

**FUZZY-BASED CONDITION ASSESSMENT MODEL FOR OFFSHORE GAS
PIPELINES IN QATAR**

by

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ABSTRACT

Fuzzy-based Condition Assessment Model for Offshore Gas Pipelines in Qatar

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Condition assessment of offshore gas pipelines is a key player in pipeline operations and maintenance. They are used to ensure better decisions for repair and/or replacement and reduce failure possibilities. Information obtained from pipelines assessments are regularly used for scheduling upcoming maintenance and inspection activities. Therefore, it is valuable to have effective condition assessment of pipelines because failure incidents could lead to catastrophic economical and environmental consequences. Furthermore, current practices of assessing gas pipelines condition are considered too primitive and simplified. They mainly depend on experts' opinions in interpreting inspection data where the process is influenced by the human subjectivity and reasoning uncertainty. In another way, they need the detailed knowledge on translation of raw inspection data into valuable information. This will surely lead to decisions lacking thorough and extensive review of the most influential aspects on pipelines condition.

To redress the weaknesses of the current practices and promote the performance of assessing offshore gas pipelines condition, this research proposes a new fuzzy-based methodology that utilizes hierarchical evidential reasoning (HER) for meticulous condition evaluation under subjectivity and uncertainty. The principle behind the posed structure is to establish an enhanced mechanism for the aggregation of different evidence bodies at multiple hierarchical levels in order to attain a reliable and exhaustive pipeline condition assessment. The essential characteristics of the proposed methodology are recapped in the following points. Firstly, the

new approach suggests a more comprehensive hierarchy of the most influential factors affecting pipeline condition under three categories: physical, external, and operational. Secondly, this methodology is designed to consider the relative importance weights of all assessment factors in the hierarchy and to account for interdependencies among compared attributes. Thirdly, a hierarchical belief structure that utilizes evidential reasoning and fuzzy set theory is applied to grasp the uncertainty in pipeline evaluation. A model that utilizes HER can help combine different bodies of evidence at different hierarchical levels using Dempster-Shafer (D-S) rule of combination to obtain a detailed pipeline assessment. Fourthly, a condition assessment scale associated with rehabilitation actions is introduced as a framework for professionals to plan for future inspection and rehabilitation works. Finally, an automated, user-friendly, tool is developed for the propounded model to assess pipeline condition. Multiple sources of data were reached to provide a reliable assessment of pipe condition through the use of a structured questionnaire distributed among professionals in oil and gas industry in the studied region. This proposed model is compared and validated with historical inspection reports that were obtained from a local pipeline operator in Qatar. It is found that this model delivers satisfactory outcomes and forecasts offshore gas pipeline condition with an Average Validity Percent (AVP) of 97.6%.

The developed fuzzy-based methodology is believed to offer a reliable condition assessment that optimizes data interpretation and usage of structured algorithms. Additionally, the introduced model and tool are compatible to researchers and practitioners such as pipeline engineers and consultants in order to prioritize inspection and rehabilitation for existing offshore gas pipelines. This immensely pictures the essence of infrastructure management to ameliorate cost and time optimization.

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LIST OF ABBREVIATIONS

AHP	Analytic Hierarchy Process
AIP	Average Invalidity Percent
ANP	Analytic Network Process
ANSI	American National Standard Institute
API	American Petroleum Institute
ASME	American Society of Mechanical Engineers
ASTM	American Society of Testing Materials
AVP	Average Validity Percent
C_i	Actual Value
CR	Consistency Ratio
DOT	Department of Transportation, USA
DS	Dempster-Shafer Theory of Belief-Function
e_i	Basic Attribute
E_i	Estimated Value
ER	Evidential Reasoning
f_i	Fit Index
FRP	Fiber-Reinforced Polymer
FTA	Fault Tree Analysis
GE	General Electric
H	Distinctive Evaluation Grade
ILI	Inline Inspection
$K_{l(i+1)}$	Normalizing Factor

LNG	Liquefied Natural Gas
MAE	Mean Absolute Error
MAOP	Maximum Allowable Operating Pressure
MCDM	Multi-Criteria Decision Making
MFL	Magnetic Flux Inspection
$m_{n, i}$	Basic Probability Mass
OPEC	Organization of Petroleum Exporting Countries
QatarGas	Operating Company Limited
QP	Qatar Petroleum
RasGas	Ras Laffan Company Limited
RBIM	Risk Based Inspection and Maintenance
RMSE	Root Mean Squared Error
ROV	Remote Operated Vehicle Inspection
$S(e_i)$	Assessment
Tcf	Trillion Cubic Feet
X	Universe of Discourse
y	General Attribute
$y_A(x)$	Degree of Membership
z^*	Defuzzified Value
β_n	Degree of Belief
ω_i	Weight

CHAPTER ONE: INTRODUCTION

1.1 Overview

Pipelines are considered the basic transportation tool of oil and gas worldwide. They transport various types of products that are worth billions of dollars either offshore or onshore. The first pipeline network was constructed in the late 19th century in Pennsylvania in the US. It was used to transport crude oil from an oil field in Pennsylvania to a railroad station in Oil Creek and it was 109 miles long and had a diameter of 6 inches. Nowadays, more than 60 countries worldwide operate pipelines networks of around 2000 km long where the longest pipeline network is operated by the US, Russia and Canada (Goodland, 2005). Oil and natural gas is being transported between continents by large diameter pipelines. For example, the Russian system has diameters up to 1422mm, and can be over 1000km in length (Hopkins, 2007). Pipelines are the most economical way to transport crude oil, natural gas and refined oil products. They are much safer than usual methods of transporting such as railroad or ships. On the other hand, a pipeline accident can cause environmental disasters and economical losses.

The worldwide demand for energy is causing the oil and gas industry to increase and get even bigger with time. This is due to certain facts such as the prediction of World Energy of the US Energy Information which states that the fossil fuels will remain the primary sources of energy, meeting more than 90% of the increase in future energy demand. Also, estimates showed that global oil demand will rise by about 1.6% per year, from 75 millions of barrels of oil per day (mb/d) in 2000, to 120 mb/d in 2030 and the demand for natural gas will rise more strongly than any other fossil fuel (Hopkins, 2007).

The fact that the oil and gas pipelines carry hazardous products and operate in various environments leads to the importance of constructing a safe and sound pipelines network. Also, regular inspections and maintenance must be provided to ensure the pipelines structural safety and prevent any future failures. The oil and gas pipelines are designed, constructed and operated according to recognized standards that mainly focus on safety. In addition, to ensure these pipelines are safe and secure, they have to satisfy the high standards and safety regulations in the place where they are being constructed since the surrounding environment changes from a country to another around the globe (Hopkins, 2007). In order to maintain the safety of operated pipelines, several inspection practices were developed in the recent years such as Magnetic Flux Leakage (MFL) and Ultrasound (UT). These inspection techniques could provide accurate and effective tools to detect any defects in the pipelines that could cause any failure in the future. Another inspection is the In Line Inspection (ILI) which could clearly detect oil pipeline anomalies. The problem is that regular inspections are time consuming and cost millions of dollars every year.

1.2 Current Practices

Condition assessment is very necessary for operating pipelines to evaluate their performance along their age. Also, they need to be monitored continuously by inspections. The type and frequency of these inspections are determined by the condition of the pipelines. This is performed to address the integrity for aging pipeline both economically and environmentally. Several methods have been used to predict the condition of oil and gas pipelines over the last years. Researchers introduced many techniques such as Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Fuzzy Sets Theory and Evidential Reasoning (ER) plus other various techniques. All these techniques were used somehow in the development of models that predict condition assessment of oil and gas pipelines. However, these models

used one or two criteria to evaluate a pipeline condition. For example, Kale et al. (2004) developed a probabilistic model that is based on internal corrosion direct assessment (ICDA) to predict the most probable corrosion damage location along the gas pipelines. This model focused on evaluating pipelines from corrosion point of view. Another example is when Bersani et al. (2010) used historical data from Department of Transportation (DOT) in the US to develop a risk assessment model that predicts the failure caused by third party activities. Many other models followed the same pattern where only one or two influential factors were considered.

1.2.1 Pipeline Condition Assessment in Qatar

Researchers have developed some software programs that are used to assess the condition of oil and gas pipelines such as ORBIT+ developed by Det Norske Veritas (DNV) and PIPEVIEWER developed by General Electric (GE). According to the pipeline condition, these programs suggest inspection frequency in order to know the possibility of service life extension of the considered pipeline. These software programs use risk analysis which is mainly based on experts' opinion (Mikhail, 2011). Unfortunately, all the developed software programs used in pipeline condition assessment depend greatly on experience and professionals' feedback.

Pipeline operators around the world face many challenges when it comes to condition assessment of oil and gas pipelines. According to Ali (2011), the main challenges that face Qatar regarding condition assessment of pipelines are:

- 1) Almost 20% of Qatar's pipelines are not suitable for inline inspection (Unpiggable).
- 2) Lack of data and the absence of data management, especially for pipelines constructed before 1990.

1.2.2 Condition Rating Procedure in Qatar

According to Hashiha (2011), General Electric (GE) services are used by most pipelines operators in Qatar to perform pipeline inspections and post-inspection programs. GE is considered one of the leading companies in the field of oil and gas pipeline inspection. It also suggests post-inspection programs which are based on risk analysis. These post-inspection programs contain many features such as future inspections frequency, corrosion growth and remaining strength as discussed in the following points.

1) Pipeline Remaining Strength

Inline Inspection (ILI) results on the discovery of multiple and various types of defects and threats to operating pipelines. So, pipeline operators require a cost-effective and safe solution to process the many information received from these inspection reports (General Electric, 2013). That is why, the most threatening metal loss areas are compared with the maximum allowable rate. These rates are determined by pipeline codes and design criteria. ASME 31.G and DNV RP 101 are the most used codes to calculate the remaining strength of operating pipelines (Hopkins, 2002). Newly installed pipelines have maximum allowable operation pressure (MAOP) but after performing the remaining strength calculations, a new MAOP is determined according to the results of these calculations. According to two experts in oil and gas industry, two examples are given below to respond to remaining strength calculations with respect to pipeline operating pressure:

- a) No maintenance will be needed in case that the pipeline operating pressure is below the calculated maximum allowable pressure after considering the safety factor. Future inspections are scheduled according to corrosion growth calculations and risk analysis (Mikhail, 2011).

- b) If the pipeline operating pressure is somewhat higher than the calculated maximum allowable pressure, the operator must respond either by repairing the areas of deficiencies or by reducing the operating pressure (Ali, 2011).

2) Corrosion Growth Rate

Another type of condition rating procedure is to calculate the corrosion growth rate. Different organizations and researchers developed many models to calculate the corrosion growth rate of operating pipelines. For example, ASME 31.8S considers environmental factors such as soil resistivity to predict the external corrosion growth rate for pipelines, as shown in Table 1-1. While other models consider different factors such as type of transported product, water flow and existence of impurities (Morbier, 2009). Inline Inspection (ILI) is frequently used in Qatar to calculate corrosion growth rate by comparing data from old and new inspection reports. By doing that, the pipeline operators could easily identify all corrosion activities and calculate the corrosion growth rate (Hashiha, 2011). GE has developed a software, called RUNCOM, to calculate such a rate based on the previous ILI inspection reports (General Electric, 2010).

Table 1 - 1: External Corrosion Growth (Morbier, 2009).

Corrosion Rate (Mils/Year)	Soil Resistivity (Ohm-cm)
3	More than 15,000 No Active Corrosion
6	1,000-15,000
12	Less than 1000

3) Risk Based Inspection and Maintenance (RBIM)

Pipeline operators used their knowledge and experience to determine inspections frequency but in the last decade risk analysis has been used to develop inspection and maintenance

schedules based on priority (Mikhail, 2011). American Society of Mechanical Engineers (ASME), American Petrol Institute (API) and many other regulatory bodies approved the risk based inspection for pipeline and stated guidelines and procedures to perform it (Ali, 2011). Usually, risk analysis in Qatar is performed by consultants such as GE or DNV but recently Qatar Petroleum (QP), a leading pipeline operator in Qatar, established a research department for risk analysis research (Salah, 2011).

GE implements *Post-Inspection Program* that is performed according to the following steps (Hashiha, 2011):

- a) Collect ILI data.
- b) Identify spots with high metal loss.
- c) Identify corrosion growth using RUNCOM software.
- d) Define new maximum allowable pressure (MAOP).
- e) Identify defects causes such as soil type, cathodic protection and coating condition.
Other causes are checked according to the type of defect detected.
- f) Identify risk of failure and its consequences using the experience-based PIPEVIEWER software.
- g) Suggest post-inspection program which include maintenance schedule and future inspection frequency.

Finally, based on the previous section, there is a need to develop a more comprehensive model that evaluates the pipeline based on several influential factors. Hence, a model to assess offshore gas pipelines condition is developed and tested in this research. This model will help pipeline operators to assess the condition of offshore gas pipelines in Qatar and can be used as a framework for predicting future condition assessments.

The current research combined several contributing factors in order to accurately predict the condition of offshore pipelines. It provided an overall picture of the offshore gas pipeline condition based on various contributing factors. Also, uncertainty in the respondents' feedback and the interdependency among influential factors were taken into account, which can affect the pipeline condition. To discuss these issues, the most influential factors that affect the offshore gas pipelines were identified. This was performed through literature review and experts' feedback from the oil and gas industry. To address the interdependency among factors, the Analytic Network Process (ANP) technique was utilized as well as Evidential Reasoning (ER) technique which was used to address the uncertainty in the experts' feedback. The ER technique was developed in the mid 1990s to account and quantify the uncertainty inherited in respondents' evaluation of factors while the ANP strength measures the interdependency between the criteria.

1.3 Problem Statement

Pipelines are considered the main part of the oil and gas industry. These pipelines transport (offshore and onshore) a wide variety of products that may worth millions of dollars such as liquid gas and crude oil. The condition of these pipelines is ambiguous and interconnected on various time-dependent attributes. Henceforth, pipeline operators are constantly confronted with the challenge of determining the most appropriate rehabilitation or replacement plans for existing pipelines and under which circumstances. Many research works were conducted to develop condition assessments and failure prediction models in order to predict the pipeline condition based on available pipeline data. However, these models focused on one type of failure only such as corrosion or third party failures. Hence, there is a need to develop a more comprehensive condition assessment model for oil and gas pipelines.

In addition, no standard condition rating system for offshore gas pipelines is developed specifically for Qatar region. This condition rating system may include the rating scale used to rank the assessed pipelines along with its associated inspection and/or rehabilitation actions. Experience-based decisions and approximations are currently used to predict the condition, life expectancy and future actions to be considered for existing offshore gas pipelines. Also, there is no standard automated tool that could analyze inspection reports and data in order to predict existing pipe condition. Furthermore, no condition prediction is being implemented in Qatar and the recently practiced Risk Analysis is very simplified.

1.4 Research Objectives

The objective of this research is not only to provide pipeline operators and consultants in infrastructure management with a competent and functional tool to evaluate existing offshore pipelines but also to address the application of ANP and fuzzy logic along with ER algorithm to predict the condition of offshore gas pipelines in Qatar. This objective was set to be achieved by first studying the previous research trials in this field and the most contributing factors. Then, analyze the three mentioned techniques and come up with an integration procedure to combine them. So, a new methodology was set.

To perform this research, several sub-objectives were considered as follows:

- 1) Identify and study the critical factors affecting the condition of offshore gas pipelines in Qatar.
- 2) Design a new condition assessment methodology to predict the condition of offshore gas pipelines in Qatar and validate its prediction.
- 3) Develop deterioration curves and propose a new condition assessment scale for offshore gas pipelines in Qatar based on the developed methodology.
- 4) Automate the developed methodology and models.

1.5 Research Methodology

The current research purpose is to develop a new methodology and automated tool to assess existing offshore gas pipelines condition in order to assist professionals and pipeline operators. Henceforth, the previously mentioned objectives can be achieved through the following procedure.

1.5.1 Literature Review

A detailed and exhaustive literature review is conducted in various fields using different resources such as books, scientific journals, internet, and interviews with specialists. The literature contains a review on pipeline design and manufacturing material. Also, it reveals few important facts about the oil and gas industry in Qatar and its pipeline network. Information about the pipelines characteristics, inspection intervals, types of manufacturing materials used in Qatar's pipelines network and the standards followed for their design are also included. In addition, a comprehensive literature review on the techniques used to conduct the current research; Analytic Network Process (ANP), Fuzzy Set Theory and Evidential Reasoning (ER). Finally, the literature review presents the time-dependent factors considered in this research which contribute in the deterioration of offshore gas pipelines in Qatar.

1.5.2 Data Collection

Data were collected from different sources. A local pipeline operator in Qatar was reached in order to obtain historical inspection reports. Also, a structured questionnaire was distributed among professionals, engineers and managers, in the oil and gas industry in Qatar and similar regions such as Saudi Arabia. This method was used to gather the feedback of practitioners and specialists in regards to the most influential factors affecting the condition of offshore gas

pipelines in Qatar, their main categories, and the condition assessment scale. These questionnaires included pair-wise comparisons between the factors and their main categories.

1.5.3 Model Development and Analysis

The steps of the performed research may include but not limited to the following:

- 1) Design an integrated model that utilizes three techniques; Fuzzy Set Theory, Analytic Network Process (ANP), and Hierarchical Evidential Reasoning (HER).
- 2) Propose a condition assessment scale.
- 3) Validate the designed model against available data.
- 4) Develop a deterioration curve based on the developed model.
- 5) Automate the newly developed methodology.

1.6 Thesis Layout

An extensive literature review on pipelines systems, types, material and protection is provided in chapter 2 along with information about the oil and gas pipelines networks in Qatar. Details about condition assessment of pipelines in Qatar are also presented. This chapter lists some of the previous researches in the field of oil and gas pipelines condition assessment. Also, the ANP technique, Fuzzy Logic principles and ER algorithm are detailed before describing the factors taken into consideration, which affects the condition of offshore gas pipelines in Qatar. Chapter 3 presents the research methodology that will summarize the development of the new model which will integrate the Analytic Network Process (ANP), Fuzzy Logic and Evidential Reasoning (ER) to develop the condition assessment model for offshore gas pipelines in Qatar. Chapter 4 demonstrates the process of collecting data in order to perform this research either by a structured questionnaire or historical data. The application of the previously mentioned techniques and how they are integrated to develop the

considered condition assessment model are detailed in chapter 5. The developed model is put through validation tests and sensitivity analysis to confirm its prediction power and discuss its sensitivity to changes in the factors' values, respectively. As shown in the same chapter, a deterioration curve is built as a result of the relation between the pipe condition and Age. In addition, this chapter includes the suggested condition assessment scale. Chapter 6 presents the proposed automated tool for the developed model. Finally, Chapter 7 contains the thesis conclusions, contributions, limitations and recommendations for future research.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Pipelines are considered the main part of the oil and gas industry. These pipelines transport (offshore and onshore) a wide variety of products that may worth millions of dollars such as liquid gas and crude oil. The first pipeline network was constructed in the late 19th century in Pennsylvania in the US. It was constructed to transport crude oil from an oil field in Pennsylvania to a railroad station in Oil Creek and it was 109 miles long and had a diameter of 6 inches. Currently, over 60 countries in the world operate pipelines networks of over 2000 km long and the longest ones are owned by the US, Russia and Canada (Goodland, 2005). Pipelines are generally the most economical way to transport crude oil, natural gas and refined oil product in comparison to the usual methods of transporting such as railroad or by ships. Also, they are safer than railroads and highway in case of transporting petroleum products since they have lower rate of accidents. However, a pipeline accident can cause disastrous damage environmentally and economically in case of oil spillages.

The Oil and Gas Industry is huge and getting even bigger with time. Hopkins (2007) listed number of facts to show the importance of Oil and Gas Industry in the coming future.

- The US Energy Information Administration's World Energy Outlook has predicted fossil fuels will remain the primary sources of energy, meeting more than 90% of the increase in future energy demand;
- Global oil demand will rise by about 1.6% per year, from 75 millions of barrels of oil per day (mb/d) in 2000, to 120 mb/d in 2030;
- Demand for natural gas will rise more strongly than for any other fossil fuel: primary gas consumption will double between now and 2030.

The expanding and large demand of energy around the globe secures the Oil and Gas Industry. In addition, it is highly profitable. Exxon Mobil, the world's largest oil company, announced in January 2006 profits of \$US36 billion which is the largest profit ever declared by a listed company. Also, Shell announced a record profit for a British company of \$US23 billion in February 2006. This can be taken as a sign of how the profits of Oil and Gas Industry could increase in the near future as the price of a barrel of oil continues to increase more and more. To support this continuously increasing demand for energy, the pipeline infrastructure has grown by a factor of 100 in approximately 50 years. There are more than 32,000km of new pipelines constructed internationally each year and 50% of these new builds are expected to be in North and South America. Also, 8,000km of offshore pipelines are being built per year with 60% in North West Europe, Asia Pacific, and the Gulf of Mexico. These large pipelines systems serve the Oil and Gas Industry in the world as follows:

- ~64% carry natural gas;
- ~19% carry petroleum products;
- ~17% carry crude oil.

Types of Oil and Gas Pipelines

The increasing use of natural gas in the State of Qatar will require the installment and development of additional pipeline systems and increased use of the existing pipeline infrastructure. Operating and maintaining a safe and environmentally-sound natural gas pipeline network is considered a huge challenge in the pipeline industry when facing this growing utilization (Group, 2011). There are four different types of pipelines that are designed and operated to accomplish the mission of the overall pipeline network which collects and transports the gas. These types are stated according to their usage as the following:

- 1- **Production or Flow Lines** which used to transport the natural gas near the wellhead and within the production facility.
- 2- **Gathering Lines** that transport natural gas from a production facility to a gas processing plant.
- 3- **Transmission Lines** which transport oil and gas from a processing plant to a distribution line. They are very long carbon steel pipelines and their maximum diameter is 56 inch. The largest transmission line in Qatar and the Middle East is the Dolphin pipeline with a diameter of 48 inch of carbon steel X60 (Husein, 2011).
- 4- **Distribution Lines** which transport natural gas from a transmission pipeline and distribute it to commercial and residential end-users. This type of pipelines has smaller diameter, up to 6 inch, and operates at lower pressure compared to transmission lines. (Group, 2011)

The Transmission Lines are the main player in the oil and gas industry. They work 24 hours per day, seven days a week and continuously supplying our energy needs. Large transmission pipelines are used to transport oil and gas from extracting facilities to refineries and power stations. The refineries and power station process the delivered oil and gas and convert them to other energy forms such as gasoline for vehicle, electricity for buildings, etc. Despite the existence of other sources of energy in the world, oil and gas provide most of that energy.

Pipeline Design and Materials

The most important point in the pipelines is safety. Because of that, most of the transmission pipelines are designed according to strict standards such as the American Society of Mechanical Engineers (ASME) standards (ASME B31.8 for gas lines and ASME B31.4 for oil lines) or standards based on these. Designing and operating a pipelines network is mostly

regulated and subjected to the local laws and regulations of the country where the network under consideration lies. For example, in the UK, the pipelines are covered by the Pipelines Safety Regulations 1996, which contains the detailed design, construction, operation and maintenance requirements for pipelines. The pipelines are usually made by welding various lengths of steel pipes following the American Petroleum Institute standard API 5L.

The pipeline, which is welded either longitudinally or spirally, is known by its physical characteristics. These characteristics may include the diameter and wall thickness of the pipe, welding type (longitudinal, spiral or seamless), and grade. By grade we mean the grade of the steel used as the pipeline material in the manufacturing process. Mostly grade X60 is used which has a minimum specified yield strength of 60,000 lbf/in² (414N/mm²). For example, Fig. 2-1 shows the typical yield strengths in operating pipelines in the USA. The highest grade in use today is X80.

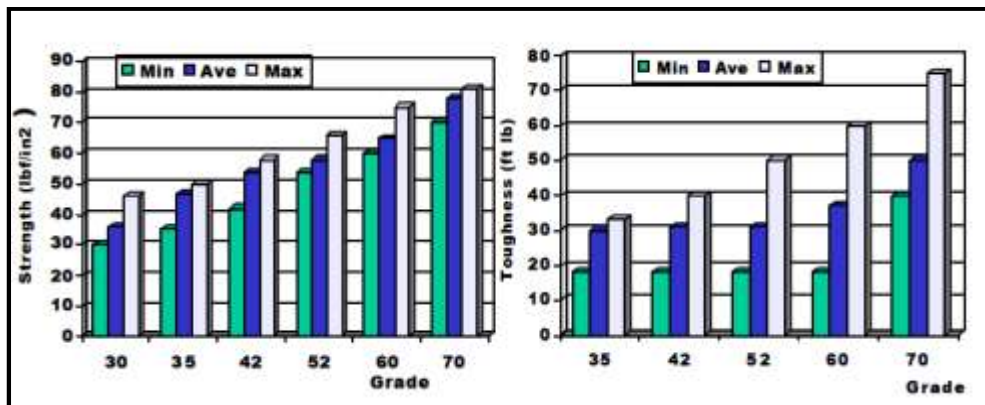


Figure 2 - 1: Variations in Yield Strength and Toughness of Older Linepipes Steels in the USA (Hopkins, 2002)

2.2 Oil and Gas Pipelines Network in Qatar

Qatar is a member of the Organization of Petroleum Exporting Countries (OPEC) and holds the world's third largest natural gas reserve. Recently, Qatar has dedicated more resources for the development of natural gas industry, especially for its export as Liquefied Natural Gas

(LNG). Now, Qatar is the world's largest supplier for LNG. Energy consumption in Qatar such as electricity and transportation depends mainly on oil and natural gas. Fig. 2-2 shows the total energy consumption in Qatar in 2010. The state owned company Qatar Petroleum (QP) holds the dominant share in all oil and gas projects (US Energy Information Administration, 2013)

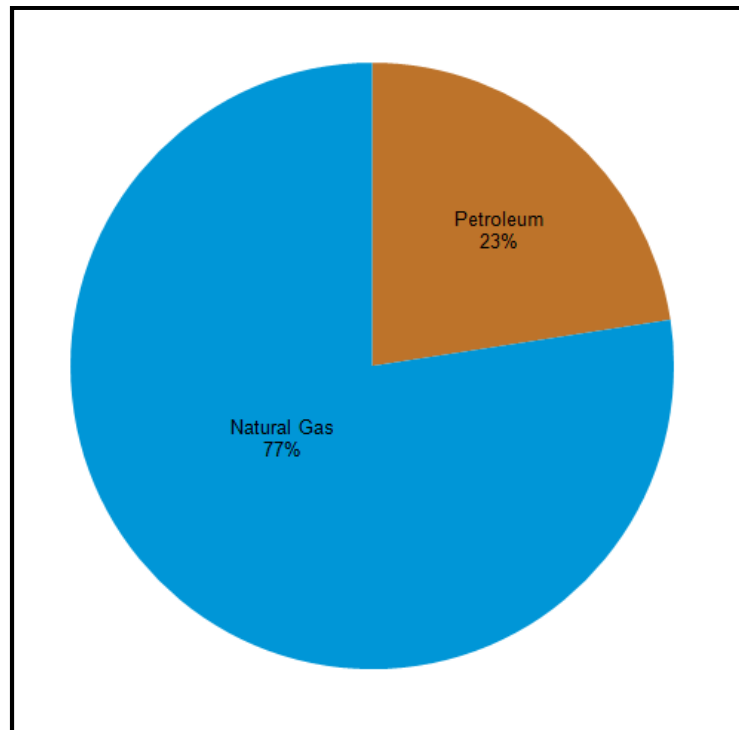


Figure 2 - 2: Total Energy Consumption in Qatar 2010 (US Energy Information Administration, 2013)

Oil

On January 2013, the *Oil and Gas Journal* stated that Qatar has an approximate of 25.4 billion barrels of proven oil reserve. Qatar is the third smallest crude oil producer in OPEC, with production exceeding only that of Libya and Ecuador as shown in Fig. 2-3. Estimates show that Qatar liquid production in 2011 reached almost a total 1.6 million barrels per day (bbl/d): 850,000 bbl/d of crude oil. Dukhan and Al-Shaheen fields produce half on the country's crude oil. The dominant company for producing Oil is Qatar Petroleum (QP) (US Energy Information Administration, 2013).

