6, 1.6, 2.8,3.8,2.6,2.5,2.2;
            1.6, 4, 3.9,3.8,2.6,2.6,1.6] ;

new_output= [6.34, 6.71, 8.93,11.24,9.11,8.52,7.2];
simulate_output= sim(net, new_input);
error = simulate_output- new_output;
plot(error)

```

6.2 ANN model of second Pipeline Risk Assessment model

```

clear all
clc
% Training input data TI and output data TO
% input TI sequence design, incorrect operation, tpd, corrosion, product hazard, dispersion, leak, receptor,
% Training data given by previous built FIS model.
original_input=[1, 1.1, 1.5, 2, 3, 2.3, 4, 4, 1.7, 1.5, 2.3, 2.5, 1.5, 2.3,2.0, 1.2, 1.3, 3.2, 3.1, 2.9, 2.8, 2.9, 1.1,
1, 1, 1, 3, 3.1, 2.1, 2.2, 2.3, 2.4, 1.5, 1.6, 2.6, 1.9, 2.7, 3.3, 3.5, 3.6, 3.9, 3.9,3.9, 4, 4, 3.2, 2.8, 2.8, 3, 1;

1, 1.0, 1.4, 3, 1, 3.2, 3.1, 2.2, 3.1, 1.5, 2.5, 2.9, 1.5, 2, 3, 1.5,2, 2.6, 2.5, 2.2, 2.2, 2.3, 1.2, 1.2, 1.1, 1, 3.0,
3.1, 2.1, 2.2, 2.3, 2.5,3.2, 3.4, 1.4, 2.3, 3.2, 3.2, 3.4, 3.6, 3.7, 3.7, 3.9, 4.4, 3.4, 3.0, 3, 3.0, 1.0;
1.0, 1.1, 1.9, 2.5, 2, 3.2, 3.4, 3.4, 2.8, 1.5, 3.5, 3.5, 1.5, 4.2, 1.7, 2.2, 2.2, 2, 1.9, 1.8, 2.2, 1.3, 1,1.1, 1, 3, 3.1,
2.1, 2.2, 2.3, 2.3, 1.8, 1.9, 3.9, 2.9, 1.7, 3.6, 3.6, 3.7, 3.7, 3.8, 4, 4.4, 3.2, 2.8, 3.0, 2.9, 1.0;

1.1, 1.1, 2.1, 3.3, 4, 3.1, 3.5, 2.2, 3.7, 1.5, 1.3, 1.8, 1.5, 2.0, 1, 2, 1.5, 3.3, 3, 2.8, 2.6, 2, 1.4, 1, 1, 1, 3, 3.1,
2.1, 2.2, 2.3, 2.6, 2.2, 2.3, 3.3, 1.3, 3.9, 3.7, 3.8, 3.9, 3.9, 3.9, 3.9, 4, 4, 2.9, 2.6, 2.8, 3.0, 1;

1, 1.2, 1.3, 3, 2, 2.2, 3.6, 2.7, 2.7, 1.5, 2.7, 2.1, 2.0, 2.2,3, 2, 1.8, 2.8, 2.7, 2.7, 3, 2.9, 1.1, 1, 1.1, 1, 3, 3, 2.4,
2.5, 3, 2.8,3.5, 3.4, 2.6, 2.2, 2.7, 3.4, 3.6, 3.6, 3.7, 3.7, 3.8,3.9, 4, 3.6, 3.2, 3.3, 3.4, 1.0;
1.1, 1.1, 1.1, 2, 2, 1.8, 2.8, 2.8, 2.7, 2, 3.3, 3.6, 3, 1.3,3, 1.3, 2.2, 3.6, 3.4, 3.2, 3, 2.6, 1, 1, 1, 1, 3, 3, 2.4, 2.4,
3, 3.2, 2.1,2.3, 2.5, 2.8, 3.1, 3.3, 3.5, 3.8, 3.8, 3.9, 3.9, 4.4, 2.7, 2.0, 2.4, 2.7, 1.0;

1, 1.1, 1.4, 1, 3, 2.7, 3.4, 3.8, 3.5, 2.5, 1.3, 1.9, 2.8, 2.0,1, 2.2, 3, 3, 3.1, 1.9, 2.4, 2.5, 1, 1, 1, 1, 3, 3, 2.4, 2.6,
3, 2.0, 1.9,1.9, 1.3, 1.6, 1.8, 3.6, 3.7, 3.6, 3.7, 3.8, 3.8, 3.9,4, 2.6, 2.2, 2.5, 2.6, 1;
1, 1.1, 1.5, 2.5, 3, 2.8, 3.7, 2, 1.6, 3.5, 3.8, 2, 2.2, 2.6, 4, 3.5, 2.1, 2.9, 2.8, 2.6, 2.8, 2.8, 1.1, 1.1, 1.1, 1, 3, 3,
2.4, 2.4,3, 2.8, 1.3, 1.3, 2.1, 2, 3.0, 3.4, 3.6, 3.9, 3.9, 3.9, 4.4, 4, 3.0, 2.9, 2.8, 2.7, 1.0];

original_output=[9.36, 9.38, 12.94, 23.97, 23.09, 23.67, 26.20, 28.71, 23.47, 19.55, 21.73,20.09, 14.01,
23.17, 20.21, 15.25, 12.84, 23.65, 23.24, 22.68, 22.27, 21.09, 10.47, 9.27, 9.28, 9.26, 23.09, 23.38, 17.64,
16.17, 18.48, 22.46, 16.47,16.86, 26.83,12.8, 23.61, 27.20, 28.59, 31.36, 31.86,32.34, 35.53,35.98,35.99,
24.47, 21.88, 23.18, 23.20,9.26]
% Network Design
pr=minmax(original_input);
si=[8,3,2, 1];
tf={'purelin' 'purelin' 'purelin' 'purelin'};
% Net training
net=newff(pr, si, tf,'trainlm');

```

```
net.trainparam.epochs= 500;
net.trainparam.goal=1e-2;
net.trainparam.show= 30;
net.trainParam.min_grad=1e-100;
net=train(net,original_input, original_output);
% introduce and simulate new input data & get corresponding output
% plot output
new_input= [1.3,3.8,1.2,3.9,3.3;
            1.0,3.9,1.1,3.8,2.5;
            1.4,3.8,1.0,3.5,2.1;
            1.3,3.8,1.2,3.7,3.2;
            1.2,3.9,1.2,3.6,2.8;
            1.1,3.9,1.0,3.8,3.4;
            1.0,3.9,1.2,3.6,3.1;
            1.0,3.9,1.1,3.8,3] ;
new_output= [10.16,32.33,9.49,30.2,23.55];
simulate_output= sim(net, new_input);
error = simulate_output- new_output;
plot(error)
```