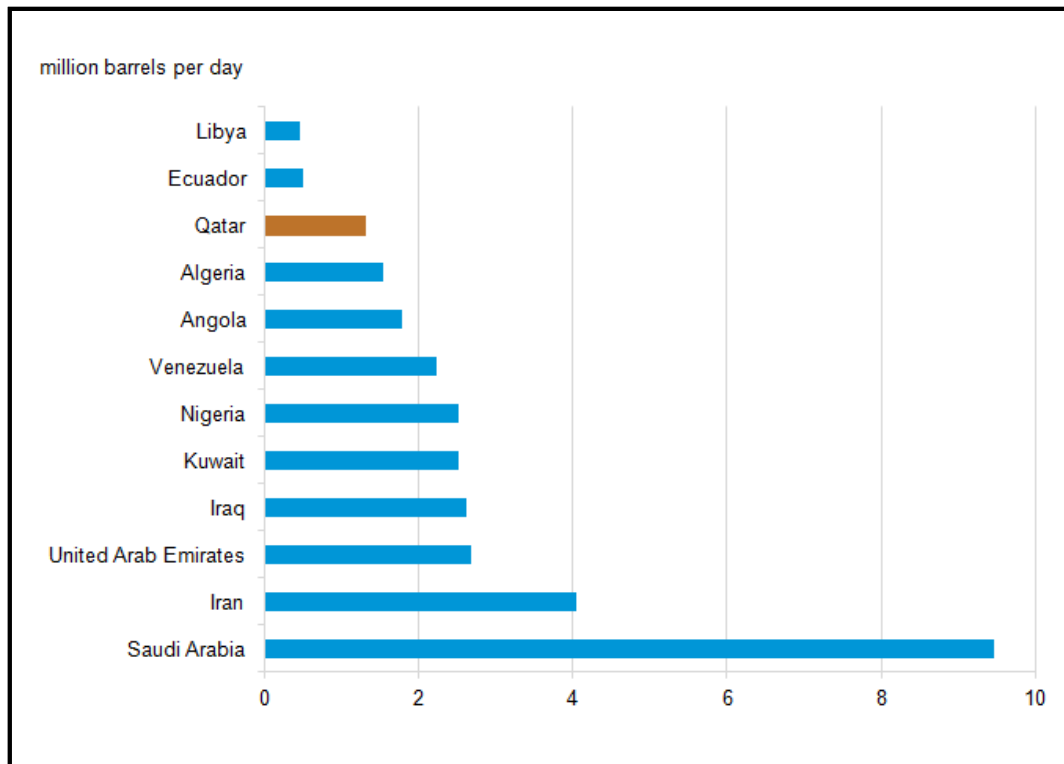


Figure 2 - 3: OPEC Crude Oil Production in 2011 (US Energy Information Administration, 2013)

Natural Gas

According to *Oil and Gas Journal* in January 1st, 2013, Qatar holds 13% of the world natural gas reserve and the third world rank of natural gas reserves after Russia and Iran with approximately 890 trillion cubic feet (Tcf) as shown in Fig. 2-4. The offshore North Field in Qatar contains majority of natural gas reserves. The dominant companies for producing LNG are Operating Company Limited (QatarGas) and Ras Laffan Company Limited (RasGas) (US Energy Information Administration, 2013). Table 2-1 shows the general profile of oil and gas industry in Qatar provided by (US Energy Information Administration, 2013).

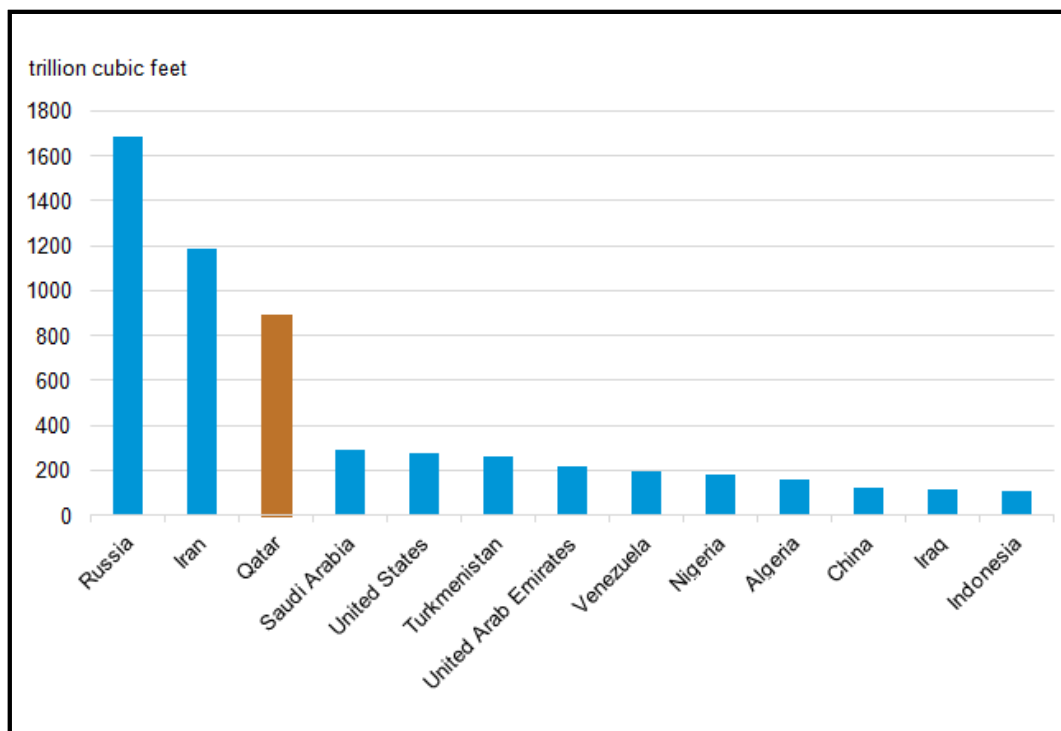


Figure 2 - 4: Natural Gas Proven Reserves by Country in 2012. (US Energy Information Administration, 2013)

Table 2 - 1: Profile of Oil and Gas Industry in Qatar (US Energy Information Administration, 2013)

Resource	Capacity/fields
Proven Oil Reserves (2013)	25.4 billion barrels
Oil production (2011)	1,600,000 barrels per day
Proven Natural Gas Reserves (2013)	890 trillion cubic feet
Natural Gas Production (2011)	5,200 billion cubic feet
Major Oil Fields	Dukhan, Al-Shaheen
Major Refineries	Umm Said (200,000 bbl/d), Ras Laffan (138,700 bbl/d)
Major Natural Gas Field	North Field
Major Oil and Gas Ports	Umm Said, Ras Laffan

Pipelines

Oil pipelines are the main method that Qatar depends on to transport oil from offshore fields to refineries then to ports for exporting. Submarine pipelines are also used to transport Gas from offshore fields to Ras Laffan port to export. Natural Gas is transported from Ras Laffan port to UAE via Dolphin pipeline. These pipelines were constructed in 2006 to export natural gas to Oman and UAE. Dolphin Pipelines contain two main submarine lines and according to Husein (2011), they are the longest submerged pipeline in the Middle East with 364 Km length and a diameter of 48 inch. Two types of pipelines are being operated by Dolphin with the following specification:

- 1) **Sea Line:** It transports gas from a refinery in Ras Laffan Port at pressure of 120 Bar through two pipelines with diameter of 36 inch and length of 80 Km (160 Km total). The transported product is highly corrosive because of the existence of H₂S and H₂O (Wet Sour Gas) causing the important need of frequent inspections since these pipelines are not coated internally.
- 2) **Export Line:** This internally coated pipeline with diameter of 48 inch and length of 364 Km transports refined gas (Dry and Sweet Gas) from Ras Laffan Port in Qatar to Taweela at UAE. The line is coated internally to reduce the friction between the transported gas and pipeline internal surface hence increasing the pipeline flow rate.

According to Husein (2011), all Export pipelines are coated externally with 2 types of coating where the outer coating is light reinforced concrete layer, width of 90 to 140 mm, to stabilize the pipelines and protect them from any external damage. The inner coating consists of three layers of polypropylene, width 12mm, to prevent external corrosion.

All the pipelines are placed above the sea bed except in marine traffic areas where a pipeline length of 4 km is buried in shallow water, depth less than 4 meters, to protect pipeline from any damage caused by third party. A summary of Dolphin pipelines specifications is shown in Table 2-2.

Table 2 - 2: Dolphin Pipeline Specification (Husein, 2011).

Name of Pipeline/specs	# of Pipes	Dia.	Length	Product Transported	Steel Grade	Coating
Sea line	2	36"	80 km	Wet sour gas	X60	External
Export line	1	48"	364 km	Dry sweet gas	X60	External and Internal

As per Dolphin company standards, the constructed pipelines in 2006 need to be inspected externally using Remote Operated Vehicle (ROV) annually in the first 5 years following installation and internally using Magnetic Flux after the first year of installation and every three years after that. Table 2-3 summarizes the previous lines.

Table 2 - 3: Inspection Interval for Dolphin Pipeline (Husein, 2011)

Inspection Method /Years	First 5 Years	After 5 Years of Installation
Remote Operated Vehicle (ROV)	Every Year	According to condition
Magnetic Flux (MFL)	After 1 year, then every 3 years	Every 3 years

2.3 Oil and Gas Pipeline Design and Material

Different types of pipelines are made to transport different products like crude oil, natural gas and refined products. The carbon steel is mainly used to manufacture pipelines with diameter from 8 to 48 inch. Smaller distribution pipelines are usually made from plastic with diameter

up to 2 inch. Manufacturing carbon steel pipelines follows the standards of different institutes or societies such as the American Petroleum Institute (API 1994-2004), the American Society of Mechanical Engineer (ASME), the American National Standard Institute (ANSI)...etc.

According to Mikhail (2011), there are three common types of impurities that may greatly affect the internal pipeline surface and increase the risk of internal corrosion which are:

- 1) **H₂S (Sour Gas):** It forms sulphuric acid when combines with water. This acid causes lamination and pitting corrosion which is a form of extremely localized corrosion that leads to creating small holes in the pipeline surface.
- 2) **CO₂:** The highly corrosive carbonic acid is formed when CO₂ combines with water.
- 3) **Chlorides:** They are considered highly corrosive materials as well.

Table 2 - 4: Steel Grade Specs used in Qatar. (Ali, 2011) (Husein, 2011) (Mikhail, 2011)

Steel Grade	A	B	X42	X60	X70	X80
Min. Yield Stress (psi)	30,000	35,000	42,000	60,000	70,000	80,000
Usage	Old Pipelines at QP			Dolphin, QP & Qatar Gas	QP	

This research is considering the main pipelines made from carbon steel with different steel grades (grade B to grade X80) and different operating pressures (10 bar to 220 bar) (Ali, 2011).

2.4 Analytic Network Process (ANP)

The Analytic Network Process (ANP) technique was introduced by Saaty in 1996 as a generalization of the Analytic Hierarchy Process (AHP) which was also introduced by Saaty in 1980s (Gorener, 2012). The AHP is a multi-criteria decision making technique which

provides a hierarchical representation of complicated decision making problems. This hierarchy is a multilevel structure that contains the decomposed set of clusters, sub-clusters and so on that were abstracted of the overall objective. Clusters or sub-cluster can have different names such as factors, forces, attributes, activities... etc. (Cheng & Li, 2001). The methodology of AHP performs a pair-wise comparison to calculate the relative importance of each cluster or attribute in the hierarchical structure to finally reach the best decision between alternatives (Gorener, 2012).

AHP and ANP are methods used to evaluate adjacent factors through judgments that follow pair-wise comparisons. These judgments represent the dominance of one factor over the other with respect to a property that is shared between them (Chung, et al., 2005). The Analytic Network Process is a generalization of the Analytic Hierarchy Process. The purpose of developing the ANP technique was to overcome the limitations of AHP in regards with the independence assumptions between compared attributes.

2.4.1 ANP Application

Recently, a number of applications were performed using AHP and ANP in many fields. For example, Ayag (2011) used ANP to evaluate simulation software alternatives. A combination between AHP and SWOT Analysis was performed by Wickramasinghe & Takano (2010) to develop a model that revises the tourism revival strategic marketing planning which was applied on Sri Lanka tourism as a case study. Greda (2009) applied both AHP and ANP in the field of food quality management. In addition, Dawotola, et al. (2009) combined AHP with Fault Tree Analysis (AHP-FTA) to assess the risk of petroleum pipelines. AHP/ANP was used again by Yang et al. (2009) to propose a system for manufacturing evaluation in the wafer fabricating industry. Nekhay et al. (2009) used ANP combined with GIS to evaluate the

soil erosion risk on Spanish mountain olive plantations. Also, an integrated AHP/ANN model was developed by Al-Barqawi & Zayed (2008) to evaluate the municipal water mains performance. Using ANP, Cheng & Li (2004) developed a model for contractor selection in construction projects. Tran et al. (2004) used ANP for environmental assessment of the Mid-Atlantic region. Finally, AHP and ANP proved themselves as a powerful decision making tools and that was represented by the large number of researches conducted using them.

2.4.2 ANP Technique

The AHP builds decision making models by decomposing a decision problem from a general goal to a set of manageable clusters, sub-clusters and so on. The decomposing process continues until the final level of the hierarchy is reached. AHP adopts pair wise comparisons to assign weights to elements that exist at the clusters and sub-clusters levels. The pair wise comparison is a process of comparing two objects or elements at a time to measure the relative importance or strength of an elements over another within the same level using a ratio scale. Then, AHP calculates the final global weights of the assessment at the final level of the hierarchy through eliminating all the middle criteria.

The Consistency Ratio (CR) is calculated by AHP to measure the consistency of the judgments given by experts. This is because some experts are often inconsistent or not serious in answering the pair-wise comparison questions. In general, if the CR value exceeds 0.1, then the results are unacceptable and not trust worthy since they are very close to the randomness zone and the comparison must be repeated as advised by Saaty (1996) .The Acceptable CR values has been set by Saaty (1994) for different matrices' sizes developed from the pair wise comparisons as shown in Table 2-5.

Table 2 - 5: Acceptable CR Values (Saaty, 1980).

Matrix Size	Average CR Value
1	0.00
2	0.00
3	0.58
4	0.90
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49

The interested reader may refer to Al-Barqawi & Zayed (2008) for a more detailed example about the main characteristics of AHP technique. In the AHP technique, the relationships between the elements of the same levels or different levels are assumed to be unidirectional. That means AHP technique is considered not appropriate for models that involve interdependent relationships. So, ANP was developed to overcome this disadvantage and enhance the analytical power of AHP (Cheng & Li, 2004). It is considered a more generic form of the AHP technique which allows the tool to deal with more complex interdependent relationships among elements of the same level or different levels. As shown Fig. 2-5 adapted from Cheng & Li (2004), the interdependence can occur in several ways:

- 1) Uncorrelated elements are connected.
- 2) Uncorrelated levels are connected.
- 3) Dependence of two levels is two-way (i.e., bi-directional).

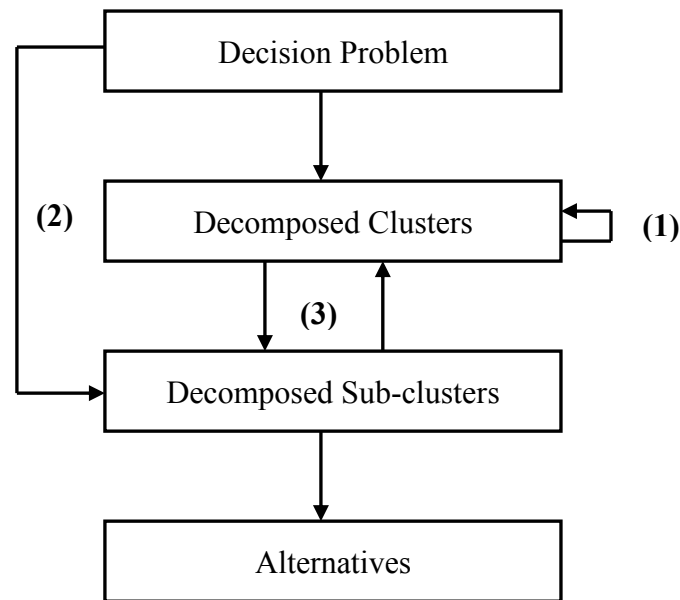


Figure 2 - 5: Interdependencies in ANP (Cheng & Li, 2004).

The working methodology of ANP is deriving relative priority scale of absolute numbers from a group of judgments or feedbacks provided by expert professionals. These judgments represent the relative influence of one cluster over the other in a pair wise comparison form with respect to control criteria. As reported by Garuti & Sandoval (2005), the ANP provides a clarification of all the relations among the compared criteria and thus decreasing the gap between the developed model and reality.

A super-matrix can be developed by incorporating interdependencies of the elements in the hierarchy. This is done by adding feedback loops in the model. The developed super-matrix adjusts the relative importance weights in individual matrices to form a new matrix called "overall" matrix with the eigenvectors of the adjusted relative importance weights (Meade & Sarkis, 1998). Sarkis (1999) mentioned four main step that form the core of ANP which are the following:

- 1) Conduct pair-wise comparisons on the elements at the cluster and sub-cluster levels.

- 2) Place the resulting relative importance weights (eigenvectors) in sub matrices within the super-matrix.
- 3) Adjust the values in the super-matrix so it can achieve column stochastic.
- 4) Raise the super matrix to limiting powers until weights have converged and remained stable.

The previous steps are explained later in details in the ANP implementation section.

2.4.3 ANP Software

For easier ANP implementation, researchers developed a software called "SuperDecisions". It is a decision making software that is based on the Analytical Hierarchy Process (AHP) and the Analytical Network Process. An ANP model can be easily developed through SuperDecisions software due to the friendly interface of the program. The interested reader may refer to the software website "www.superdecisions.com" for more details. Many tutorials are available in the website including tutorials for developing AHP or ANP models. Also, the website provides a variety of detailed examples from different study fields. The SuperDecisions software can be easily downloaded and installed. A temporary serial key is given for registered members.

2.5 Fuzzy Set Theory

The fuzzy set concept was first introduced by Zadeh (1965) as a mathematical representation to deal with uncertainties that are not of statistical nature. Since its development, fuzzy decision making has been applied in numerous areas such as civil engineering application and many others (Salah, 2012). According to Zadeh (1965), a fuzzy set is characterized by its membership function. This means that elements are described in way to permit a gradual transition from being a member of a set to a nonmember. Each element has a membership

degree that ranges from Zero to One, where zero indicates non-membership and one signifies full membership. The case is different in the conventional crisp sets where elements are not considered members unless their membership is full (i.e. membership degree of one).

Years after Zadeh (1965) introduced the fuzzy set theory, researchers were paying considerable attention to this theory in various types of industries that are experiencing rapid development. The use of fuzzy numbers became so common in many research fields since it provides the user with a linguistic representation which cannot be provided by other theories (e.g. probabilistic theory). For example, Ayyub & Halder (1984) and Lorterapong & Moselhi (1996) used fuzzy logic in project scheduling and project-network analysis. Also, Chao & Skibniewski (1998) and Wong & Albert (1995) used it in evaluating alternative construction technology and contract selection strategy & decision making. Raoot & Rakshit (1991) and Dweiri & Meier (1996) applied fuzzy approach in facilitating lay-out planning. Fuzzy Sets theory was used in many civil engineering application by Wong (1986) and Furuta (1994). The advantage of using a fuzzy set instead of the conventional set is that the fuzzy sets provide a representation of the degree of which an element belong to a certain set of elements.

Fuzzy subset "A" can be defined as a set of ordered pairs, $[x, y_A(x)]$, where x is an element in the universe of discourse X , and $y_A(x)$ is the degree of membership associated with the element x which range from Zero to One. The membership value of x is $y_A(x)$, which represents "if x belongs to fuzzy number "A" or not": $y_A(x) = 1$ means x fully belongs to fuzzy number "a", $y_A(x) = 0$ means x does not belong to "a". (Salah, 2012)

2.5.1 Fuzzy Sets Shapes

There are different shapes to represent the membership function in the fuzzy, however, the most commonly used shapes are linear approximations such as the trapezoidal and triangular shapes (Dubois & Prade, 1988; Cheng & Hwang, 1992).

Fig. 2-6 shows two types of fuzzy sets representations which are:

- 1) Trapezoidal Fuzzy Set: It can be represented by four points (a, b, c, d), where a and d are the lower and upper bounds, b and c are the lower and upper middle values.
- 2) Triangular Fuzzy Set: It is considered as a special case of the trapezoidal fuzzy set with $b = c$.

The membership function can be formulated as:

$$y_A(x) = \begin{cases} \frac{x - a}{b - a} & a < x < b \\ 1 & a \leq x \leq b \\ \frac{x - d}{c - d} & c < x < d \\ 0 & \text{otherwise} \end{cases} \quad (2-1)$$

A membership can be represented graphically by many shapes such as triangles, or trapezoidal, but it is usually convex. For a given value $y_A(x) = 0$ means that x has a null membership in fuzzy set A, and $y_A(x) = 1$ means that x has full membership. These membership functions can be determined subjectively; the closer an element to satisfy the requirements of a set, the closer its grade of membership is to 1, and the opposite is true (Raoot & Rakshit, 1991).

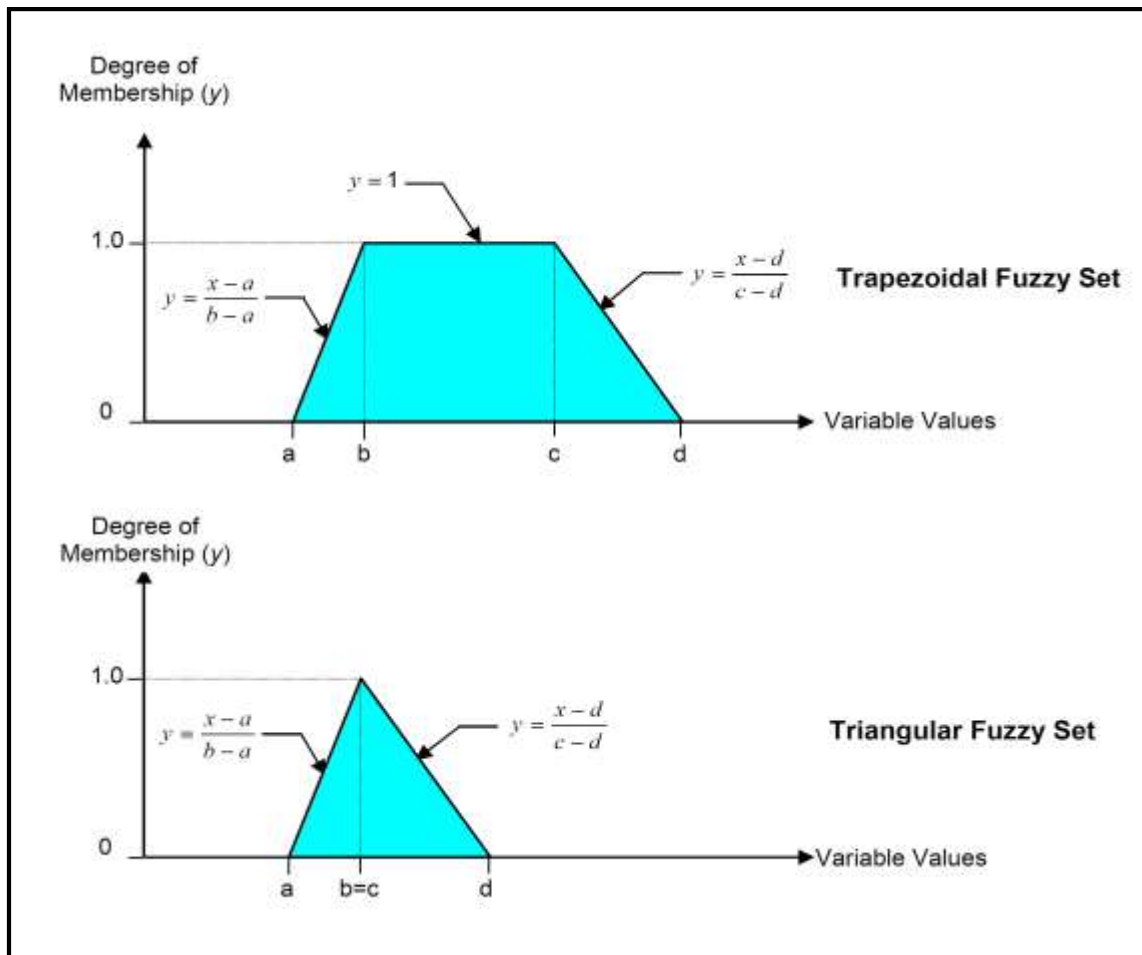


Figure 2 - 6: Fuzzy Sets Representation.

2.5.2 Fuzzification and Defuzzification

Fuzzification and defuzzification are two important processes associated with the use of fuzzy sets. Fuzzification is defined as the process of converting raw data from the practical terms (e.g. high, low, very low, etc.) into membership functions (Wong & Albert, 1995). The application of the fuzzification process is detailed in the next chapter. On the other hand, defuzzification is defined as a process where the aggregated output or the overall membership functions is converted into a crisp (non-fuzzy) value which is the opposite of fuzzification (Mamdani, 1974).

The output of a fuzzy process is the union if two or more fuzzy memberships. For example, suppose a fuzzy output comprises of two parts: (1) C_1 , a trapezoidal membership shape and (2) C_2 , a triangular membership shape as shown in Fig. 2-7. The union of these two membership functions is $C = C_1 \cup C_2$. This union uses the max. operator which graphically is the outer envelope of the two shapes. Also, the output fuzzy membership can be the union of more than two membership functions with different shapes other than triangular and trapezoidal but the union procedure is the same (Ross, 2010). After defuzzification, a fuzzy number can be represented by a crisp value. Many defuzzification methods can be used to defuzzify the overall membership function such as (Ross, 2010):

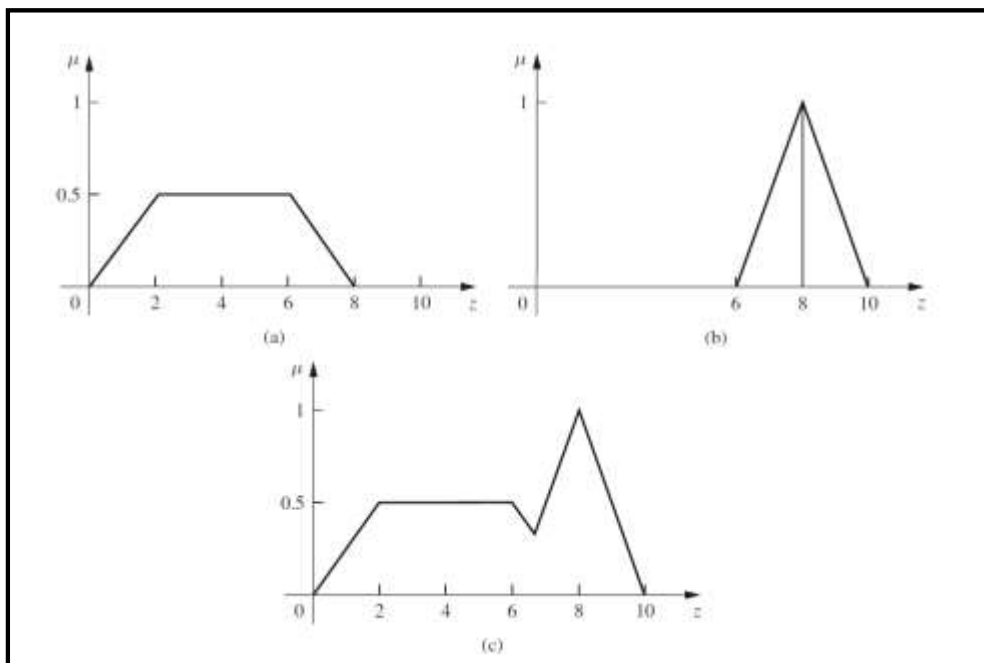


Figure 2 - 7: Typical fuzzy process output: (a) first part of fuzzy output; (b) second part of fuzzy output; and (c) union of both parts (Ross, 2010).

1) **Centroid Method:** Also called "Centre of Area" or "Centre of Gravity". It is the most prevalent defuzzification method and can be calculated using Eq. (2-2).

$$z^* = \frac{\int \mu_C(z) \cdot z \, dz}{\int \mu_C(z) \, dz}$$

for all $z \in Z$, (2-2)

where z^* is the defuzzified value and \int denotes an algebraic integration.

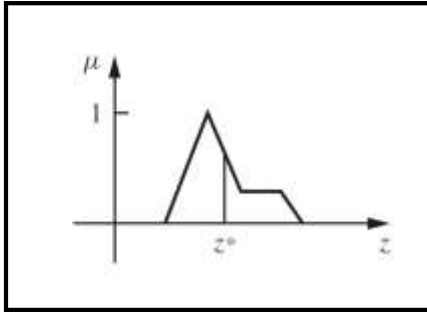


Figure 2 - 8: Centroid Defuzzification Method (Ross, 2010).

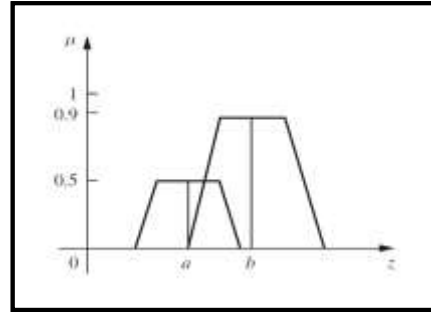


Figure 2 - 9: Weighted-Average Defuzzification Method (Ross, 2010).

2) Weighted-Average Method: It is used most frequently because of its computational efficiency. Its main disadvantage is that it works only on symmetrical output membership functions. The algebraic formula is expressed in Eq. (2-3).

$$z^* = \frac{\sum \mu_C(\bar{z}) \cdot \bar{z}}{\sum \mu_C(\bar{z})}$$
(2-3)

where \sum donates the algebraic sum and \bar{z} is the centroid of each symmetrical membership function. Fig. 2-9 shows a brief example on how Weighted-Average method works.

$$z^* = \frac{a(0.5) + b(0.9)}{0.5 + 0.9}$$
(2-4)

where a and b are the centroids of the two symmetrical membership functions in Fig. 2-9.

3) **Mean-Max Membership (middle of maxima):** This method can be used when the peaked output membership function is a plateau rather than a single point. This method is given by the following expression which is shown in Fig. 2-10.

$$z^* = \frac{a + b}{2}$$

(2-5)

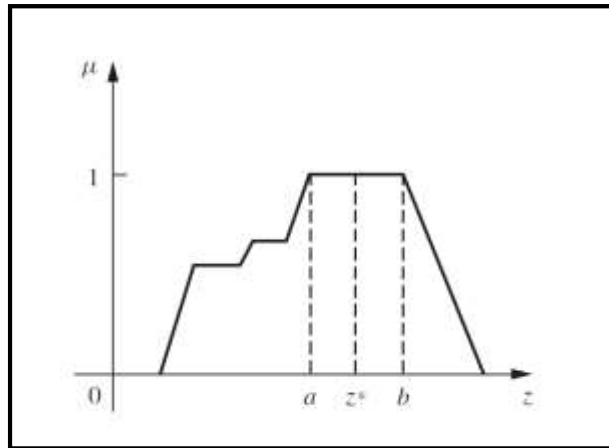


Figure 2 - 10: Mean-Max membership Defuzzification Method (Ross, 2010).

4) **Center of Sums:** It is considered one of the fastest defuzzification methods and it is not restricted to symmetrical membership functions. Fig. 2-11 shows an example of its use. The defuzzified value z^* is given as follows:

$$z^* = \frac{\sum_{k=1}^n \mu c_k(z) \int_z \bar{z} dz}{\sum_{k=1}^n \mu c_k(z) \int_z dz}$$

(2-6)

where the symbol \bar{z} is the distance to the centroid of each of the respective membership functions.

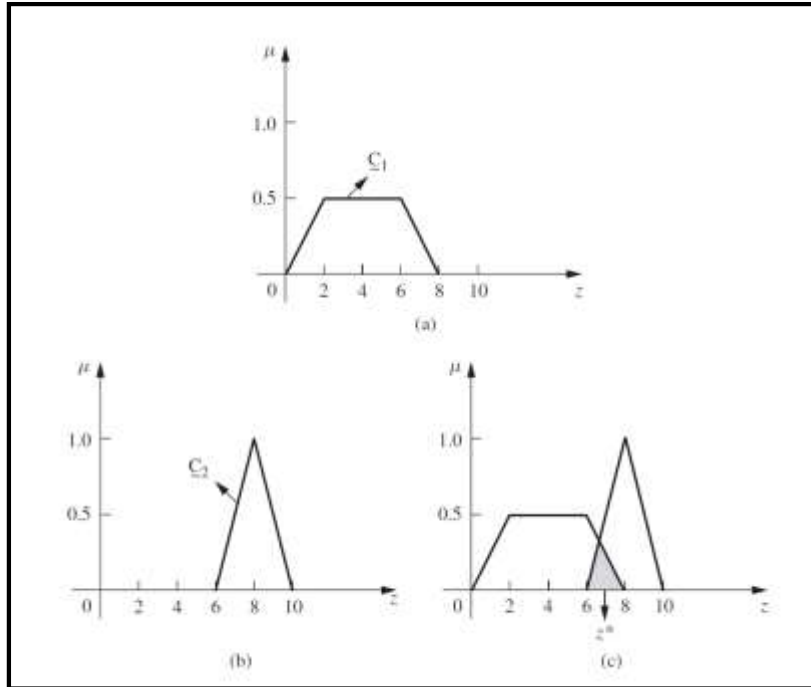


Figure 2 - 11: Center of sums method: (a) First Membership Function; (b) Second Membership Function; and (c) Defuzzification Step (Ross, 2010).

C_1 and C_2 are two individual output fuzzy sets that need to be summed algebraically. There are two disadvantages for this method which are:

- a) The intersecting areas are added twice.
- b) It involves finding the centroids of the individual membership functions.

It is important to note that the previously mentioned defuzzification methods are the most commonly used and there are many other defuzzification methods.

2.6 Evidential Reasoning (ER) Approach

2.6.1 Theory of Evidence

"Evidential Reasoning basically means reasoning with evidence" as stated by Srivastava (2010). These are common situations in the real world in all domains such as legal, medical or even business domain. ER Approach uses two frameworks to manage uncertainties:

Bayesian Theory and Dempster-Shafer (DS) Theory of Belief-Functions which is considered a powerful technique to address the ignorance and uncertainty. The basics of Bayesian and DS theories are introduced by Srivastava (2010). DS theory has been used relatively for data fusion as a generalization of the Bayesian theory. It was first introduced to the academic society by Dempster in 1967 and extended later by Shafer in 1976. (Hua, et al., 2007)

The main purpose of developing the Evidential Reasoning as a research methodology is to address Multi-Criteria Decision Making (MCDM) problems under uncertainty. It is different from other conventional MCDM methods because it represents any assessment as a distribution using belief structures. Another difference is that ER aggregates the degrees of belief using an algorithm developed basically on decision theory and combination rule of DS theory of evidence instead of aggregating average scores as conventional MCDM methods.

2.6.2 ER Application

Since the development of Evidential Reasoning (ER) Theory and throughout the years, many researchers used it to develop assessment models in various fields. Starting from 1992 till 2010, ER has been applied by Srivastava and his colleagues in information systems domains to assess risks such as audit risks, information security risks, fraud risks and so on (Srivastava & Shafer, 1992 and Srivastava & Mock, 2000 & 2010). A model was developed by Wang & Elhag (2008) used the Evidence Theory of Dempster and Shafer to deal with condition assessment of structural bridges. Hua et al. (2007) translated pipe inspection results to assess the condition of buried pipelines using theory of evidence. Also, DS theory of evidence was applied by Sadiq et al. (2006) to estimate the risk of contaminant intrusion in distribution networks. Wang et al. (2006) used the evidential reasoning approach to perform environmental impact assessments.

Sonmez et al. (2002) developed a model using basic concept of DS theory in Evidential Reasoning to perform a typical MCDM problem in construction projects. This is the process of contractors prequalification that takes into consideration multiple criteria both, quantitative and qualitative. Similarly to the contractors' pre-qualification ER model performed by Sonmez et al. (2002), Teng (2002) developed a model for suppliers pre-qualification for a UK company using evidential reasoning. Also, Morcoux et al. (2002) proposed a case-based reasoning system for infrastructure deterioration. Yang & Sen (1994) proposed a hierarchical analysis for design selection of ship retro-fit options using evidential reasoning based methodology.

2.6.3 ER Technique

This section provides a summarized explanation for the ER Technique as discussed in Yang & Xu (2002). The evidential reasoning is a technique that combines many pieces of evidence. It aggregates two factors at a time (i.e. ER is a one-by-one based technique) which keeps the concept of the ER approach clear. Then, the resulting combined of the first two pieces of evidence is aggregated with the third piece of evidence and so on.

The ER algorithm provides more flexibility to the ER technique when combining large number of factors affecting the condition of a structure. This results in an easier way to conduct sensitivity analysis for the parameters of the ER approach such as degrees of belief and weights.

To explain the procedure of the ER approach, suppose we have a two-level hierarchy of attributes with a general attribute at the top level and a number of basic attributes at the

bottom level. Suppose there are basic attributes $e_i (i = 1, \dots, L)$ associated with a general attribute y . Define a set of L basic attributes as follows:

$$E = \{e_1, e_2 \dots e_i \dots e_L\} \quad (2-7)$$

Each of the given attributes has its own weight (Calculated by ANP technique for the developed model). The weights of the attributes are given by

$$\omega = \{\omega_1, \omega_2 \dots \omega_i \dots \omega_L\} \quad (2-8)$$

where ω_i is the relative weight of the i th basic attribute (e_i) with $0 \leq \omega_i \leq 1$ and $\sum_{i=1}^L \omega_i = 1$.

These weights of the attributes play a major role in the assessment process. There are different ways to estimate the relative weights of the given attributes. It could be done by simple rating methods or more advanced methods based on the pair-wise comparisons of attributes such as ANP as illustrated in the later sections.

N distinctive evaluation grades are supposedly defined which provide a complete set of standards for assessing an attribute. It is represented by

$$H = \{H_1, H_2 \dots H_n \dots H_N\} \quad (2-9)$$

where H_n is the n th evaluation grade. Without loss of generality, it is assumed that H_{n+1} is preferred to H_n .

A given assessment for $e_i (i = 1, \dots, L)$ of an alternative may be mathematically represented as the following distribution:

$$S(e_i) = \{(H_n, \beta_{n,i}), n = 1, \dots, N\} \quad (2-10)$$

where $\beta_{n,i} \geq 0$, $\sum_{n=1}^N \beta_{n,i} \leq 1$, and $\beta_{n,i}$ be a degree of belief to which the general attribute y is assessed to the grade H_n .

The given distributed assessment can be read as that the attribute e_i is assessed to the grade H_n with the degree of belief of $\beta_{n,i}, n = 1, \dots, N$.

An assessment $S(e_i)$ is considered a complete assessment if the summation of all degrees of belief is one (i.e. $\sum_{n=1}^N \beta_{n,i} = 1$). Similarly, the assessment $S(e_i)$ is incomplete when the summation is less than one (i.e. $\sum_{n=1}^N \beta_{n,i} < 1$). A special case is $\sum_{n=1}^N \beta_{n,i} = 0$ (or $\beta_{n,i} = 0$ for all $n = 1, \dots, N$), which denotes a complete lack of information on e_i .

Note: All the assessments in the developed model are complete assessments since the degrees of belief are extracted from the fuzzified thresholds' charts that consider a degree of fuzziness of 0.5 (i.e. $\sum_{n=1}^N \beta_{n,i} = 1$ for any given assessment).

The purpose of the aggregation is to generate $\beta_n (n = 1, \dots, N)$ by aggregating the assessments for all the associated basic attributes $e_i (i = 1, \dots, L)$ as given in Eq. (2-10). The following evidential reasoning algorithm can be used for this purpose.

ER Algorithm

The ER algorithm is explained in details in Yang & Xu (2002), Yang et al. (2006) and Wang & Elhag (2008). The first step in the ER algorithm is to transform the degrees of belief into basic probability masses $m_{n,i}$. This is performed by combining the relative weights and the degrees of belief as shown in Eq. (2-11). And ω_i need be normalized.

$$m_{n,i} = m_i(H_n) = \omega_i \beta_{n,i} \quad n = 1, \dots, N; i = 1, \dots, L \quad (2-11)$$

The basic probability mass $m_{n,i}$ represents the degree to which the i th basic attribute e_i supports the hypothesis that the attribute y is assessed to the n th grade H_n .

Let $m_{H,i}$ be a remaining probability mass unassigned to any individual grade after all the N grades have been considered for assessing the general attribute as far as e_i is concerned. $m_{H,i}$ is calculated as follows:

$$m_{H,i} = m_i(H) = 1 - \sum_{n=1}^N m_{n,i} = 1 - \omega_i \sum_{n=1}^N \beta_{n,i}, \quad i = 1, \dots, L \quad (2-12)$$

$$\bar{m}_{H,i} = \bar{m}_i(H) = 1 - \omega_i, \quad i = 1, \dots, L \quad (2-13)$$

$$\tilde{m}_{H,i} = \tilde{m}_i(H) = \omega_i(1 - \sum_{n=1}^N \beta_i), \quad i = 1, \dots, L \quad (2-14)$$

with

$$m_{H,i} = \bar{m}_{H,i} + \tilde{m}_{H,i} \quad \text{and} \quad \sum_{i=1}^L \omega_i = 1,$$

where, $\bar{m}_{H,i}$ is the remaining probability mass that is not yet assigned to individual grades caused by the relative importance of the attribute i (denoted by e_i). $\bar{m}_{H,i}$ is a linear decreasing

function of ω_i . $\bar{m}_{H,i}$ will be one if the weight of e_i is zero or $\omega_i = 0$; $\bar{m}_{H,i}$ will be zero if e_i dominates the assessment or $\omega_i = 1$. And $\tilde{m}_{H,i}$ is the remaining probability mass unassigned to individual grades caused by the incompleteness of the assessment $S(e_i)$. $\tilde{m}_{H,i}$ will be zero if $S(e_i)$ is complete, or $\sum_{n=1}^N \beta_{n,i} = 1$; otherwise, $\tilde{m}_{H,i}$ will be positive. $\tilde{m}_{H,i}$ is proportional to ω_i and will cause the subsequent assessments to be incomplete.

$m_{n,I(i)}$ and $m_{H,I(i)}$ can be generated by combining the basic probability masses $m_{n,j}$ and $m_{H,j}$ for all $n = 1, \dots, N, j = 1, \dots, i$.

Table 2-6 illustrates the process of ER algorithm used in the model developed in this thesis.

Table 2 - 6: ER Algorithm Process as described in (Yang & Xu, 2002).

$S(e_i) \oplus S(e_j)$		$S(e_i)$							
		$(m_{1,i})$ $\{H_1\}$	$(m_{2,i})$ $\{H_2\}$...	$(m_{n,i})$ $\{H_n\}$...	$(m_{N,i})$ $\{H_N\}$	$(\tilde{m}_{H,i})$ $\{H\}$	$(\bar{m}_{H,i})$ $\{H\}$
$S(e_j)$	$(m_{1,j})$ $\{H_1\}$	$(m_{1,i} m_{1,j})$ $\{H_1\}$	$(m_{2,i} m_{1,j})$ $\{\Phi\}$...	$(m_{n,i} m_{1,j})$ $\{\Phi\}$...	$(m_{N,i} m_{1,j})$ $\{\Phi\}$	$(\tilde{m}_{H,i} m_{1,j})$ $\{H_1\}$	$(\bar{m}_{H,i} m_{1,j})$ $\{H_1\}$
	$(m_{2,j})$ $\{H_2\}$	$(m_{1,i} m_{2,j})$ $\{\Phi\}$	$(m_{2,i} m_{2,j})$ $\{H_2\}$...	$(m_{n,i} m_{2,j})$ $\{\Phi\}$...	$(m_{N,i} m_{2,j})$ $\{\Phi\}$	$(\tilde{m}_{H,i} m_{2,j})$ $\{H_2\}$	$(\bar{m}_{H,i} m_{2,j})$ $\{H_2\}$
	\vdots	\vdots	\vdots	\ddots	\vdots	\ddots	\vdots	\vdots	\vdots
	$(m_{n,j})$ $\{H_n\}$	$(m_{1,i} m_{n,j})$ $\{\Phi\}$	$(m_{2,i} m_{n,j})$ $\{\Phi\}$...	$(m_{n,i} m_{n,j})$ $\{H_n\}$...	$(m_{N,i} m_{n,j})$ $\{\Phi\}$	$(\tilde{m}_{H,i} m_{n,j})$ $\{H_n\}$	$(\bar{m}_{H,i} m_{n,j})$ $\{H_n\}$
	\vdots	\vdots	\vdots	\ddots	\vdots	\ddots	\vdots	\vdots	\vdots
	$(m_{N,j})$ $\{H_N\}$	$(m_{1,i} m_{N,j})$ $\{\Phi\}$	$(m_{2,i} m_{N,j})$ $\{\Phi\}$...	$(m_{n,i} m_{N,j})$ $\{\Phi\}$...	$(m_{N,i} m_{N,j})$ $\{H_N\}$	$(\tilde{m}_{H,i} m_{N,j})$ $\{H_N\}$	$(\bar{m}_{H,i} m_{N,j})$ $\{H_N\}$
	$(\tilde{m}_{H,j})$ $\{H\}$	$(m_{1,i} \tilde{m}_{H,j})$ $\{H_1\}$	$(m_{2,i} \tilde{m}_{H,j})$ $\{H_2\}$...	$(m_{n,i} \tilde{m}_{H,j})$ $\{H_n\}$...	$(m_{N,i} \tilde{m}_{H,j})$ $\{H_N\}$	$(\tilde{m}_{H,i} \tilde{m}_{H,j})$ $\{H\}$	$(\bar{m}_{H,i} \tilde{m}_{H,j})$ $\{H\}$
	$(\bar{m}_{H,j})$ $\{H\}$	$(m_{1,i} \bar{m}_{H,j})$ $\{H_1\}$	$(m_{2,i} \bar{m}_{H,j})$ $\{H_2\}$...	$(m_{n,i} \bar{m}_{H,j})$ $\{H_n\}$...	$(m_{N,i} \bar{m}_{H,j})$ $\{H_N\}$	$(\tilde{m}_{H,i} \bar{m}_{H,j})$ $\{H\}$	$(\bar{m}_{H,i} \bar{m}_{H,j})$ $\{H\}$

Given the previous definitions and discussions, the evidential reasoning algorithm can be summarized as follows

$$m_{n,I(i+1)} = K_{I(i+1)}(m_{n,I(i)}m_{n,i+1} + m_{n,I(i)}m_{H,i+1} + m_{H,I(i)}m_{n,i+1}) \quad n = 1, \dots, N \quad (2-15)$$

where $m_{H,I(i)} = \bar{m}_{H,I(i)} + \tilde{m}_{H,I(i)}$

$$\tilde{m}_{H,I(i+1)} = K_{I(i+1)}[\tilde{m}_{H,I(i)}\tilde{m}_{H,i+1} + \bar{m}_{H,I(i)}\tilde{m}_{H,i+1} + \tilde{m}_{H,I(i)}\bar{m}_{H,i+1}] \quad (2-16)$$

$$\bar{m}_{H,I(i+1)} = K_{I(i+1)}[\bar{m}_{H,I(i)}\bar{m}_{H,i+1}] \quad (2-17)$$

$$K_{I(i+1)} = \left[1 - \sum_{t=1}^N \sum_{j=1, j \neq t}^N m_{t,I(i)} m_{j,i+1} \right]^{-1} \quad i = 1, \dots, L-1 \quad (2-18)$$

where $K_{I(i+1)}$ is a normalizing factor so that $\sum_{n=1}^N m_{n,I(i+1)} + m_{H,I(i+1)} = 1$.

After aggregating all the assessments L , $\bar{m}_{H,I(L)}$ is assigned back to all individual grades proportionally to generate the combined degrees of belief as shown in the following equations:

$$\beta_n = \frac{m_n}{1 - \bar{m}_{H,I(L)}}, \quad n = 1, \dots, N \quad (2-19)$$

$$\beta_H = \frac{\tilde{m}_{H,I(L)}}{1 - \bar{m}_{H,I(L)}} \quad (2-20)$$

where β_n represents the degrees of belief for the aggregated assessment where the final assessment is assessed to the grades H_n . β_H represents the incompleteness of the overall assessment assigned to H .

2.7 Factors Affecting Offshore Gas Pipelines

In previous researches that handled condition assessment of oil and gas pipelines, the focus was mainly directed to factors that are related to corrosion or third party characteristics (Ahammed 1998; Sinha and Pandey 2002; Li et al. 2009; Hallen et al. 2003; Bersani et al. 2010 and Noor et al. 2011) which are insufficient to successfully develop an efficient condition assessment model. Therefore, other factors are needed to be identified in order to build an accurate model. For example, Senouci et al. (2014a and 2014b) implemented Regression Analysis and Artificial Neural Network (ANN) to develop models that predict the possible failure types other than corrosion. Also, El-Abbasy et al. (2014a, 2014b & 2014c) proposed three condition assessment models for oil and gas pipelines using integrated simulation & ANP, regression analysis, and ANN. These models considered various factors categorized into physical, external and operational factors.

As discussed in the previous section, the factors identification process started with performing literature review on the previous studies related to pipeline condition assessment. At the same time, several interviews were conducted with professional experts in the oil and gas industry in Qatar to identify the factors that may affect the pipeline condition according to their experience. Later on, the two factors' list, from literature and from interviews, were compared to each other to come up with a comprehensive list of the most important factors affecting pipeline condition. Then, the factors were divided into three categories: physical, external and operational as shown in Fig. 2-12. The physical factors deal with the pipeline

general characteristics such as Age, Diameter, Metal Loss and Coating Condition. The external factors group deals with the pipeline surrounding environment and included factors like number of crossings of other pipelines, the applied cathodic protection, existence of marine routes and the water depth. The final group, which is the operational factors group, deals with operational condition on the pipeline. It included three factors: existence of corrosive impurities, the operating pressure and the flow rate. Deterioration of offshore gas pipelines systems can be caused by numerous factors. Table 2-7 summarizes these physical, external and operational factors.

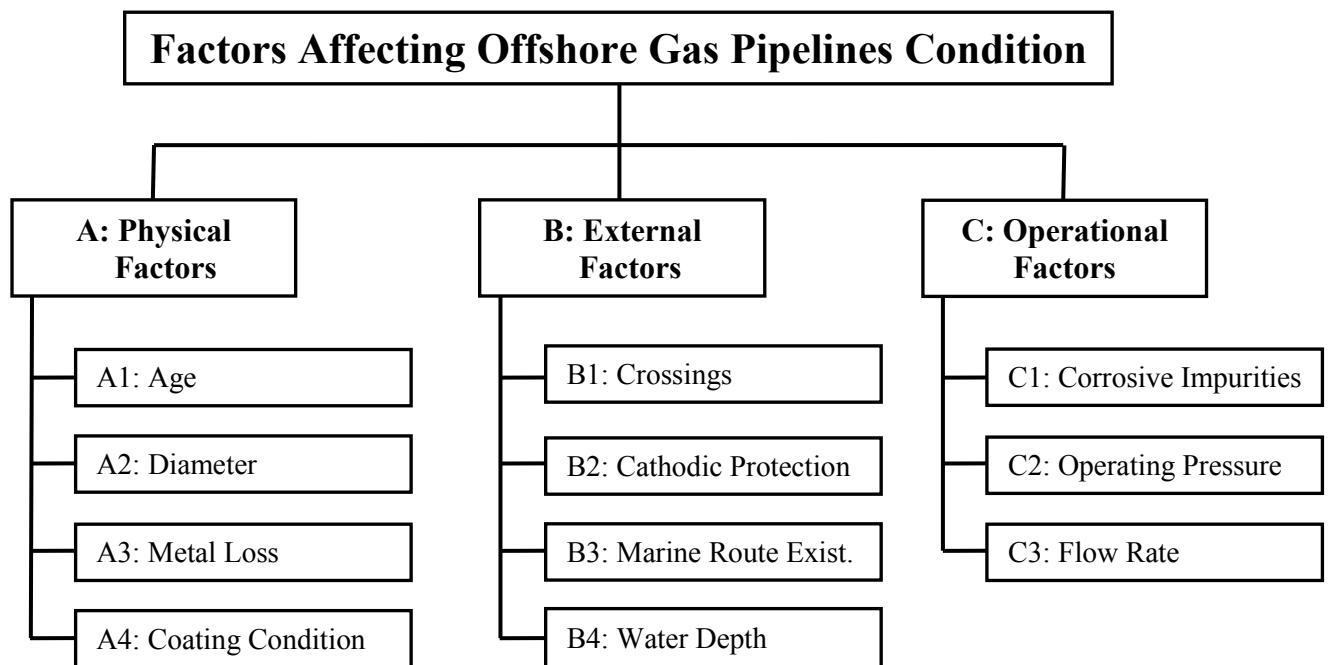


Figure 2 - 12: Hierarchy of Factors Affecting Offshore Gas Pipelines Condition (El-Abbasy et al., 2014a).

Table 2 - 7: Explanation of Factors Affecting Offshore Gas Pipelines (El Chanati et al. 2013).

Factor		Explanation
Physical	Age	Pipeline usually degrades as it ages, resulting in a pipeline condition decrease.
	Diameter	Smaller pipeline diameter has a higher probability of failure than larger ones possibly because smaller standard dimension ratio (SDR) affects the structural performance of a pipeline and makes it more vulnerable to external impact or third party damage.
	Metal Loss	The pipeline condition decreases when the metal loss as a percentage of the wall thickness increases.
	Coating Condition	Well maintained applied coating enhances the pipeline condition.
External	Crossings	As the number of pipelines crossing over or under the considered pipeline increases, the pipeline becomes less stable and its condition eventually decreases.
	Cathodic Protection	Cathodic protection is essential to protect a pipeline against corrosion. As the protection potential decreases, the pipeline condition decreases due to the absence of corrosion resistance.
	Marine Route Existence	Existence of marine routes near the considered pipeline may lead to third party damage.
	Water Depth	Pipeline depth under the water greatly affects the pipeline condition. Shallow pipelines are easily exposed to third party damage while deep pipelines are subjected to high water pressure.
Operational	Corrosive Impurities	The existence of high level of corrosive impurities in the transported product severely affect the inner pipe wall resulting in internal corrosion.
	Operating Pressure	The maximum allowable operating pressure decreases the pipeline condition when it gets close to the design pressure because it can induce more stresses on the pipeline.
	Flow Rate	Low flow rates could increase the chances of liquid or solid dropout and accumulation in low places of the pipeline, whereas high flow rates may lead to pipeline erosion.

2.8 Infrastructure Condition Assessment Models

In the recent years, serious efforts have been carried out to assess infrastructure systems including oil & gas, water, and sewer pipelines. This is due to the significant environmental and economical importance of these systems. As a result, different condition assessment models have been developed to predict the condition rating and possibilities of future failure. This section provides a brief summary about some of these developed models.

2.8.1 Oil & Gas Pipelines

Oil and gas pipelines hold an important place in any nation's economy since they transport millions of dollars' worth of oil and gas various products. So, condition assessment is very necessary for operating pipelines to evaluate their performance along their age and prevent any future disasters caused by pipeline failures. Different models have been promoted for this purpose. For example, Ahammed (1998) developed a new methodology to assess the remaining service life of a pressurized pipeline containing active corrosion defects. Following that, Analytical Hierarchy Process (AHP) was utilized by Dey (2001) to propose a decision model to help decision makers and pipeline operators select a suitable type of inspection or monitoring technique for pipelines. Sinha & Pandey (2002) developed a simulation-based probabilistic fuzzy neural network model to estimate failure probability of aging oil and gas pipelines that have corrosion vulnerability. Hallen et al. (2003) presented a probabilistic analysis framework to assess corroding pipelines and its failure probability in the future. Kumar & Taheri (2004) were concerned about pipeline material effect on oil and gas pipelines. So, they developed an automated data interpretation system using neural networks for fiber-reinforced polymer composites (FRP) oil and gas pipelines, which is applicable to metallic pipes as well.

In 2006, historical failure data were adapted using statistical analysis classification and regression tree to develop a tool that predicts a spillage class in oil pipes (Bertolini & Bevilacqua, 2006). After three years, Peng et al. (2009) used fuzzy neural network to suggest a model that is based on failure tree and fuzzy computing to predict the rate of failure for long-distance oil and gas pipelines. In the same year of 2009, Dawotola et al. combined Analytic Hierarchy Process (AHP) and Fault Tree Analysis to present an optimal selection strategy, based on the probability and consequences of failure, in order to support the design, the construction, and the inspection and maintenance of oil and gas pipelines. In addition, Noor et al. (2010) and (2011) used a semi-probabilistic and deterministic methodology to predict the remaining strength of offshore pipelines subjected to internal corrosion. Also, Bersani et al. (2010) used historical data from Department of Transportation (DOT) in the US to develop a risk assessment model that predicts the failure caused by third party activities. Recently, El-Abbasy et al. (2014a, 2014b & 2014c) proposed three condition assessment models for oil and gas pipelines using integrated simulation & ANP, regression analysis, and ANN. Similarly, Senouci et al. (2014a and 2014b) implemented Regression Analysis and Artificial Neural Network (ANN) to develop models that predict the possible failure types other than corrosion.

2.8.2 Water Pipelines

Water pipelines condition assessment was and still the focus of many researchers in order to predict the performance and condition rating of these pipelines. For example, Yan and Vairavamoorthy (2003) assessed the condition of water mains using fuzzy multi-criteria decision-making (MCDM) techniques. In the same year, Geem (2003) employed the Artificial Neural Networks (ANN) to develop a decision support system for water pipeline condition assessment. Two other models were prepared by Al-Barqawi and Zayed (2006a &

2006b) in which AHP and ANN were utilized to predict the condition rating of water pipelines based on physical, operational, and environmental deterioration factors. In 2008, Al-Barqawi and Zayed prepared an integrated model using AHP and ANP concurrently to evaluate the sustainability of water pipelines.

2.8.3 Sewer Pipelines

Similarly to water pipelines, many models have been developed to assess the condition of sewer pipelines. In 2000, Moselhi and Shehab-Eldeen presented a Back-Propagation Neural Network for the purpose of analysis and classification of defects in sewer pipelines. At the same time, a sewer management system for prioritizing sewer pipelines inspection based on the Bayesian belief networks was proposed by Hahn et al. (2000). One year later, Chae & Abraham (2001) developed a neuro-fuzzy approach for more accurate analysis and data interpretation of sewer pipelines condition. Also, Najafi and Kulandaivel (2005) proposed a model that predicts the condition of sewer pipelines based on historical condition assessment data. In the same year of 2005, Stein et al. developed a model which analyzes the defect-caused environmental impacts on sewer pipelines using Monte Carlo simulation.

2.9 Summary

To conclude this chapter, we can say that fuzzy set theory is considered a powerful tool when it comes to modeling complex systems. It is very useful in problems that involve vagueness and uncertainty. Fuzzy sets theory is a tool that converts linguistic terms into mathematical data that can be easily managed and interpreted (Mamdani, 1974). The decision maker can use the fuzzy approach to produce simple evaluation systems according to their own values and judgments while maintaining tractability. Fuzzy sets theory was successfully used in

many applications in different fields. The interested reader may refer to the book "Fuzzy Logic with Engineering Applications" third edition by Timothy J. Ross published in 2010.

The previous sections introduced the Evidential Reasoning Technique which uses two frameworks: Bayesian frameworks and the Dempster-Shafer (DS) Theory of Evidence. Also, the ER algorithm used to develop the model of this research was stated in details to illustrate the methodology used to aggregate the degrees of belief of Multiple-Criteria Decision-Making (MCDM) problems. In addition, some of the previous research works were introduced since the development of ER technique till the current time. Many efforts were put to develop the previously discussed ER algorithm so it satisfies many theorems, such as the basic, consensus, complete, and incomplete synthesis theorems. These theorems are discussed in details in Yang & Xu (2002) for interested readers.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

The current research aims to develop a condition assessment tool to evaluate offshore gas pipelines in Qatar. The presented research methodology consists of different steps as shown in Fig. 3-1: Literature Review, Data Collection, Model Development, Condition Assessment Scale, Sensitivity Analysis, Deterioration Curve, Condition Assessment Automated Tool, and Conclusion and Recommendation. The following sections provide a brief description of the planned methodology.

3.2 Literature Review

This part summarizes the literature related to the scope of current research. Section 2.1 includes a shortened introduction about pipelines importance nowadays along with some associated statistics. This section also contains a review about pipeline design and manufacturing material. Section 2.2 reveals few important facts about the oil and gas industry in Qatar and its pipeline network. Information about the pipelines characteristics and inspection interval are also included. These information were collected from extensive research and interviews with professionals in the oil and gas industry in Qatar. Section 2.3 illustrates the types of manufacturing materials used in Qatar's pipelines network and the standards followed for their design. Sections 2.4, 2.5 and 2.6, contains a detailed and comprehensive literature review of the techniques used to conduct the current research; Analytic Network Process (ANP), Fuzzy Set Theory (FST) and Evidential Reasoning (ER) respectively. Finally, Section 2.7 presents the time-dependent factors considered in this research which contribute in the deterioration of offshore gas pipelines in Qatar. These factors provide the main structure to develop the condition prediction model. They are classified into three categories; physical, external, and operational. The hierarchy of the

factors affecting offshore gas pipelines was made through extensive literature review and interviews with professionals in oil and gas industry in Qatar.

3.3 Data Collection

Data needed to conduct this research were collected from different sources. First, a structured questionnaire was distributed among professionals, engineers and managers, in the oil and gas industry in Qatar and similar regions such as Saudi Arabia. This method was used to gather the feedback of practitioners and specialists in regards to the most influential factors affecting the condition of offshore gas pipelines in Qatar, their main categories, and the condition assessment scale. These questionnaires included pair-wise comparisons between the factors and their main categories; added to the proposed condition assessment scale. Only 28 were received back from the 55 distributed questionnaires and 25 of them were considered in this research which represents 45.5% of the distributed sample.

Also, a local pipeline operator in Qatar was reached in order to obtain historical inspection reports. Three data sets were received which include pipeline age, diameter, wall thickness, metal loss, coating condition, cathodic protection, metallic debris, operating pressure, manufacturing material, crossings, ..., etc. The received data was prepared and 20% sample was randomly selected for validation. The remaining 80% was used as further verification as discussed in the validation section later on.

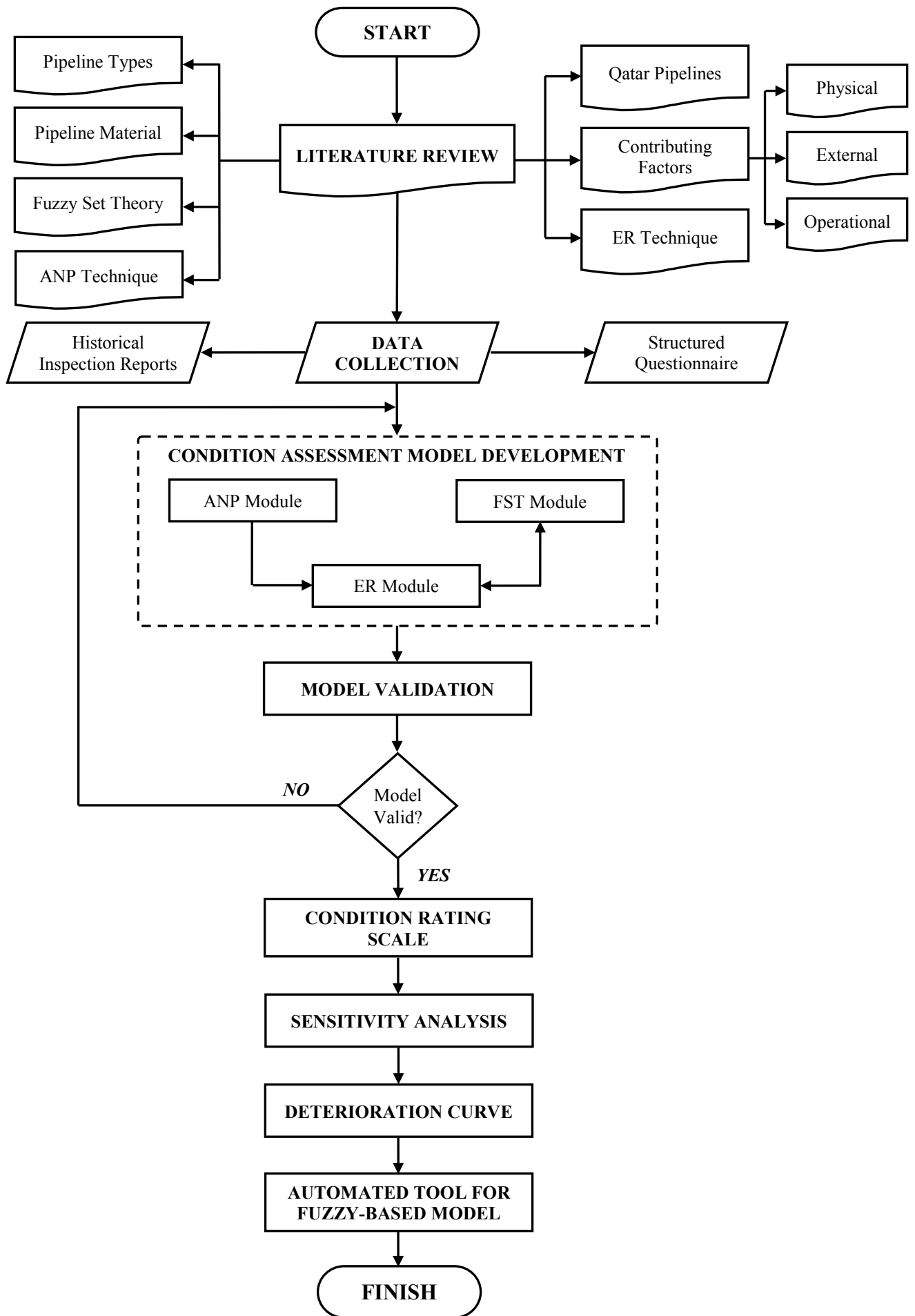


Figure 3 - 1: Research Methodology.

3.4 Condition Assessment Scale

A new condition assessment scale is proposed in this research based on experts' feedback from the distributed questionnaires. In this condition assessment scale, five evaluation grades were suggested; *Excellent*, *Very Good*, *Good*, *Fair* and *Critical* where the fuzzy set theory is applied. The condition numerical scale value ranges from 0 to 10 where 0 indicates pipeline's worst condition and 10 indicates the best. Each of the suggested evaluation grades is described linguistically and numerically along with its associated required action which includes inspection, rehabilitation or both. This scale could be of great benefit to engineers and pipeline operators to prioritize future inspection and rehabilitation works for existing offshore gas pipelines.

3.5 Model Development

Analytic Network Process (ANP) and Evidential Reasoning (ER) are both integrated to develop the model in hand with the help of Fuzzy sets theory. However, ER technique is the backbone of the developed model. The steps of the integration process will be discussed in this section as follows.

3.5.1 Factors Relative Weights Using ANP

Fig. 3-2 describes the methodology used to calculate the factors' relative weights from the collected questionnaires using ANP technique. The procedure to implement the ANP technique can be summarized in the following steps:

- 1) Collect received questionnaires' responses from experts and professionals.

- 2) Conduct pair-wise comparisons between factors and their main categories to form pair-wise comparison matrices. Saaty's scale of measurement (1 to 9) is used to measure the importance of compared elements.
- 3) Estimate the relative weights of the factors and main categories by calculating vectors of priorities and normalizing each one to a sum of 1.00 or 100%.
- 4) Determine the consistency ratio (CR) to validate the questionnaires' responses. This step can be performed by comparing the calculated CR with acceptable values.
- 5) Develop the unweighted super-matrix which is translation of the pair-wise comparisons into a two-dimensional super-matrix under the influence of interdependency.
- 6) The weighted super-matrix is derived from the unweighted super-matrix by dividing each entry in each row in the unweighted super-matrix by the total summation of its relative intersecting column.
- 7) The next step is to develop the limit super-matrix which is the result of raising the weighted super-matrix to sufficient large power until convergence occurs. This is done until the numbers in all the columns of the limit super-matrix are identical.
- 8) Finally, the final global weights of the factors and their main categories are obtained by proportioning the elements of each cluster to themselves so the summation of the final global weights for all the factors is 1.00.

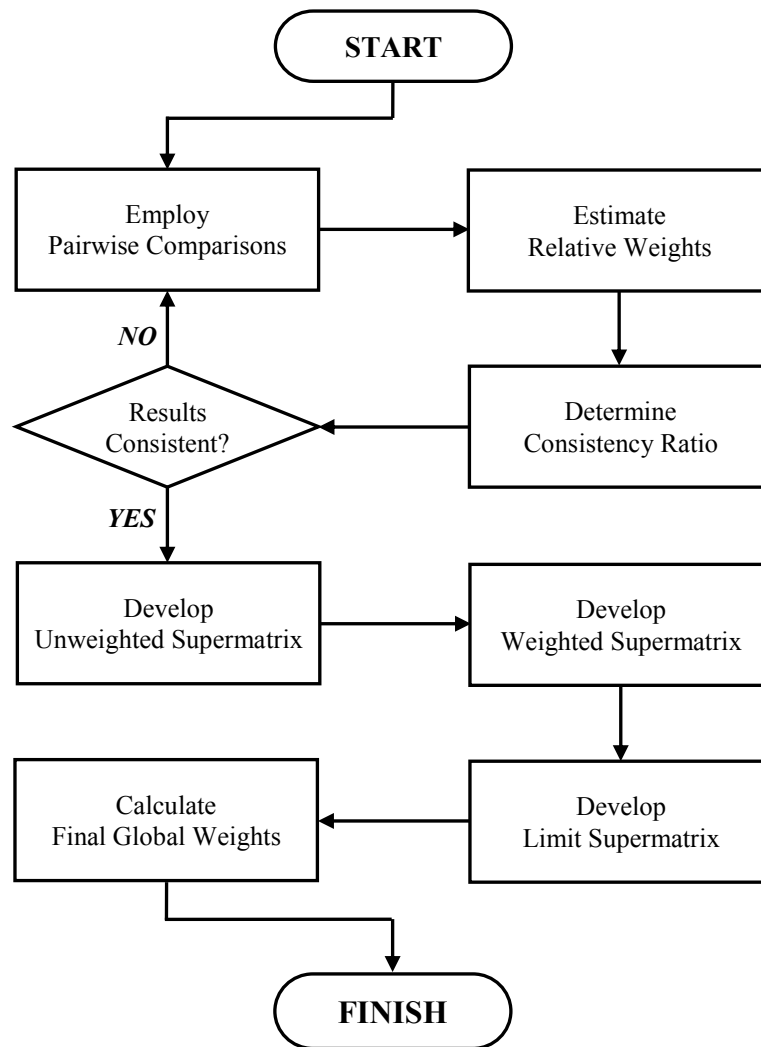


Figure 3 - 2: ANP Technique Methodology.

3.5.2 Threshold Determination Using Fuzzy Set Theory

The collected responses are used to develop the factors' thresholds and their membership functions which were later used as input in the proposed condition assessment model. Fig. 3-3 illustrates the methodology of implementing the fuzzy set theory. The methodology of the fuzzy set theory can be described in the following steps:

- 1) The fuzzy inputs and outputs of the developed model are identified after literature review and interviews with experts.
- 2) The experts' feedback on the distributed questionnaires are used to develop the thresholds of the factors considered in this research.

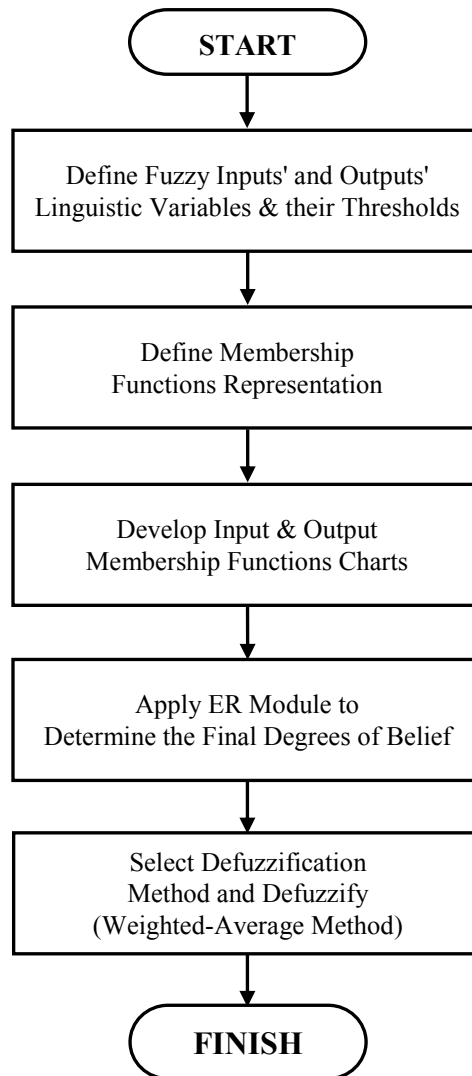


Figure 3 - 3: Fuzzy Set Theory Methodology.

- 3) After various trials, the suitable membership function is chosen to represent the inputs and outputs of the developed model. This representation adapted trapizoidal shape for both membership function ends and triangular shape for the middle ones.
- 4) Then, the factors' thresholds are fuzzified and converted into the membership functions used to represent the input and output variables.
- 5) The output of the developed model is in the form of a membership function. So, a defuzzification method is chosen to convert these fuzzy membership funcntions into a

crisp value. A comparison between two defuzzification methods, Centroid and Weighted-Average, is conducted in the validation process to choose the most suitable method.

3.5.3 Degree of Belief Determination Using ER

The application of the ER technique is performed in the background of the automated tool. The purpose of using the ER technique is to address uncertainty in Multi-Criteria Decision Making (MCDM) problems. It represents any assessment as a distribution using belief structures. The ER aggregates the degrees of belief using an algorithm developed basically on decision theory and combination rule of DS theory of evidence instead of aggregating average scores as conventional MCDM methods. Fig. 3-4 illustrates the main steps required to employ the ER technique in the developed condition assessment model.

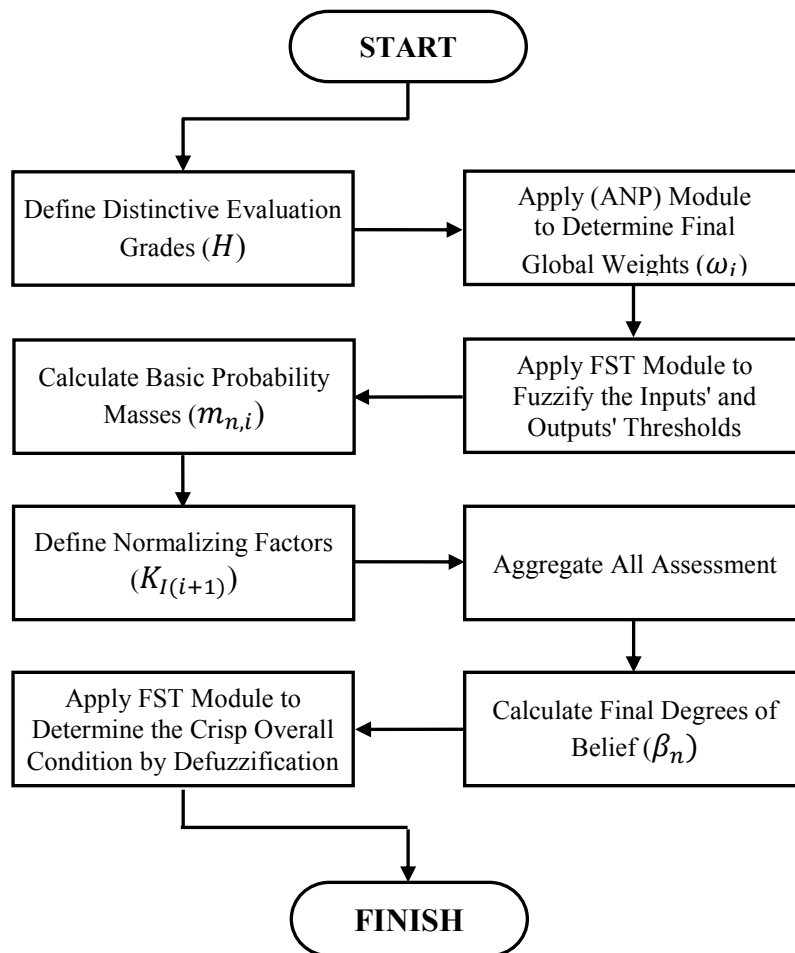


Figure 3 - 4: Evidential Reasoning (ER) Methodology.

The procedure to employ the ER technique in the current research is summarized as follows:

- 1) To start, the distinctive evaluation grades (H) must be identified. This is performed in the fuzzy set theory stage. These evaluation grades are *Excellent*, *Very Good*, *Good*, *Fair*, and *Critical*.
- 2) Define each input's relative weight (ω_i) which is performed by the ANP module.
- 3) The fuzzy set theory, FST module, is used here to fuzzify the factors' thresholds in order to obtain a distributed assessment of any given input or output. It can be represented by Eq. (2-10).
- 4) All the belief structures are then transformed into basic probability masses ($m_{n,i}$) using Eq. (2-11).
- 5) The normalizing factor ($K_{I(i+1)}$) is calculated with Eq. (2-18) which is used to combine two probability masses.
- 6) The previous steps are repeated for the rest of the factors until all the probability masses are combined together.
- 7) Using Eq. (2-19) and (2-20), the final combined probability masses are then converted into the final degrees of belief (β_n) which is defuzzified later into a crisp value.
- 8) Finally, FST module is applied again to determine the crisp overall condition through defuzzification.

3.5.4 Integrated Condition Assessment Model

The model developed in this research proposed the idea to integrate the abovementioned three modules, i.e. relative weights, thresholds, and degrees of belief, to assess the condition of offshore gas pipelines in Qatar. These modules are developed utilizing three techniques:

Analytic Network Process (ANP), Fuzzy Set Theory (FST) and Evidential Reasoning (ER). The ER module requires two main inputs to operate, relative weights of criteria and belief structures. First, ANP is used to calculate the relative weights of the factors and their main categories resulted from the experts' feedback on the distributed structured questionnaires. For this purpose, the ANP procedure explained in Literature Review is followed. Second, Fuzzy Set Theory is applied to build membership functions for all the factors identified in the current research. The objective is to fuzzify the factors' thresholds developed from questionnaire responses in order to systemize the generation of their belief structures.

The outputs obtained from implementing ANP and Fuzzy Set Theory are used as inputs for ER module. Then, ER algorithm is utilized to combine all factors' belief structures. The ER output is one belief structure that represents the condition of the studied offshore gas pipeline based on the identified factors' values. It must be noted that the ER technique were not used to this extent as a condition assessment tool, especially with the integration of both, ANP and Fuzzy Set Theory. The integration of these three techniques proved its efficiency in predicting the offshore gas pipelines condition as demonstrated later in the model validation section.

3.5.5 Defuzzification and Model Validation

After calculating the final degrees of belief, defuzzification is needed to convert the final degrees of belief into a score out of ten. Two commonly used defuzzification methods, *Centroid* and *Weighted-Average*, were used for this purpose. Any used defuzzification method should be evaluated in terms of the validity of the final output value in the context of available data. Two validation studies are performed to compare between the results of the chosen defuzzification methods, Centroid and Weighted-Average.

3.5.6 Sensitivity Analysis

A Sensitivity Analysis is conducted to test the robustness of the developed fuzzy-based model under uncertainty. In other words, it is performed to examine how the uncertainty in inputs could affect the model's results and to increase the understanding of the relationship between input and output variables. Also, unexpected relationships between inputs and outputs can be encountered which is another advantage of performing a sensitivity analysis. This analysis was based on changing a factor's value (input) from lowest to highest while keeping other factors constant at average condition to check the individual effect on the overall pipe condition.

3.5.7 Deterioration Curve

Deterioration of pipelines is a natural phenomenon. Forecasting this occurrence is considered an indispensable component that directs pipeline operators to successfully schedule future pipeline rehabilitation and replacement. Consequently, researchers devoted a considerable amount of their efforts in the last years to focus on infrastructure deterioration modeling. In this research, a deterioration curve is created based on the developed fuzzy-based condition assessment model by building a relationship between final pipeline condition and the *Age* factor. In return, this curve can help the decision makers in scheduling for maintenance and rehabilitation.

3.6 Condition Assessment Automated Tool

After building the fuzzy-based condition assessment model and verifying its prediction powers against historical inspection data, the automated fuzzy-based condition evaluator is developed. Third party software, MS Excel, is used for this purpose. The automated tool will help professionals and pipeline operators in the oil and gas industry to predict the condition of existing offshore gas pipelines.

This tool displays the hierarchy of factors contributing in the condition assessment of offshore gas pipelines which are considered in the development of this model after performing extensive literature review and interviews with experts. These factors are classified into three categories; physical, external, and operational. Physical factors includes pipe age, diameter, metal loss and coating condition while number of crossings, cathodic protection effectiveness, existence of marine routes and water depth are categorized under external factors. The operational factors category contains corrosive impurities, operating pressure and flow rate.

Later, the user has the choice whether to use the default ANP weights, generated previously in the data collection phase, or to generate their own customized weights. In case the user chose to generate new ANP weights, he/she will be guided through the process, detailed later in this research, which leads to using a pre-arranged SuperDecisions software file. Then, the user will be asked to enter the factors' values such as pipeline age, diameter and so on, under the condition that entered factor's value do not exceed the pre-determined thresholds limits.

The output of this tool is the final evaluation of the considered pipeline as a crisp value ranging between "0" and "10" where "0" indicates the worst condition and "10" the best. Also included in the outputs, a mathematical and graphical comparison between Centroid and Weighted-Average as defuzzification methods where the membership function cut of the Centroid method is represented graphically.

3.7 Summary

This chapter presents the methodology of the current research. This methodology includes literature review, data collection, model development steps and validation, proposing a new

condition assessment scale, and the automation of the fuzzy-based condition assessment model. In this research, three techniques are employed to propose a new methodology to assess the condition of offshore gas pipelines in Qatar. First, ANP is utilized to calculate the relative weights of the identified factors and to account for interdependency between factors where one factor's category is compared to another with respect to the third one and so on. For example, the physical factors category is compared to the external factors category with respect to operational factors category. Then, Fuzzy Set theory is applied to generate membership functions of these factors in order to acquire distributed belief structures. Finally, the Hierarchical Evidential Reasoning (HER) is used to combine all belief structures leading to the final assessment distribution of the studied gas pipeline. This final assessment is then translated into a crisp value, "0" to "10", using a defuzzification method. A comparison is performed between two defuzzification methods, Centroid and Weighted-Average, to investigate the most appropriate. The FST and ER were used in order to account for uncertainty in respondent's feedback. For example, a professional is not certain that a specific age value falls under which evaluation grade. After that, a sensitivity analysis is conducted on the results of current research. Also, a deterioration curve is generated in the process. In addition, a new adapted condition scale is proposed. Finally, an automated tool is developed for the model in hand to facilitate this model's application. It is worth mentioning that the model developed in this research is based on two models presented previously by El-Abbasy et al. (2014a, 2014b & 2014c) in which integrated simulation & ANP, regression analysis, and ANN techniques were used to predict and assess the condition of oil and gas pipelines.

CHAPTER FOUR: DATA COLLECTION

4.1 Introduction

In the literature review section, a list of the most important factors affecting the pipeline condition was prepared. This list was compared with another list of factors that were identified from interviews with professional experts in Qatar and similar regions. A comprehensive list of factors was then developed and used to design a structured questionnaire that was distributed among professional experts in the oil and gas industry in Qatar by different ways such as emails and direct meetings. As illustrated in Table 4-1 and Fig. 4-1, fifty five samples of the questionnaire were distributed among engineers from various fields in the oil and gas industry. Only 28 were received back from the 55 distributed questionnaires and 25 of them were considered in this research. This represents almost 45.5% of the distributed sample. The experts who responded to the distributed questionnaires worked in different departments such as Asset Management, Inspections Management, Operation Management, and others. From the received questionnaires, the range of professional experience of the respondents varied from 5 to 20 years in the oil and gas industry. The targeted sample of professionals was mainly from Qatar and from Saudi Arabia which has similar weather and operating conditions to Qatar.

Table 4-2 demonstrates the details of the professionals who responded to the distributed questionnaire. It is noticed that the majority of questionnaire responses were from inspection and operation managers having experience ranges of 16 to 20 years and more than 20 years. This observation leads to the idea that the conducted research is of interest to the previously mentioned parties and they could benefit greatly from it due to the importance and criticality of the research subject especially in a country like Qatar.

Table 4 - 1: Distributed Questionnaires.

Questionnaires	Number (#)	Percentage (%)
Considered	25	45.5
Disregarded	3	5.5
Not Received	27	49
Total	55	100

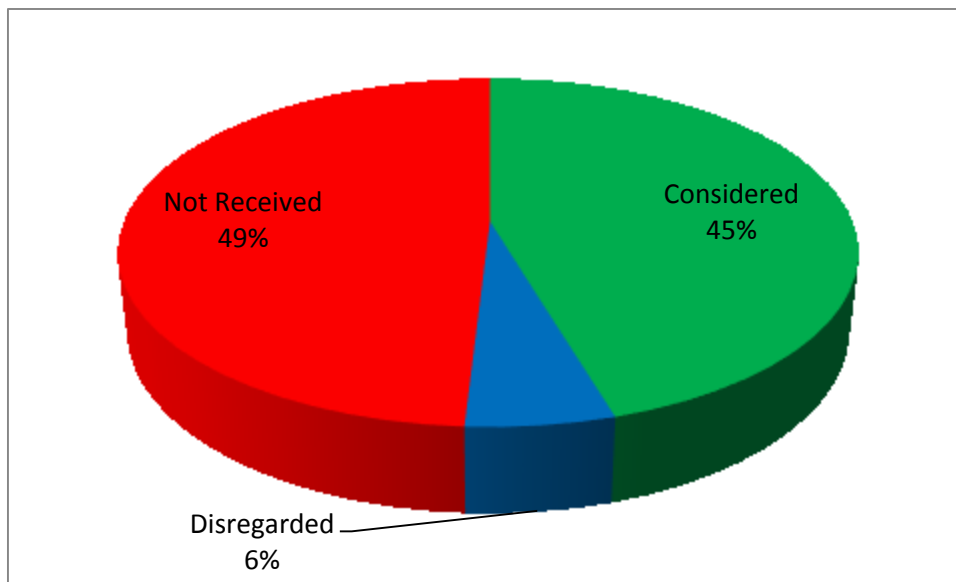


Figure 4 - 1: Distributed Questionnaires.

Table 4 - 2: Details of Questionnaire Respondents.

Job Position	Experience (Years)				Total
	6 - 10	11 - 15	16 - 20	More than 20	
Asset Manager	-	-	2	1	3
Inspection Manager	-	-	7	3	10
Operation Manager	-	-	4	3	7
Inspection / Operation Manager	1	3	1	-	5
Total	1	3	14	7	25

4.2 Structured Questionnaire

The structured questionnaire contained a small introduction about the conducted research along with the most influential factors affecting offshore gas pipelines in Qatar. Also, the questionnaire included another four parts as described below (See Appendix A). This questionnaire is adapted from a questionnaire designed by El-Abbasy et al. (2014a).

Part (1): General Information.

Several questions were asked to the expert filling the questionnaires regarding their occupation, experience, their organization and the type of projects implemented by their organization.

Part (2): Pair-wise Comparison between Factors.

This section of the questionnaire was designed to identify the importance of the factors and their categories using the concept of pair-wise comparison. The comparisons were performed on three levels as follows:

- 1) Comparison among factors' categories with respect to Goal (Offshore Gas Pipeline Condition).
- 2) Comparison among factors within each category.
- 3) Comparison among factors' categories with respect to each other.

Fig. 4-2 which was adapted from (El-Abbasy et al., 2014a) explains graphically the three levels of comparison. The first two levels of comparison is what is called AHP techniques. The third level handles interdependency between the factors. It is one of the characteristics that are added by ANP technique which is an extension of the AHP. The level of importance in the questionnaire was designed to match up with Saaty's scale (1996) from 1 to 9 where

"1" means "No Significant Importance" and "9" means "Absolute Importance" of the considered factor with respect to a selected set of criteria. An example explaining each part is included in the distributed questionnaires to assure that the experts understand the pair-wise comparison and how to fill the questionnaire properly as shown in Fig. 4-3.

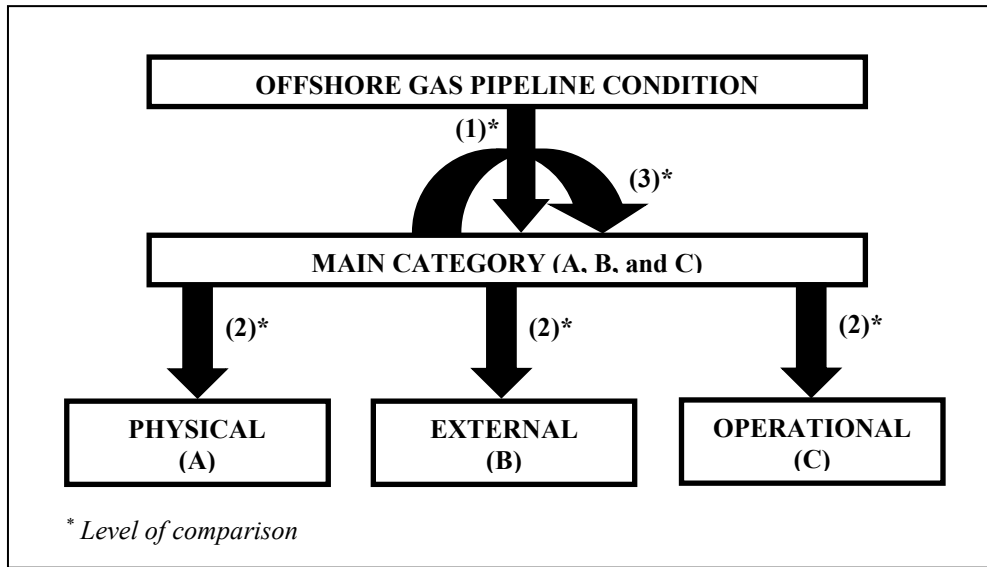


Figure 4 - 2: ANP Framework in Distributed Questionnaires. (El-Abbasy et al., 2014a)

Example:
 In the table below, consider comparing "Pipeline Age" (Criterion X) with "Pipeline Diameter" (Criterion Y) with respect to the "Physical Factors".

Criterion (X)	Degree of Importance									Criterion (Y)	Remarks
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		
Pipeline Age										Pipeline Diameter Wall Thickness Condition of Interior/ Exterior Coating	

If you consider that "Pipeline Age" is more important than "Pipeline Diameter" and the degree of this importance is "Strong" then tick (✓) here.

If you consider both "Pipeline Age" and "Pipeline Diameter" have "Equal" importance; then tick (✓) here.

If you consider the "Pipeline Diameter" is more important than "Pipeline Age" and the degree of importance is "Absolute" then tick (✓) here.

The same procedure is then followed when comparing "Pipeline Age" with "Wall Thickness" and "Condition of Interior/Exterior Coating".

Figure 4 - 3: Example of Pair-Wise Comparison in Distributed Questionnaires. (El-Abbasy et al., 2014a)

Part (3): Determining the Score of Factors.

Since the factors are not similar in their effect on the gas pipeline condition and have different attributes, the experts were asked to assign a score value for each of the different factors' attributes. The scale used for the scores is from "0" to "10" where "0" indicates the worst or lowest score and "10" indicates the best or highest score. A simple example was included also in the distributed questionnaires as shown in Fig. 4-4.

Example:
In the table below, consider evaluating the "Pipeline Age" factor.

Main Factor	Sub-factors	Unit Of Measure (if applicable)	Qualitative Description (Parameters)	Quantitative Value Range (if applicable)	Quantitative Scale Range (0 – 10)
PHYSICAL	Pipeline Age	Years	Old	35 to 50 years	0 to 3
			Medium	15 to 35 years	4 to 7
			New	0 to 15 years	8 to 10

The "Unit of Measure" can be "Years"

The "Quantitative Value Range" can be "35 to 50 years", "15 to 35 years", and "0 to 15 years" for the "old", "Medium", and "New" parameters respectively.

The "Quantitative Scale Range" can be "0 to 3", "4 to 7", and "8 to 10" for the "old", "Medium", and "New" parameters respectively.

Figure 4 - 4: Example of Determining the Score of Factors in Distributed Questionnaires. (El-Abbasy et al., 2014a)

Part (4): Gas Pipelines Condition Index.

The purpose of this part of the questionnaire is to propose a condition rating scale for the offshore gas pipelines. The same scale used in Part (3), from "0" to "10", was used in this part where "0" indicates the worst condition and "10" indicates the best. Also, the experts were requested to assign a suitable qualitative description for the pipeline condition along with suggested required action to be performed.

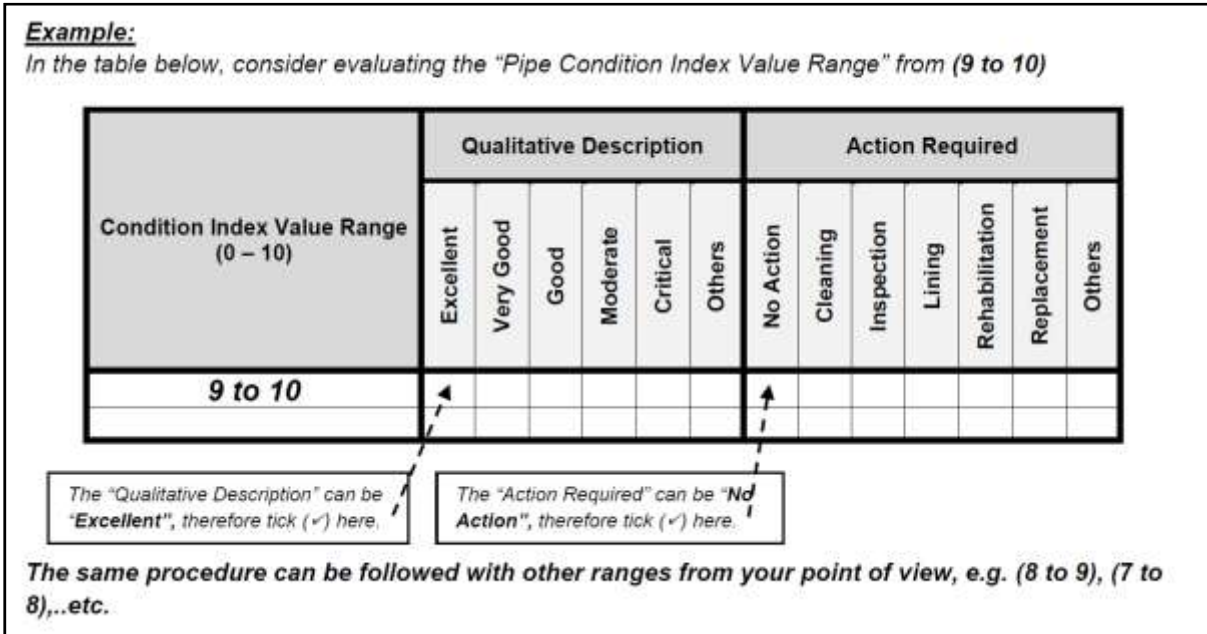


Figure 4 - 51: Example of Gas Pipeline Condition Index. (El-Abbasy et al., 2014a)

4.3 Historical Inspection Data

In order to validate the developed model, inspection data for three major pipelines was collected from a famous state-owned pipeline operator in Qatar. The collected data included inspection reports from four types of inspections: Inline Inspection (ILI), Remotely Operated Vehicle Inspection (ROV), Cathodic Protection Monitoring System, and Direct Current Voltage Gradient (DCVG) inspection. These inspections were executed in 1996, 2001, 2004, 2008 and 2009. The oldest pipeline (20 inch.) was constructed in 1972 with a length of 45 km offshore. The second one (24 inch.) was installed in 1979 with a total length of 121 km (89 offshore and 32 km onshore). The most recent pipeline (12 inch.) was commissioned in 1990 consisting of 80 km of offshore pipeline and 131 km onshore leading to 211 km in total. However, the inspections were not performed for the total length of pipelines except the oldest one, constructed in 1972, which was fully inspected. A length of 85 km was inspected from the second pipeline and 77 km from the most recent one which had a total length of 211

km. The model validation is based on the offshore inspection data. The specifications of these three pipelines are shown in the Table 4-3.

The collected inspection reports contained raw data about some of the factors considered in this research without the pipelines actual conditions. These data needed to be prepared for the validation process. The data preparation phase is divided into two stages. Some factors' values were not constant along the whole length of the pipeline in the gathered inspection data in which a factor's value is high in certain areas of the pipeline and low in others. For this reason, the first stage was to organize the raw data values as per 100-meter segments along each pipeline for more accurate results. The second stage is to generate the actual conditions for these inspection data. The gas model developed by El-Abbasy et al. (2014a) was chosen for this purpose.

Table 4 - 3: Details of Received Inspection Reports.

Specifications		12-inch Pipeline	20-inch Pipeline	24-inch Pipeline
Total Length (km)		211	45	121
Location (km)	Offshore	80	45	89
	Onshore	131	-	32
Offshore Inspected Length (km)		77	45	85
Steel Grade		X65	B	X52
Design Pressure (Bars)		139	50	107
Transported Product		Gas	Oil	Gas
Installation Year		1990	1972	1979
Inspection Year		1996 and 2004	2001 and 2009	1996, 2001, and 2008

A point to be taken into consideration is that the 20-inch pipeline transports oil products but is treated as a gas pipeline where the actual pipeline conditions were calculated using the same gas model applied on the other two pipelines. This is to provide a wide variety of pipeline diameters and ages. Furthermore, the received inspection data sets contained information about seven out of the eleven factors considered in this research; Age, Diameter, Metal Loss, Coating Condition, Crossings, Cathodic Protection and Operating Pressure. Thus, adjustments were required for the relative weights of these factors as shown later in the model validation section.

CHAPTER FIVE: MODEL DEVELOPMENT

5.1 Introduction

The goal of this research is to develop a condition assessment model of offshore gas pipelines in Qatar using Evidential Reasoning (ER), Analytic Network Process (ANP) and Fuzzy Set Theory (FST). The following chapter describes the methodology of the current research. This methodology started by performing a short literature review to investigate the previous research trials in the field of condition assessment of oil and gas pipelines. It was also necessary to study the different methods and techniques used for pipeline condition assessment. In the literature review, a list of factors was determined which mostly affect the condition of offshore gas pipelines. That was carried out in three steps. First, a number of professional experts in the oil and gas industry were asked to give a list of the most influential factors that affect the pipeline condition. At the same time, another list was being prepared from literature and previous studies. Then, the two lists were compared to each other to select the similar factors agreed upon by both, academics and professionals. Thus, the most important factors that needed to be considered in the pipeline condition assessment process was identified. Then, a questionnaire was structured, based on the selected factors, and distributed among professionals in the oil and gas industry in Middle-East but with a strong focus on Qatar and Saudi Arabia.

The distributed questionnaire served as a ranking tool for the factors that affect the condition assessment process of offshore gas pipelines. In addition, a condition rating scale was developed from the responses of the distributed questionnaires. Also, the professionals were asked to assign an attribute effect value for each factor affecting the pipeline condition. These

effect values were later used to develop the factors thresholds and their fuzzy membership functions as explained later in this chapter.

The structured questionnaire was designed on an open-ended basis where the respondents had the option to add any other missing factors, that weren't listed in the questionnaire, which may affect the pipeline condition assessment process. This step was performed to assure that the distributed questionnaire included the most influential factors on the pipeline condition. The respondents agreed that the questionnaire listed the most important factors needed to be considered for the condition assessment. The ANP technique was then applied on the collected data, Experts Feedback, to calculate the relative weight of each of the listed factors. The factors' relative weights along with the developed thresholds' membership functions are used as an input for the proposed Evidential Reasoning (ER) module for the offshore gas pipelines condition assessment. Then, the developed model was tested using actual inspection data for existing gas pipelines. These data was obtained from Qatar. After that, a deterioration curve was developed using the proposed ER module for different ages of the gas pipeline. Later, a sensitivity study was executed to study the effect of changing the factors' values on the model's output. Finally, a condition rating scale was proposed based on the outputs of the previous steps.

It is important to note that Evidential Reasoning algorithm was previously applied on pipeline condition assessment but not as deep as this research. Also, this research applied ANP technique, fuzzy membership functions and ER algorithm to perform a comprehensive condition assessment analysis. It integrated Evidential Reasoning Algorithm with ANP which dealt with interdependencies and multi-criteria decision analysis under various uncertainties. This integration considered factors' interdependency using ANP, made decisions under

uncertainty using ER algorithm, and handled problems involving large numbers of both qualitative and quantitative variables using integrated ER, ANP and FST. This combination of techniques used to develop the proposed model is considered more than satisfying due to the validation results, shown later in this chapter, where the output of the developed model was compared to real life inspection data from a pipeline operator in Qatar.

5.2 Relative Weight Determination

The data collection task resulted to 25 received questionnaires from professional experts in the oil and gas industry. ANP technique was applied to the data gathered from the received questionnaires to calculate the relative weights of the factors affecting the offshore gas pipeline condition. The relative weights were calculated manually with Excel software file that was designed for the specified purpose. The results were then checked with "SuperDecisions® software" which is a famous software that was designed to easily perform the ANP technique calculations. The results from both softwares were almost identical. It is recommended to use SuperDecisions software for ANP calculation in order to facilitate the application of the ANP steps explained previously. The reader may refer to Chapter 3 for more details.

The previously mentioned ANP steps were followed to determine the final global weights for the factors considered in the condition assessment of offshore gas pipelines. The ANP steps were applied on the data collected from received questionnaires which were distributed among professionals in the oil and gas industry. A brief description for the ANP process implementation is given later in this section. In order to determine the weights of the factors and their main categories, ANP process was applied on the collected data from questionnaires as follows:

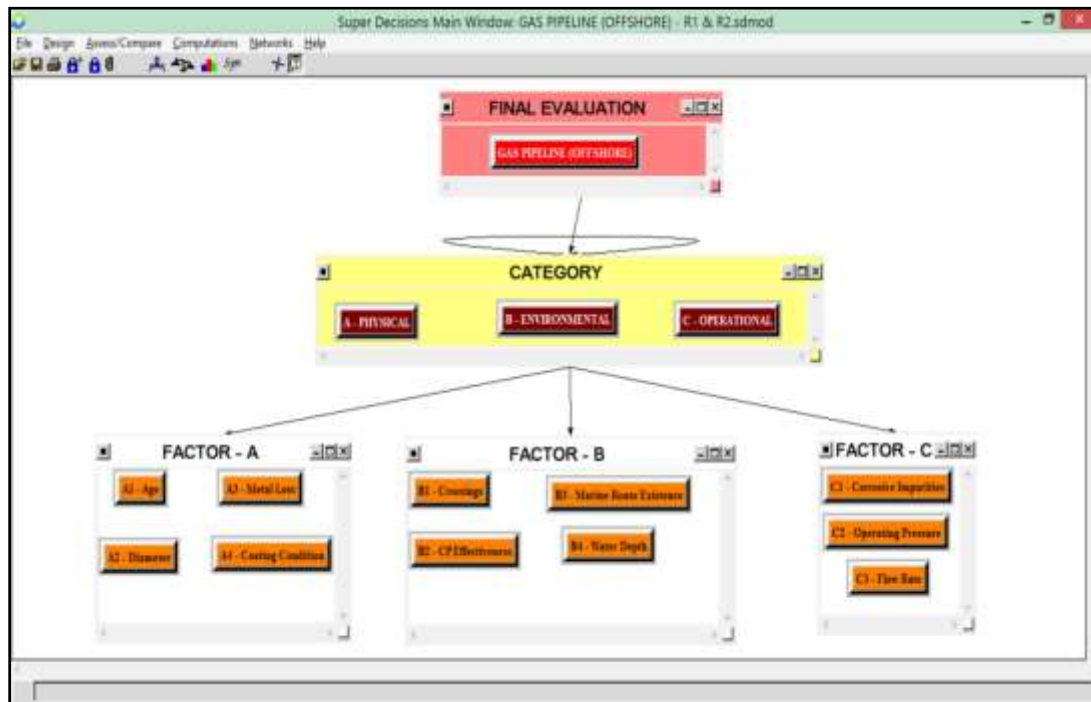


Figure 5 - 1: ANP Network for Offshore Gas Pipelines.

1) Conduct Pair-wise Comparisons.

In the distributed questionnaires, the experts were asked to rate the elements of each level of network hierarchy using the pair-wise comparison concept according to Saaty's scale of measurement (1 to 9) mentioned earlier. That will lead into developing a pair-wise comparison matrix after all elements have been compared with the priority scale pair by pair.

2) Estimate Relative Weights.

After developing the pair-wise comparison matrix, a vector of priorities in the matrix is calculated and then normalized to sum of 1.00 or 100%. It can be performed by dividing the elements of each column of the matrix by the sum of that column. The elements of each resulting row are added to obtain a "row sum" and then divided by the number of elements in the row to obtain the relative weight or priority.

3) Determine Consistency Ratio (CR).

The term "Consistency Ratio" was developed because humans are sometimes inconsistent or not serious in answering questions in the distributed questionnaires. To overcome this issue, CR is used to validate the results and measure the consistency in the pair-wise comparison process. Saaty (1994) presented a set of acceptable CR values for different sizes of matrices. In the earlier sections, a table of acceptable CR values was introduced. The CR values were calculated for all matrices in this research and the results showed that all of them were consistent and within acceptable limits.

4) Develop the Unweighted Super-matrix.

After checking the consistency, the pair-wise comparisons between the main categories and factors are translated into a two-dimensional super-matrix under the influence of interdependency. The unweighted super-matrix, shown in Table 5-1, for one of the questionnaire responses, is constructed from the priorities (i.e. relative weights) derived from the different pair-wise comparisons that were carried out in the previous steps. The nodes, grouped by the clusters they belong to, are the labels of rows and columns of the super-matrix. The following tables does not show the entire matrices sizes due to their large sizes. For this reason, only the main categories are shown in the column side against the factors in the row side of the presented matrices.

5) Develop the Weighted Super-matrix.

The weighted super-matrix is derived from the unweighted super-matrix. It is developed by dividing each entry in each row in the unweighted super-matrix by the total summation of its relative intersecting column. For example, the summation of column A in Table 5-1 (unweighted super-matrix) is equal to 2.00 and the corresponding entry in row B is 0.875;

therefore, dividing 0.875 by 2.00 results in the weighted value of this entry, which is 0.438. This value is entered into the intersecting cell of row B and column A in Table 5-2 (weighted super-matrix). This step is repeated for the rest of the values in the unweighted super-matrix. In Table 5-2 (weighted super-matrix), it can be seen that the summation of each column is equal to 1.00.

Table 5 - 1: Developed Unweighted Super-Matrix for Response (1) of Received Questionnaires.

	GOAL	A: PHYSICAL FACTORS	B: EXTERNAL FACTORS	C: OPERATIONAL FACTORS
GOAL	0	0	0	0
A: PHYSICAL FACTORS	0.778	0	0.750	0.125
B: EXTERNAL FACTORS	0.111	0.875	0	0.875
C: OPERATIONAL FACTORS	0.111	0.125	0.250	0
A1: Age	0	0.066	0	0
A2: Diameter	0	0.009	0	0
A3: Metal Loss	0	0.462	0	0
A4: Coating Condition	0	0.462	0	0
B1: Crossing	0	0	0.071	0
B2: CP Effectiveness	0	0	0.643	0
B3: Marine Route Existence	0	0	0.214	0
B4: Water Depth	0	0	0.071	0
C1: Corrosive Impurities	0	0	0	0.122
C2: Operating Pressure	0	0	0	0.854
C3: Flow Rate	0	0	0	0.024
Total	1	2	2	2

6) Develop the Limit Super-matrix.

Tables 5-1 and 5-2 showed only the unweighted and weighted super-matrices for the main categories (column side) only due to size limitations. The rest of the sub-matrices were entered into the super-matrix and the weighted super-matrix was completed. The next step is to obtain the limit super-matrix by raising the weighted super-matrix to a sufficient large power until convergence occurs. This is repeated until the numbers in all columns of limit super-matrix are identical. Table 5-3 shows the limit-super matrix for Response (1) of the collected questionnaires. The previous steps were applied to all questionnaire responses until

all the limit super matrices for all the responses are obtained. The obtained limit super-matrix defines the preliminary local weights for the factors and their main categories. After that, the final local weights, within each cluster, were calculated from Response (1) by dividing each value in the row side by the column summation. It can be seen from Table 5-4 that the total summation for the preliminary local weights column is 1 but for the final local weight column it is 4. This step is additional because the mean global weights were needed since this research deals with many questionnaire responses.

Table 5 - 2: Developed Weighted Super-Matrix for Response (1) of Received Questionnaires.

	GOAL	A: PHYSICAL FACTORS	B: EXTERNAL FACTORS	C: OPERATIONAL FACTORS
GOAL	0	0	0	0
A: PHYSICAL FACTORS	0.778	0	0.375	0.063
B: EXTERNAL FACTORS	0.111	0.438	0	0.438
C: OPERATIONAL FACTORS	0.111	0.063	0.125	0
A1: Age	0	0.033	0	0
A2: Diameter	0	0.005	0	0
A3: Metal Loss	0	0.231	0	0
A4: Coating Condition	0	0.231	0	0
B1: Crossing	0	0	0.036	0
B2: CP Effectiveness	0	0	0.321	0
B3: Marine Route Existence	0	0	0.107	0
B4: Water Depth	0	0	0.036	0
C1: Corrosive Impurities	0	0	0	0.061
C2: Operating Pressure	0	0	0	0.427
C3: Flow Rate	0	0	0	0.012
Total	1	1	1	1

7) Calculate Final Global Weights.

After calculating the mean local weights for all the responses, the final global weights were obtained by proportioning the elements of each cluster to themselves. The goal from this step is to eliminate the middle level (main categories level) and get the final global weights for all the factors so that the summation of the final global weights for all the factors is 1. For example, from table 5-4, to get the final global weight for "Age" the local weight value of

"0.019" was multiplied by the global weight value of the "Physical" which is 0.370 for all the factors under this category. This will result to 0.039 as global weight for "Age". This step was repeated for the rest of the factors and for all questionnaire responses. Then, the mean values of the global weights for all the factors were calculated.

Table 5 - 3: Developed Limit Super-Matrix for Response (1) of Received Questionnaires.

	GOAL	A: PHYSICAL FACTORS	B: EXTERNAL FACTORS	C: OPERATIONAL FACTORS
GOAL	0	0	0	0
A: PHYSICAL FACTORS	0.185	0.185	0.185	0.185
B: EXTERNAL FACTORS	0.233	0.233	0.233	0.233
C: OPERATIONAL FACTORS	0.081	0.081	0.081	0.081
A1: Age	0.019	0.019	0.019	0.019
A2: Diameter	0.006	0.006	0.006	0.006
A3: Metal Loss	0.080	0.080	0.080	0.080
A4: Coating Condition	0.080	0.080	0.080	0.080
B1: Crossing	0.017	0.017	0.017	0.017
B2: CP Effectiveness	0.150	0.150	0.150	0.150
B3: Marine Route Existence	0.050	0.050	0.050	0.050
B4: Water Depth	0.017	0.017	0.017	0.017
C1: Corrosive Impurities	0.014	0.014	0.014	0.014
C2: Operating Pressure	0.063	0.063	0.063	0.063
C3: Flow Rate	0.005	0.005	0.005	0.005
Total	1	1	1	1

Table 5-5 lists the final local and global weights for the factors and their main categories for all questionnaire responses. It can be noted from the final global weights of the first two main categories, Physical with 0.400 and External with 0.447, that these two categories affect the offshore gas pipeline condition almost equally. The late factors' category which is the Operational factors has a final global weight of 0.153. This makes it the least affecting category. Also, the final global weight for each of the factors was calculated.

The factors "Metal Loss" and "Cathodic Protection", with mean global weight values of 0.211 and 0.180 respectively, were the most important criteria affecting the offshore gas pipeline

condition. The third factor to be considered is "Coating Condition" with a mean global weight of 0.166. These three factors are related to the protection of the operated pipeline. This is due to the hot weather condition in Qatar and Saudi Arabia which greatly affect the pipelines physical condition. The "Operating Pressure" as well is a key factor in the offshore gas pipelines condition with the global weight value of "0.114".

Table 5 - 4: Preliminary and Final Local Weights developed from the Limit Super-matrix for Response (1).

FACTOR	Preliminary Local Weight	Final Local Weight (Within Each Cluster)
A: PHYSICAL FACTORS	0.185	0.370
B: EXTERNAL FACTORS	0.233	0.467
C: OPERATIONAL FACTORS	0.081	0.163
A1: Age	0.019	0.105
A2: Diameter	0.006	0.033
A3: Metal Loss	0.080	0.431
A4: Coating Condition	0.080	0.431
B1: Crossing	0.017	0.071
B2: CP Effectiveness	0.150	0.643
B3: Marine Route Existence	0.050	0.215
B4: Water Depth	0.017	0.071
C1: Corrosive Impurities	0.014	0.173
C2: Operating Pressure	0.063	0.772
C3: Flow Rate	0.005	0.055
Total	1	4

To check the sensitivity of each of the factors mentioned earlier, a sensitivity study was performed later in this research. Mainly, the relative weights calculated from the ANP module have a great effect on how the condition value will change when the factor's value changes from worse to better or vice versa.

Table 5 - 5: Final Local and Global Weights for Main Categories and factors affecting Offshore Gas Pipeline Condition.

Category	Global Weight	Factor		Local Weight	Global Weight
Physical Factors	0.400	A1	Age	0.100	0.040
		A2	Diameter	0.034	0.014
		A3	Metal Loss	0.450	0.180
		A4	Coating Condition	0.416	0.166
External Factors	0.447	B1	Crossings	0.064	0.029
		B2	Cathodic Protection	0.472	0.211
		B3	Marine Route Existence	0.213	0.095
		B4	Water Depth	0.251	0.112
Operational Factors	0.153	C1	Corrosive Impurities	0.199	0.031
		C2	Operating Pressure	0.746	0.114
		C3	Flow Rate	0.055	0.008
Total	1.000			3.000	1.000

5.3 Fuzzy-based Threshold Model Implementation

5.3.1 Developing Membership Functions

As mentioned in the previous sections, eleven factors were considered in developing the model in hand. These factors are divided into three categories: Physical, External and Operational. Tables 5-6, 5-7 and 5-8 show the thresholds for the eleven factors which were developed from the feedbacks on the distributed questionnaires among professionals in the oil and gas industry. The factors' thresholds were developed carefully to adapt the experts' responses from the gathered questionnaires. It can be seen that the thresholds have overlapping intervals due to uncertainty of the exact limits of the five intervals for each of the conditions in each factor. For example, an expert cannot define exactly the limits or range of

years of the condition "Good" in the "Age" factor. The next tables provide the developed thresholds for all eleven factors.

5.3.1.1 Fuzzy Input Variables

As discussed in the previous sections, eleven input variables were identified as the most influential factors that affect the condition of offshore gas pipelines. These factors are Age, Diameter, Metal Loss, Coating Condition, Number of Crossings, Cathodic Protection Effectiveness, Marine Route Existence, Water Depth, Corrosive Impurities, Operating Pressure and Flow Rate. Fuzzy sets theory was applied in this step and a group of fuzzy sets were identified so that each input variable is expressed by five membership functions: *Excellent*, *Very Good*, *Good*, *Fair* and *Poor* as shown in Fig. 5-2 to Fig. 5-12.

The thresholds developed in the previous section were later used as a basis to determine the range and shape of the developed membership functions. The maximum and minimum limits from the thresholds represent the Excellent and Poor membership functions, respectively, which adapt trapezoidal shapes. The three remaining membership functions in the middle which adapt triangular shapes were placed to overlap the Excellent and Poor membership functions and to overlap each other taking into consideration the limits in the developed thresholds. Water Depth and Flow Rate are exceptions since they do not follow the regular order of conditions, Excellent to critical or the opposite, as shown later. The overlap between the five membership functions was placed to achieve a degree of fuzziness of 0.5. This is performed so that:

- 1) The total summation of membership functions of any input value will be "1.0",
- 2) And to eliminate the ignorance in the developed ER module.

It is reasonable for the decision maker to be confused between two adjacent evaluation grades for any given factor's value but they are sure that the given value falls totally between these two evaluations. Also, a membership degree cannot be expressed by more than two adjacent evaluation grades since it violates the membership design properties which states that "Each membership function overlaps only with the closest neighboring membership functions" (Zhang & Liu, 2006).

Table 5 - 6: Physical Factors Thresholds.

Factor	Unit	Linguistic Variable	Threshold Interval
Age	Years	Excellent	0 -- 10
		V. Good	6 -- 20
		Good	16 -- 30
		Fair	26 -- 41
		Critical	36 -- 55 & more
Diameter	inches	Excellent	38 -- >48
		V. Good	23 -- 48
		Good	16 -- 26
		Fair	9 -- 18
		Critical	0 -- 12
Metal Loss	%	Excellent	0 -- 17
		V. Good	9 -- 35
		Good	26 -- 55
		Fair	46 -- 74
		Critical	66 -- 100
Coating Condition	%	Excellent	84 -- 100
		V. Good	66 -- 94
		Good	46 -- 75
		Fair	27 -- 55
		Critical	0 -- 35

Table 5 - 7: External Factors Thresholds.

Factor	Unit	Linguistic Variable	Threshold Interval
Crossing	number	Excellent	0 -- 1
		V. Good	1 -- 3
		Good	3 -- 5
		Fair	5 -- 7
		Critical	7 -- >9
Cathodic Protection Effectiveness	mV	Excellent	951 -- 1300
		V. Good	851 -- 1000
		Good	751 -- 900
		Fair	676 -- 800
		Critical	<600 -- 700
Marine Route Existence	%	Excellent	0 -- 17
		V. Good	9 -- 35
		Good	27 -- 55
		Fair	46 -- 75
		Critical	66 -- 100
Water Depth	meters	Excellent	26 -- 40
		V. Good	9 -- 33
		Good	34 -- 60
		Fair	51 -- >60
		Critical	0 -- 10

Table 5 - 8: Operational Factors Thresholds.

Factor	Unit	Linguistic Variable	Threshold Interval
Corrosive Impurities	%	Excellent	0 -- 17
		V. Good	9 -- 34
		Good	26 -- 52
		Fair	44 -- 70
		Critical	61 -- 100
Operation Pressure	% of Design	Excellent	0 -- 27
		V. Good	14 -- 49
		Good	41 -- 67
		Fair	59 -- 81
		Critical	76 -- 100
Flow Rate	% of Design	Excellent	42 -- 63
		V. Good	56 -- 85
		Good	14 -- 55
		Fair	0 -- 27
		Critical	81 -- 100

Figures 5-2 to 5-12 show the membership functions for the input values of the eleven considered factors that form the core of the developed model. They are extracted from the thresholds tables illustrated previously.

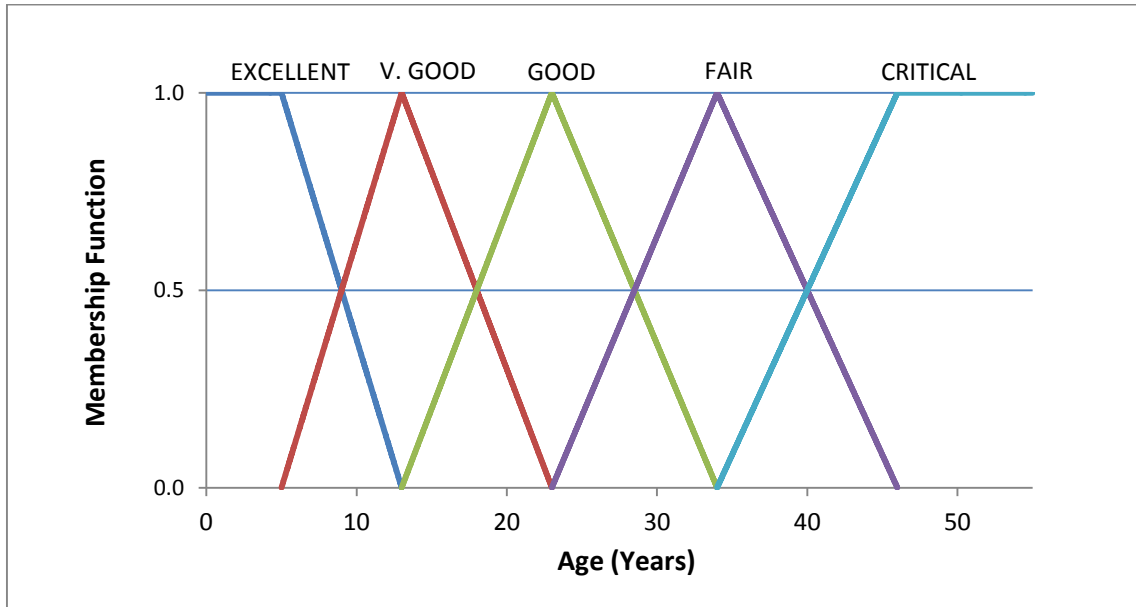


Figure 5 - 2: Fuzzy Input Variable (Age).

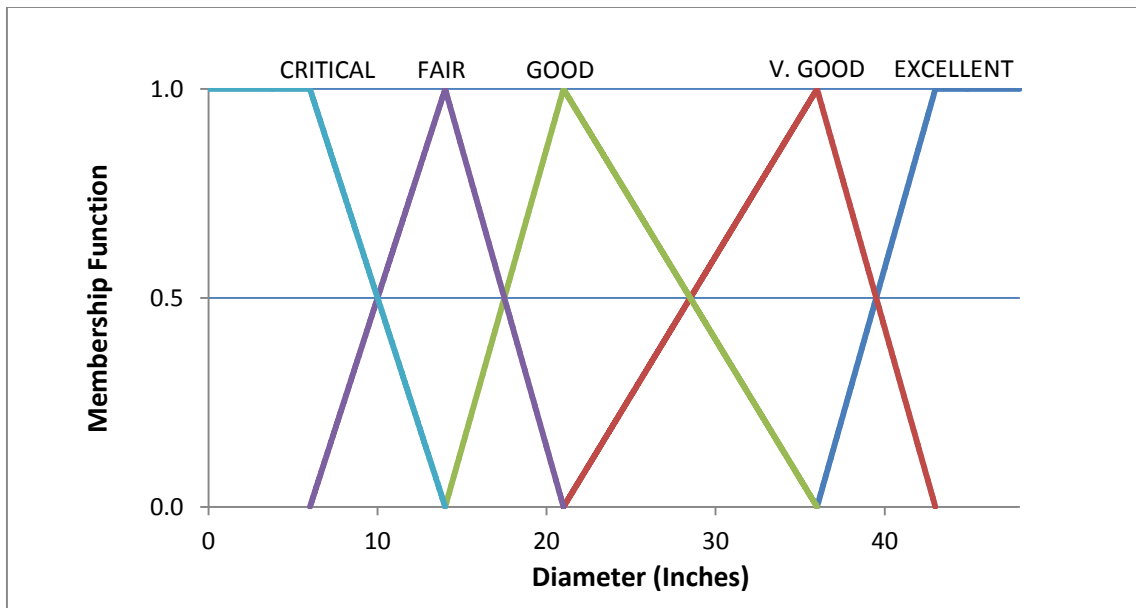


Figure 5 - 3: Fuzzy Input Variable (Diameter).

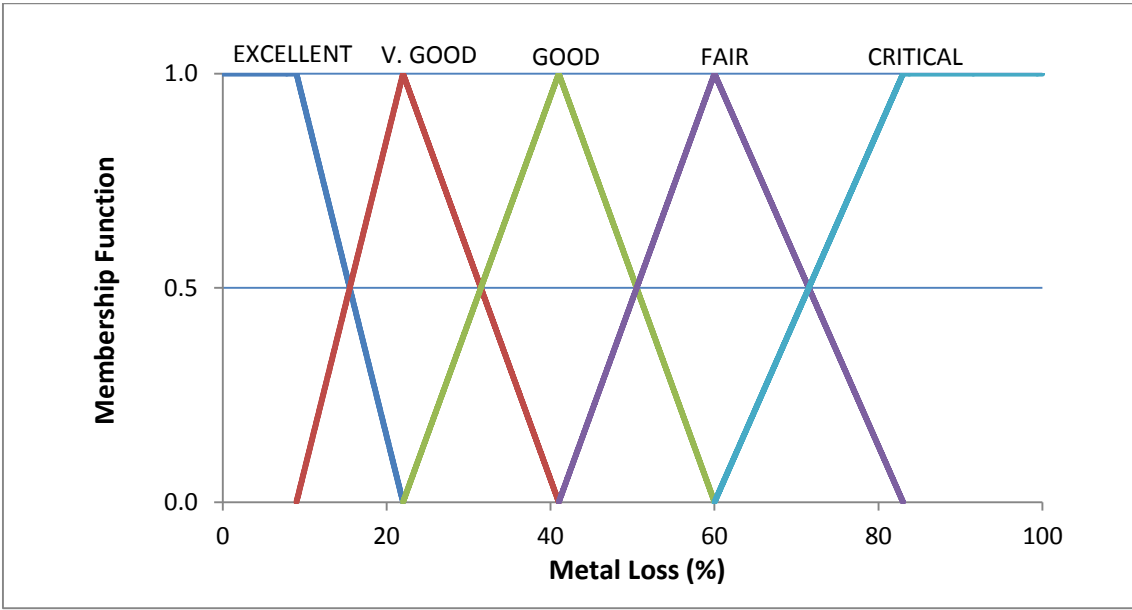


Figure 5 - 4: Fuzzy Input Variable (Metal Loss).

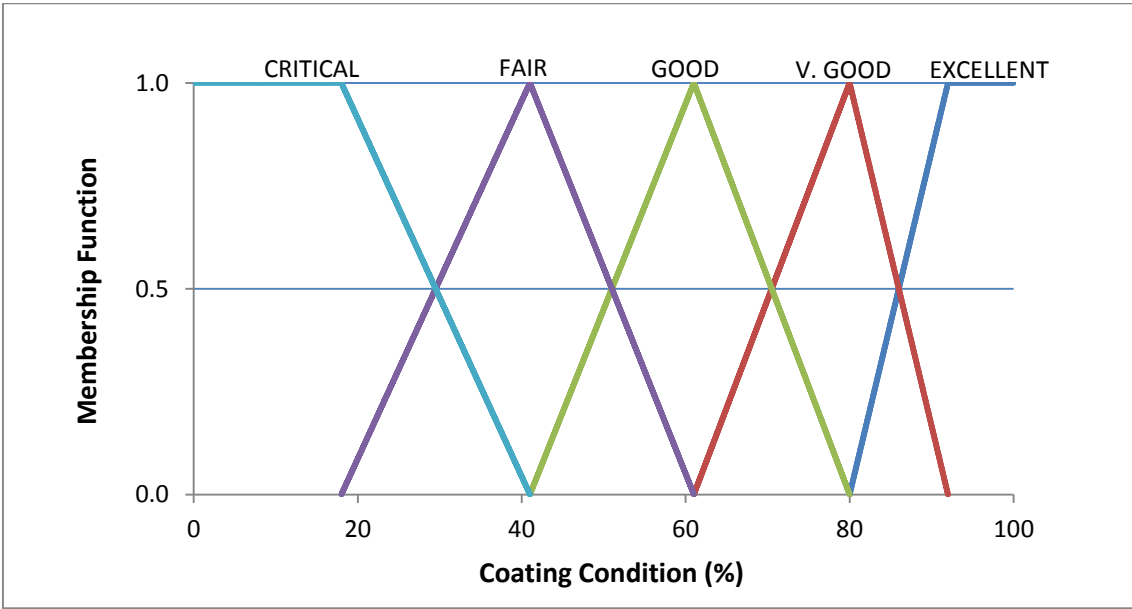


Figure 5 - 5: Fuzzy Input Variable (Coating Condition).

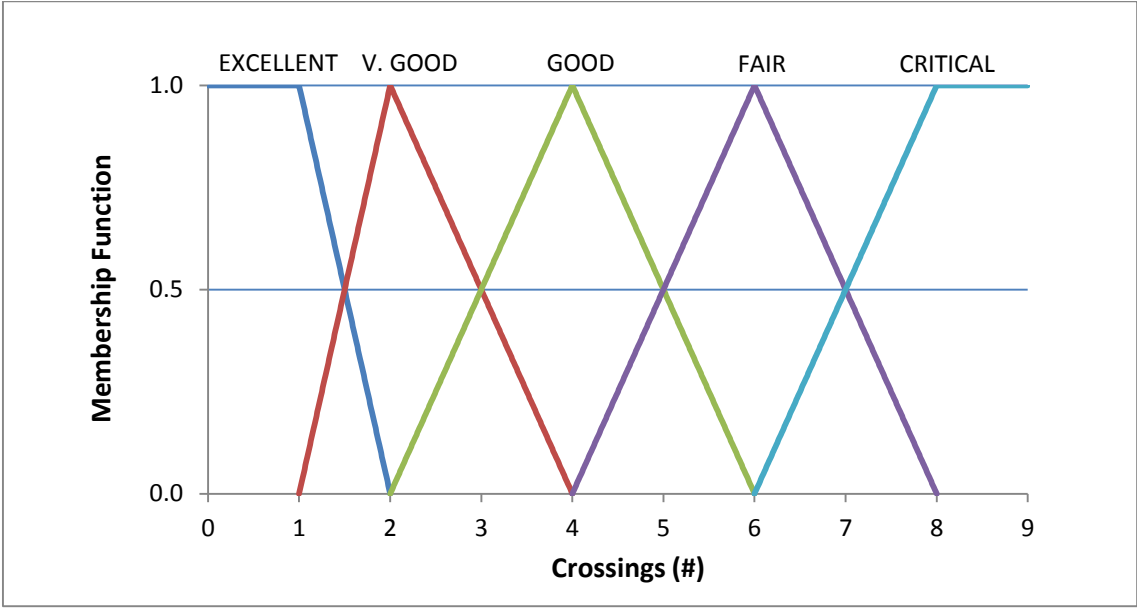


Figure 5 - 6: Fuzzy Input Variable (Crossing).

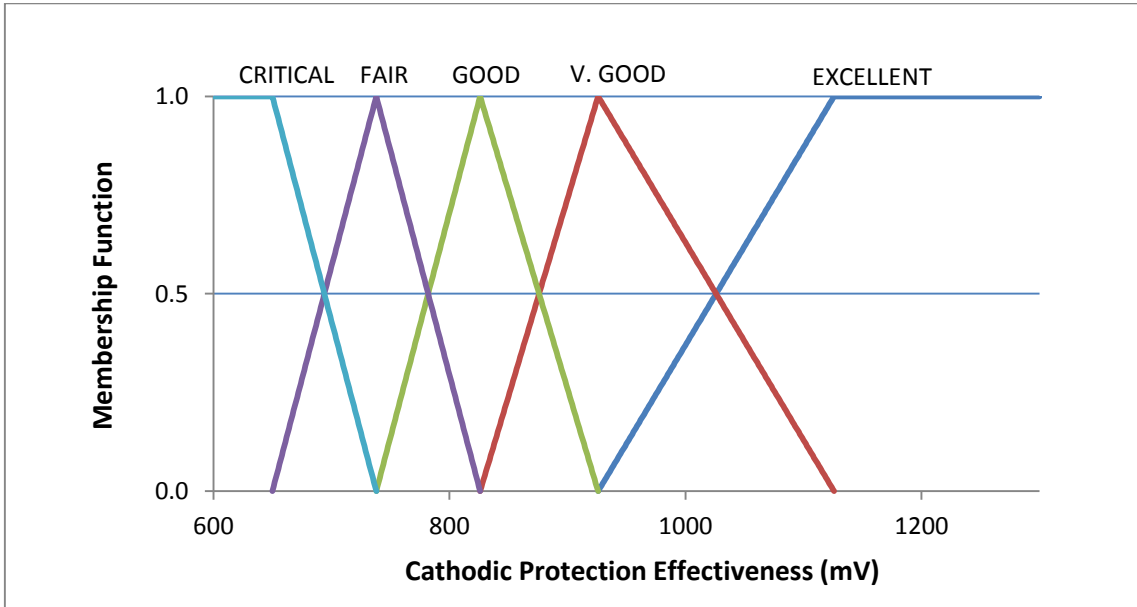


Figure 5 - 7: Fuzzy Input Variable (Cathodic Protection Effectiveness).

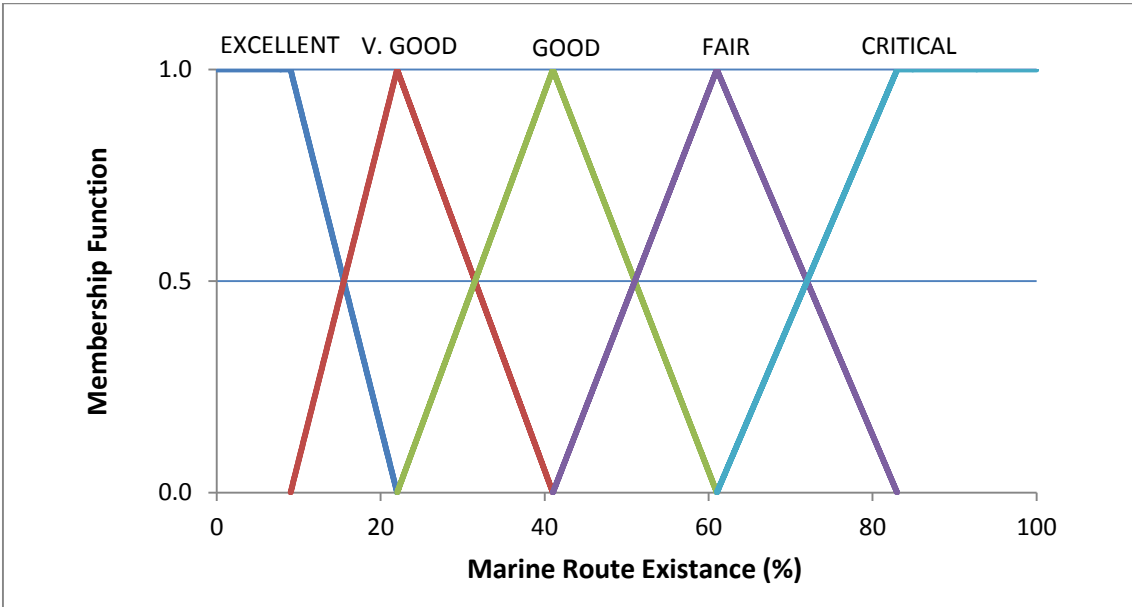


Figure 5 - 8: Fuzzy Input Variable (Marine Route Existence).

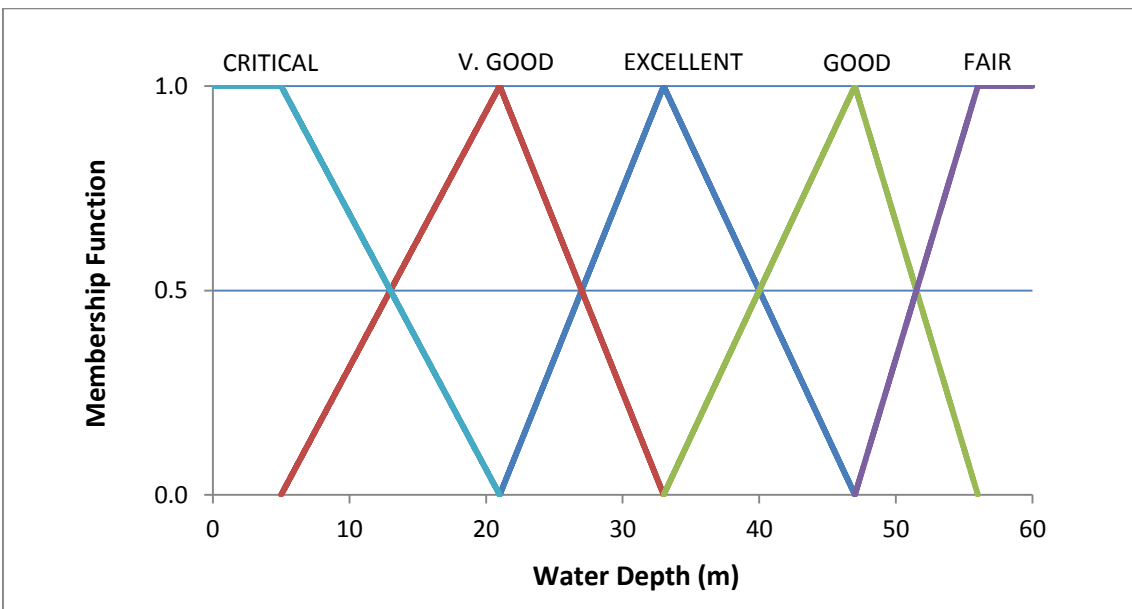


Figure 5 - 9: Fuzzy Input Variable (Water Depth).

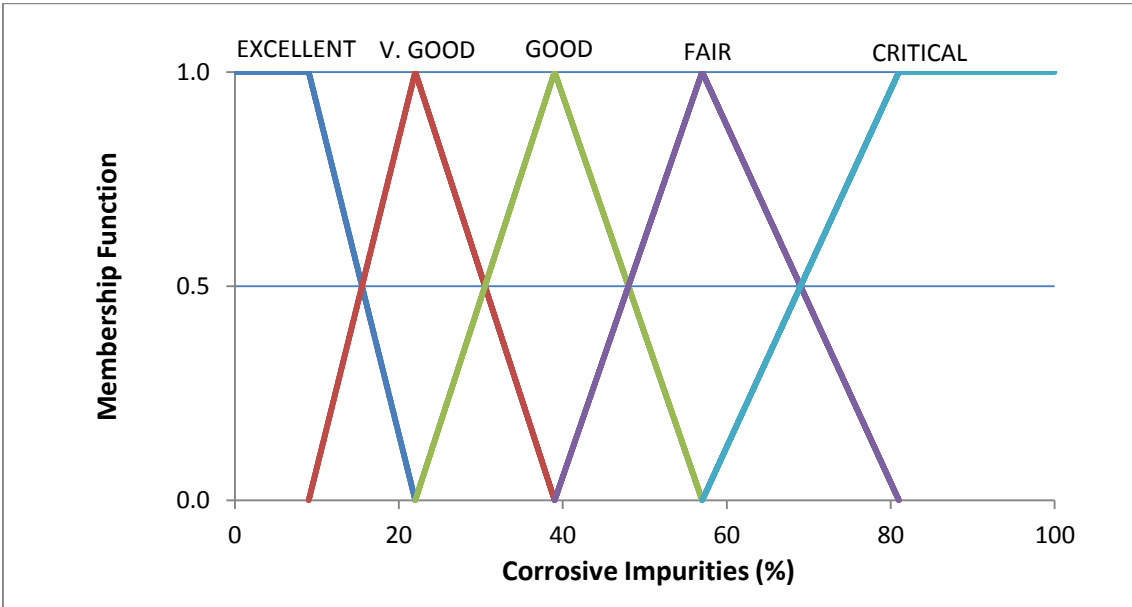


Figure 5 - 10: Fuzzy Input Variable (Corrosive Impurities).

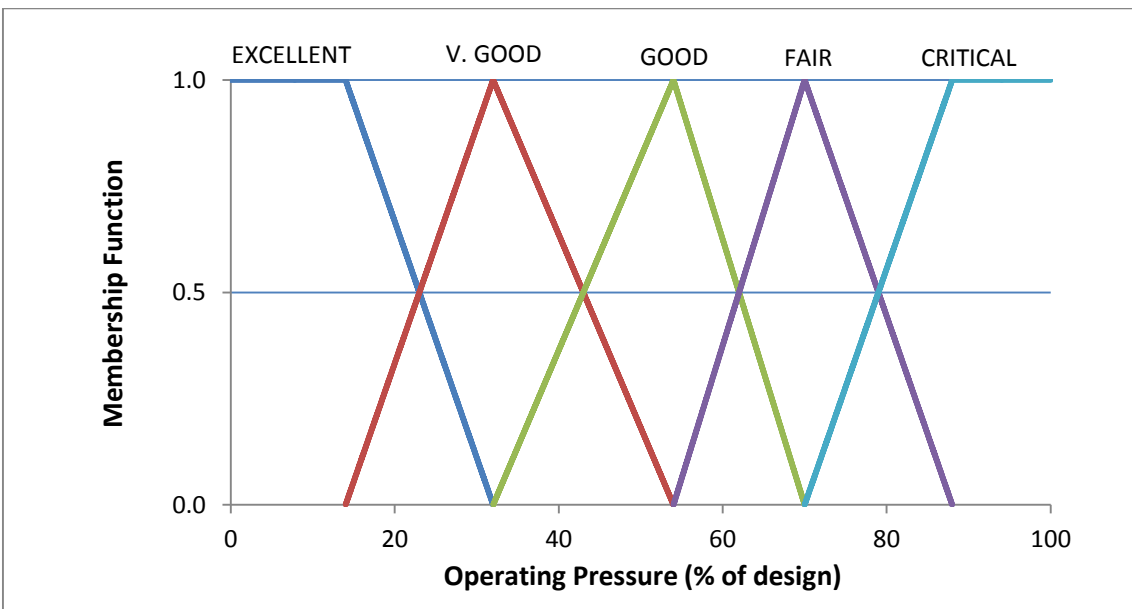


Figure 5 - 11: Fuzzy Input Variable (Operating Pressure).

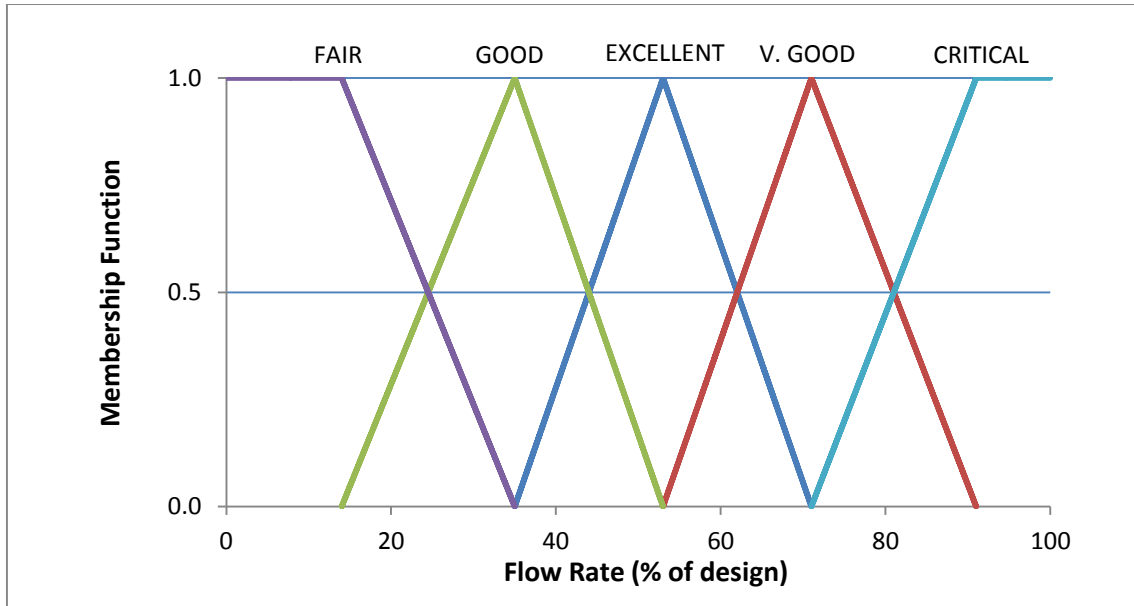


Figure 5 - 12: Fuzzy Input Variable (Flow Rate).

5.3.1.2 Fuzzy Output Variables

Table 5-9 presents the proposed evaluation grades for the developed model along with their numerical scale. This table was used to develop the membership function for the output variable which is the final evaluation as shown in Fig. 5-13.

Table 5 - 9: Proposed Condition Rating Scale.

Linguistic Scale	Numeric Scale
Excellent	9 -- 10
V. Good	7 -- 9
Good	5 -- 7
Fair	3 -- 5
Critical	0 -- 3

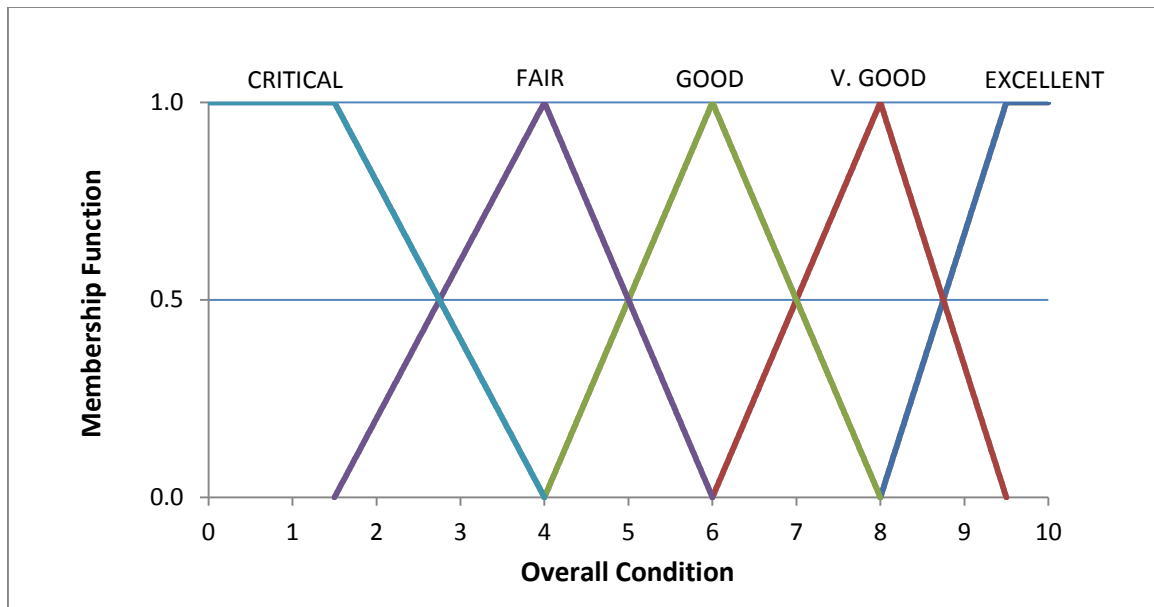


Figure 5 - 13: Fuzzy Output Variable (Overall Condition).

5.4 Degree of Belief ER-Based Model Implementation

The purpose of using the ER technique is to address uncertainty in Multi-Criteria Decision Making (MCDM) problems. It represents any assessment as a distribution using belief structures. Then, ER aggregates the degrees of belief using an algorithm developed basically on decision theory and combination rule of DS theory of evidence instead of aggregating average scores as conventional MCDM methods. The following steps illustrate the implementation of ER techniques through a sample aggregation of the degrees of belief for two factors, Age and Diameter.

- 1) After identifying the distinctive evaluation grades (H), the FST module is used here to obtain distributed assessments of the given factors' values (Input). For Age and Diameter factors, Six years and twelve inches are chosen respectively. Then, the degrees of belief are extracted from the membership function charts and expressed using Eq. (2-10) as follows:

$$S(Age) = \{(Ex, 0.88), (VG, 0.13), (G, 0), (F, 0), (C, 0), (H, 0)\}$$

$$S(Dia.) = \{(Ex, 0), (VG, 0), (G, 0), (F, 0.75), (C, 0.25), (H, 0)\}$$

Where,

Ex = Excellent, VG = Very Good, G = Good, F = Fair, C = Critical and H = Ignorance.

- 2) The factors relative weights (ω_i) which are calculated by the ANP module:

$$\omega_{Age} = 0.040$$

$$\omega_{Dia.} = 0.014$$

- 3) Later, the belief structures are then transformed into basic probability masses ($m_{n,i}$) using Eq. (2-11) where the relative weight is multiplied with each grades' belief value. $m_{H,i}$ is the remaining probability mass unassigned to any individual grade after all the N grades have been considered for assessing the general attribute and is calculated using Eq. (2-12), (2-13) & (2-14).

$$\begin{aligned} m(Age) &= 0.040 \times \{(Ex, 0.88), (VG, 0.13), (G, 0), (F, 0), (C, 0), (H, 0)\} \\ &= \{(Ex, 0.04), (VG, 0.01), (G, 0), (F, 0), (C, 0), (H, 0.96)\} \end{aligned}$$

$$\begin{aligned} m(Dia.) &= 0.014 \times \{(Ex, 0), (VG, 0), (G, 0), (F, 0.75), (C, 0.25), (H, 0)\} \\ &= \{(Ex, 0), (VG, 0), (G, 0), (F, 0.01), (C, 0), (H, 0.99)\} \end{aligned}$$

- 4) The normalizing factor ($K_{I(i+1)}$) is calculated with Eq. (2-18). After that, Eq. (2-15), (2-16) & (2-17) are used to combine the two probability masses which results into an individual probability mass distribution that represents both Age and Diameter factors.

$$K_{I(Age+Dia.)} = 1.001$$

$$m(Age + Dia.) = \{(Ex, 0.04), (VG, 0), (G, 0), (F, 0.01), (C, 0), (H, 0.95)\}$$

5) Using Eq. (2-19) and (2-20), the final combined probability mass distribution is converted into the final degrees of belief (β_n) which is defuzzified later into a crisp value.

$$S(\text{Age} + \text{Dia.}) = \{(Ex, 0.80), (VG, 0), (G, 0), (F, 20), (C, 0), (H, 0)\}$$

6) The previous steps are repeated for the rest of the factors until all the probability masses are combined together.

7) Finally, the appropriate defuzzification method is utilized to convert the final belief structure into a crisp value.

5.5 Defuzzification and Model Validation

5.5.1 Results of Defuzzification Process

There are situations where the output of a model may be a fuzzy set as in the developed model. This output needs to be in the form of a crisp value. As mentioned earlier, two methods, Centroid and Weighted-Average, were chosen to perform defuzzification of the developed ER module results. The characteristics of these two methods plus other defuzzification methods were discussed in the previous chapter. These methods will be used to convert the final degrees of belief of the pipeline condition into a score out of ten. Other methods of defuzzification can be used for the same purpose of this section.

Also, this section presents a comparison between using the Centroid method versus the Weighted-Average method in defuzzifying the results of the developed model in terms of validation and to check the prediction accuracy of the model using both methods.

5.5.2 Model Validation

In order to validate the model, a full inspection data for an existing gas pipeline in Qatar was collected as described later in the model testing section. After examining the collected data, it was observed that some of the factors considered when developing this model were not constant along the whole length of the inspected pipeline. As an example, the metal loss depth was low in a certain location of the pipeline where it was high in another. Coating Condition, Cathodic Protection Effectiveness and Crossings underwent this change as well. To overcome this problem and produce accurate and acceptable evaluation, the pipeline was divided into similar segment each has 100 m length. The condition of each pipeline segment is assessed and the overall condition of the whole length of the pipeline can be obtained by calculating the average condition of the total number of segments. After analyzing the data, a total number of 4090 data points were summarized to perform the model validation.

Also, the collected inspection data contained information about only 7 out of the 11 factors considered when developing this model. These factors are Age, Diameter, Metal Loss, Coating Condition, Crossings, Cathodic Protection and Operating Pressure. So, another model was developed based on these 7 factors. Therefore, the final global weights of the new updated factor list was adjusted to keep the summation of weights equal to 100%. Table 5-10 lists the adjusted global weight for the considered 7 factors in the new model.

This section's main purpose is to test the efficiency of the prediction power of the developed model through mathematical validation. Equations (5-1) and (5-2) show the average validity and invalidity percentages (AVP & AIP) in order to measure how accurate can the developed model predict the pipeline condition. If AIP value is closer to 0.0, the model is sound and a value closer to 100 shows that the model is not appropriate (Zayed & Halpin, 2005).

Table 5 - 10: Adjusted Global Weights for factors affecting Offshore Gas Pipeline Condition for Model Validation.

Category	Factor		Original Global Weight	Adjusted Global Weight
Physical Factors	A1	Age	0.040	0.053
	A2	Diameter	0.014	0.019
	A3	Metal Loss	0.180	0.239
	A4	Coating Condition	0.166	0.220
External Factors	B1	Crossings	0.029	0.038
	B2	Cathodic Protection	0.211	0.280
Operational Factors	C2	Operating Pressure	0.114	0.151
Total			0.754	1.000

$$AIP = \frac{\sum_{i=1}^n \left| 1 - \left(\frac{E_i}{C_i} \right) \right|}{n} \times 100 \tag{5-1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (C_i - E_i)^2}{n}} \tag{5-2}$$

$$AVP = 100 - AIP \tag{5-3}$$

$$MAE = \frac{\sum_{i=1}^n |C_i - E_i|}{n} \tag{5-4}$$

$$f_i = \frac{1000}{1 + MAE} \tag{5-5}$$

Where:

AIP = Average Invalidity Perce
RMSE = Root Mean Squared Error.
E_i = Estimated Value,
f_i = Fit Index.

AVP = Average Validity Percent.
MAE = Mean Absolute Error.
C_i = Actual Value.

Similarly, the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) are estimated. Both RMSE and MAE values varies from 0 to infinity. If their values are close to 0, the model is sound and vice versa (Dikmen, et al., 2005). MAE can be used to calculate the fitness function f_i as defined by Eq. 5-5. The equation of the fitness function illustrates that if the value of f_i is closer to 1000, the developed model is fit for the validation data and the opposite is true. If f_i is closer to 0, then the model is inappropriate for the representation of the validation data.

The inspection data had 4090 points in which 20% of them, 818 points, were randomly chosen to perform the first stage of validation. To ensure randomness and elimination of the human factor, the selection process was performed through the MATLAB computer software. For the first stage of validation, two methods of defuzzification, Centroid and Weighted-Average, are used in order to check the difference between them. The validation results for the developed model are summarized in Table 5-11.

The use of the Centroid method resulted into an AVP of 90.7% and RSME of 0.758. This may be considered acceptable but an additional measure was used which is the fit index f_i . It was calculated for the Centroid method and found to be equal to 571.73 which is not acceptable since it is far from 1000. On the other hand, using the Weighted-Average method produced better results. The AVP increased to 97.5%, and RMSE decreased to 0.250 but fit index f_i increased dramatically to 836.32 which is very close to 1000. The reason of this change in results is discussed in the next section.

After testing the two chosen defuzzification methods on 20% of the data chosen randomly, the Weighted-Average was selected for defuzzification for the final degrees of belief of the

developed model. An additional step to verify the selection of Weighted-Average method was to test the model against all the collected inspection data which contained 4090 data points. Table 5-11 which shows the summary of the additional step of validation proved that the selection of the Weighted-Average method was a correct decision.

Table 5 - 11: Validation Results.

Defuzzification Method	Centroid	Weighted-Average	Weighted-Average
Data Used	20%	20%	100%
No. of Pipe Segments (n)	818	818	4090
AIP	0.093	0.025	0.024
AVP	0.907	0.975	0.976
RMSE	0.758	0.250	0.241
MAE	0.749	0.196	0.192
f_i	571.73	836.32	839.18

The results show that the AVP is 97.6%, RMSE is 0.241, MAE is 0.192 and the f_i is 839.18 which is close to 1000. This means that the predicted values by the developed model are within the acceptable limits. Therefore, the validation test's results are satisfactory and it can be said that the developed model is acceptable and appropriate.

5.5.3 Results Discussion

Although the Centroid defuzzification method is more prevalent and physically appealing than Weighted-Average method and other defuzzification methods, the results shown in the previous tables indicate that using the Weighted-Average defuzzification method to convert the final degrees of belief of the developed model provides better results than using the Centroid method for the same purpose. The Centroid involves complex calculations and the

more complex the output membership shape, the more complex the calculations. On the other hand, Weighted-Average is used most frequently in fuzzy applications because of its computational efficiency (Ross, 2010).

It is noted that the Weighted-Average defuzzification always gives higher crisp values than the Centroid for the same degrees of belief which gives better validation results as demonstrated in this section. This means that the Weighted-Average defuzzification gives more accurate results for the pipeline condition in this case. In the future, the model user can choose to use the Centroid defuzzification which gives lower crisp values, i.e. lower pipeline condition, than the weighted-Average to be more cautious and plan for early maintenance.

Many other methods are mentioned in the literature review that can be used for defuzzification in this model. In addition, other defuzzification methods are not presented in this report. The question is "What is the best defuzzification method to use?". Ross (2010) gave an answer to this question by stating that it is "context or problem dependent". As an answer to this question Hellendoorn & Thomas (1993) put five criteria to specify the best defuzzification method to use, as follows:

- 1) **Continuity:** A fuzzy output should not change dramatically when the input slightly changes.
- 2) **Disambiguity:** The result of defuzzification should always be a unique value of z^* . For example, when using *Centre of Largest Area* method, there is ambiguity in selecting z^* in case if having equal membership functions.

3) **Plausibility:** z^* should have a high degree of membership and be in the middle of the support region. As shown in Fig. 5-14, although z^* is in the middle of the region, it does not have a high degree of membership which conflicts with the plausibility criteria.

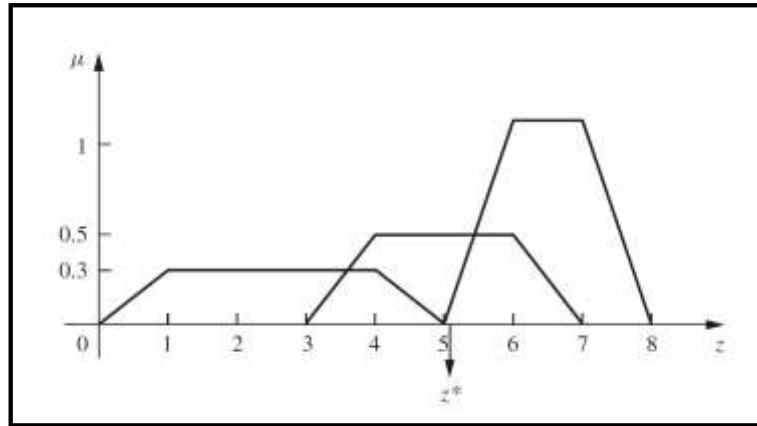


Figure 5 - 14: Centroid Defuzzification (Plausibility).

4) **Computational Simplicity:** The used defuzzification method should not be time consuming. For example, *Mean Max* and *First of Maxima* methods are faster than the *Centroid* method.

5) **Call of Weighting Method:** This criterion shows the difference between using different methods such as *Centroid*, *Weighted-Average* and *Centre of Sums*. There is little by which to decide the best method that weights the fuzzy output. That is why it depends mainly on the problem in hand.

Similar to many fuzzy logic applications, the used defuzzification method should be evaluated in terms of the validity of the final output value in the context of the available data, which was performed in the previous section. A comparison between the *Centroid* and *Weighted-Average* was performed to choose the best method to use in the developed model. Other methods can be used and the final decision lays on the suitability of the chosen method for the studied problem, Ross (2010).

5.6 Sensitivity Analysis

A Sensitivity Analysis is conducted to test the robustness of the developed fuzzy-based model. In other words, it is performed to examine how the uncertainty in inputs could affect the model's results and to increase the understanding of the relationship between input and output variables. Also, unexpected relationships between inputs and outputs can be encountered which is another advantage of performing a sensitivity analysis.

A sensitivity analysis is carried out for the developed model in order to examine the effect of changing the factors' values entered in the model on the pipeline condition. The sensitivity was based on changing a factor's value (input) from lowest to highest while keeping other factors constant at average condition to check the individual effect on the overall pipe condition. In other words, each factor's value was changed within the range of its scale or thresholds presented earlier to study the effect of this factor on the pipeline condition. The changing procedure of the factor's value took place on a 10% intervals of their thresholds shown earlier. Accordingly, the overall pipeline condition was calculated against each change and plotted as shown in the below figures. This process was repeated individually for all the factors considered in the developed model as shown in Figures 5-15, 5-16 and 5-17. The charts in Figures 5-15, 5-16 and 5-17 can be re-categorized according to their proportionality to the overall pipe condition as follows; (1) Directly Proportional Factors, (2) Inversely Proportional Factors, and (3) Irregularly Proportional Factors.

Figures 5-18, 5-19 and 5-20 display the three new classifications of the contributing factors. These factors use different units of measure. Therefore, factor's normalization is required to combine them in one figure as shown in Table 5-12.

Table 5 - 12: Factors' Normalization.

Category	Factor		Unit	Used Method
A: PHYSICAL	A1	Age	Years	$A1 / 60$
	A2	Diameter	Inches	$(A2 - 2) / (52 - 2)$
	A3	Metal Loss	%	$A3 / 100$
	A4	Coating Condition	%	$A4 \times 100$
B: EXTERNAL	B1	Crossings	Number	$B1 / 10$
	B2	Cathodic Protection Effectiveness	mV	$(B2 - 600) / (1300 - 600)$
	B3	Marine Route Existence	%	$B3 / 100$
	B4	Water Depth	meters	$B4 / 60$
C: OPERATIONAL	C1	Corrosive Impurities	%	$C1 / 100$
	C2	Operating Pressure	% of Design	$C2 / 100$
	C3	Flow Rate	% of Design	$C3 / 100$

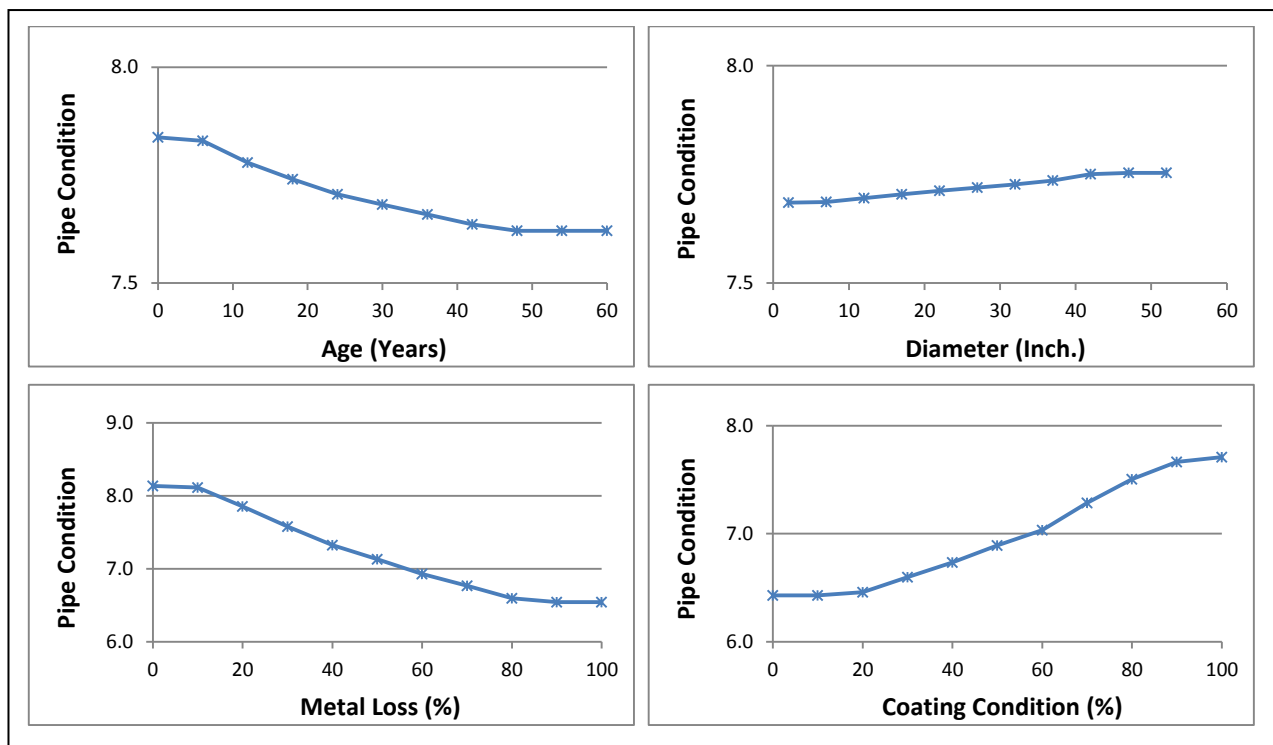


Figure 5 - 15: Sensitivity Analysis for Physical Factors.

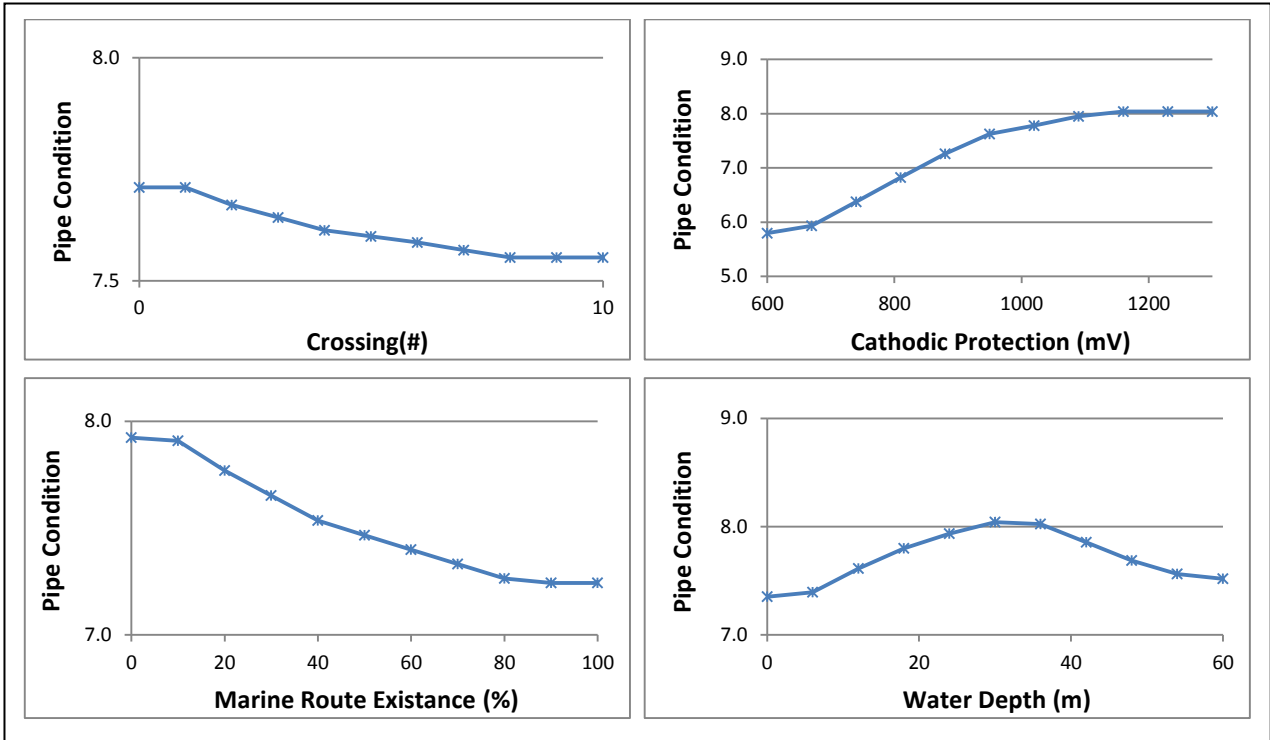


Figure 5 - 16: Sensitivity Analysis for External Factors

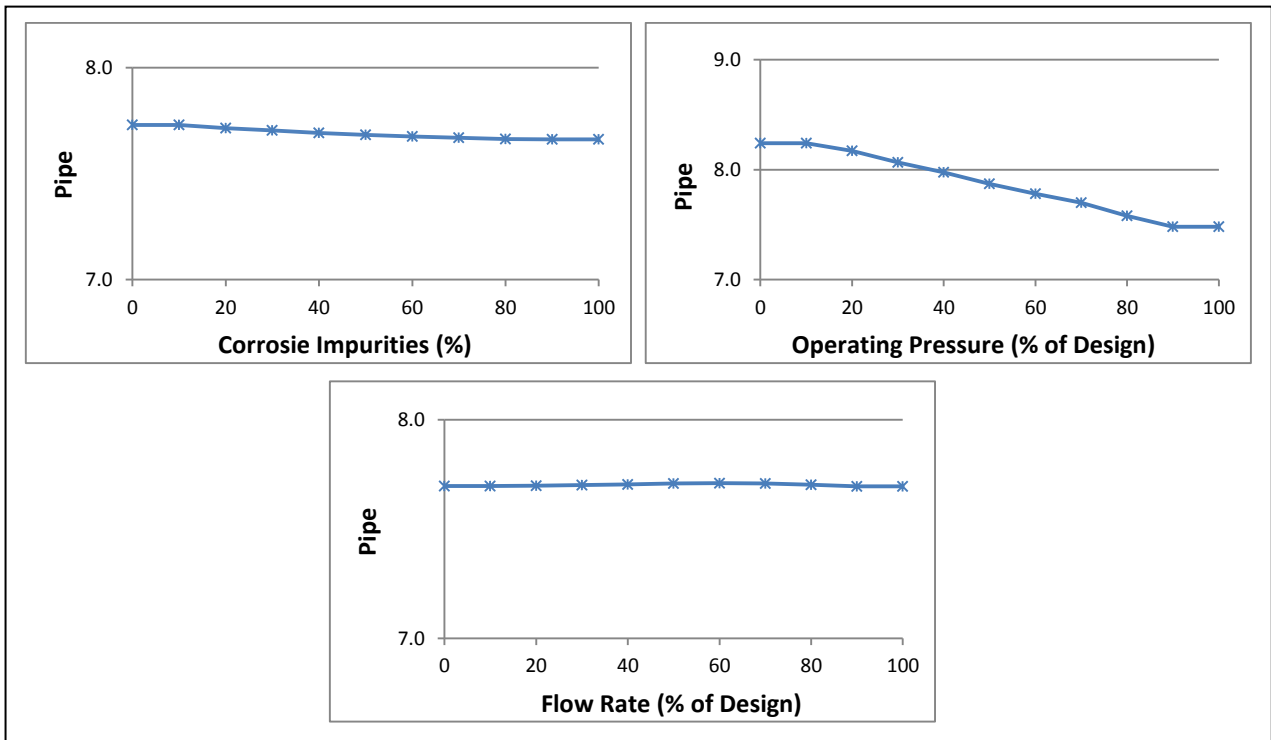


Figure 5 - 17: Sensitivity Analysis for Operational Factors.

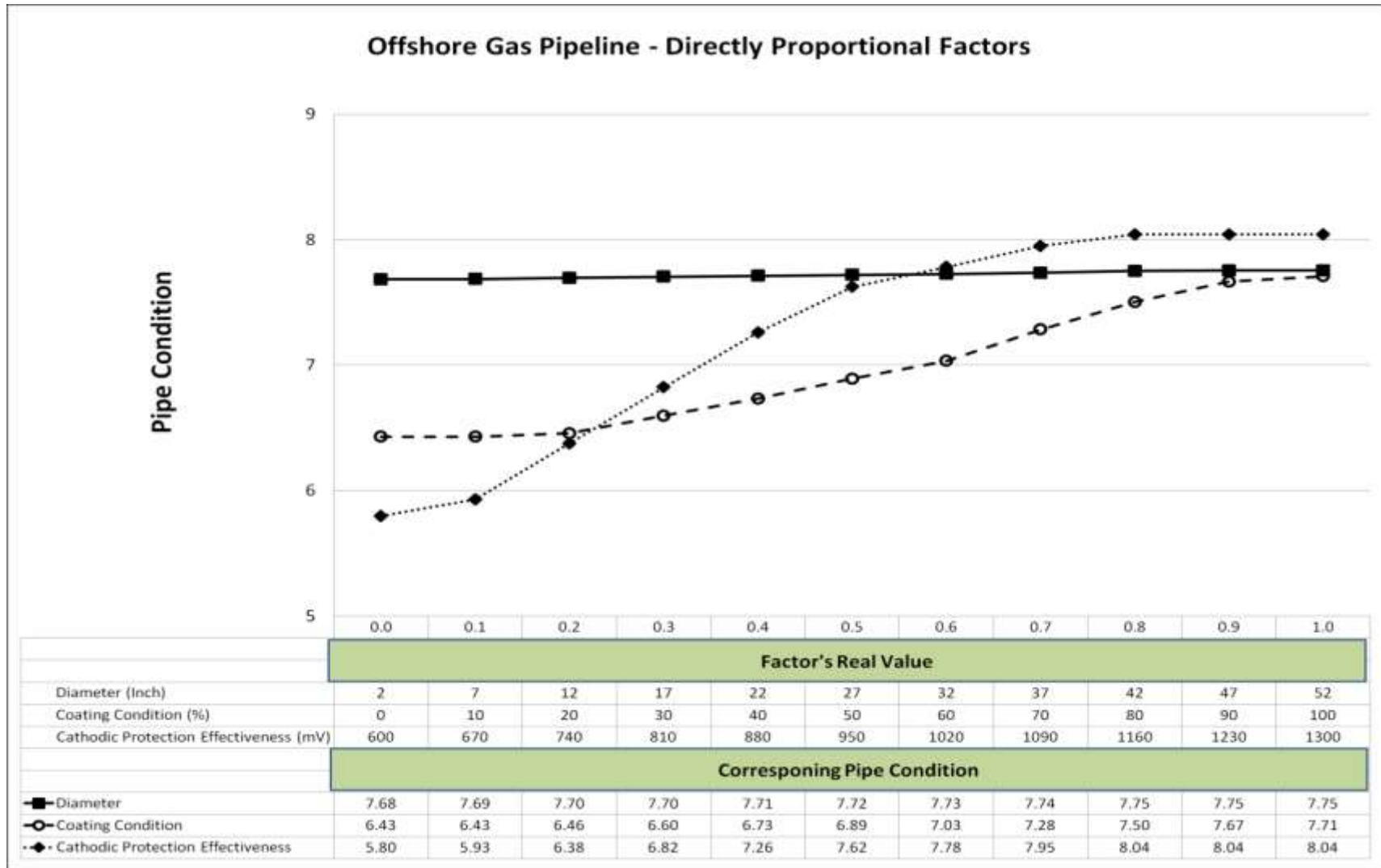


Figure 5 - 18: Directly Proportional Factors.

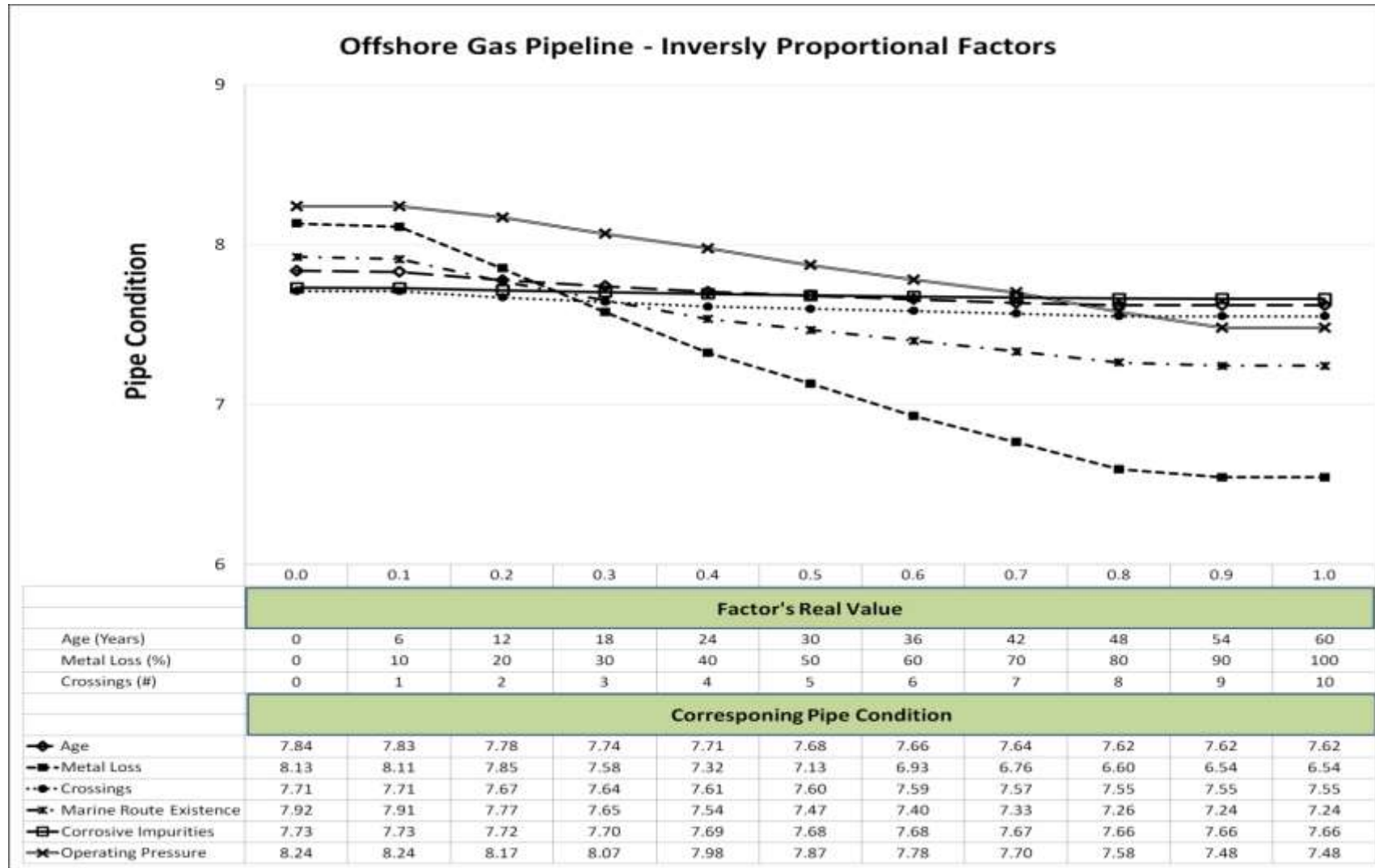


Figure 5 - 19: Inversely Proportional Factors.

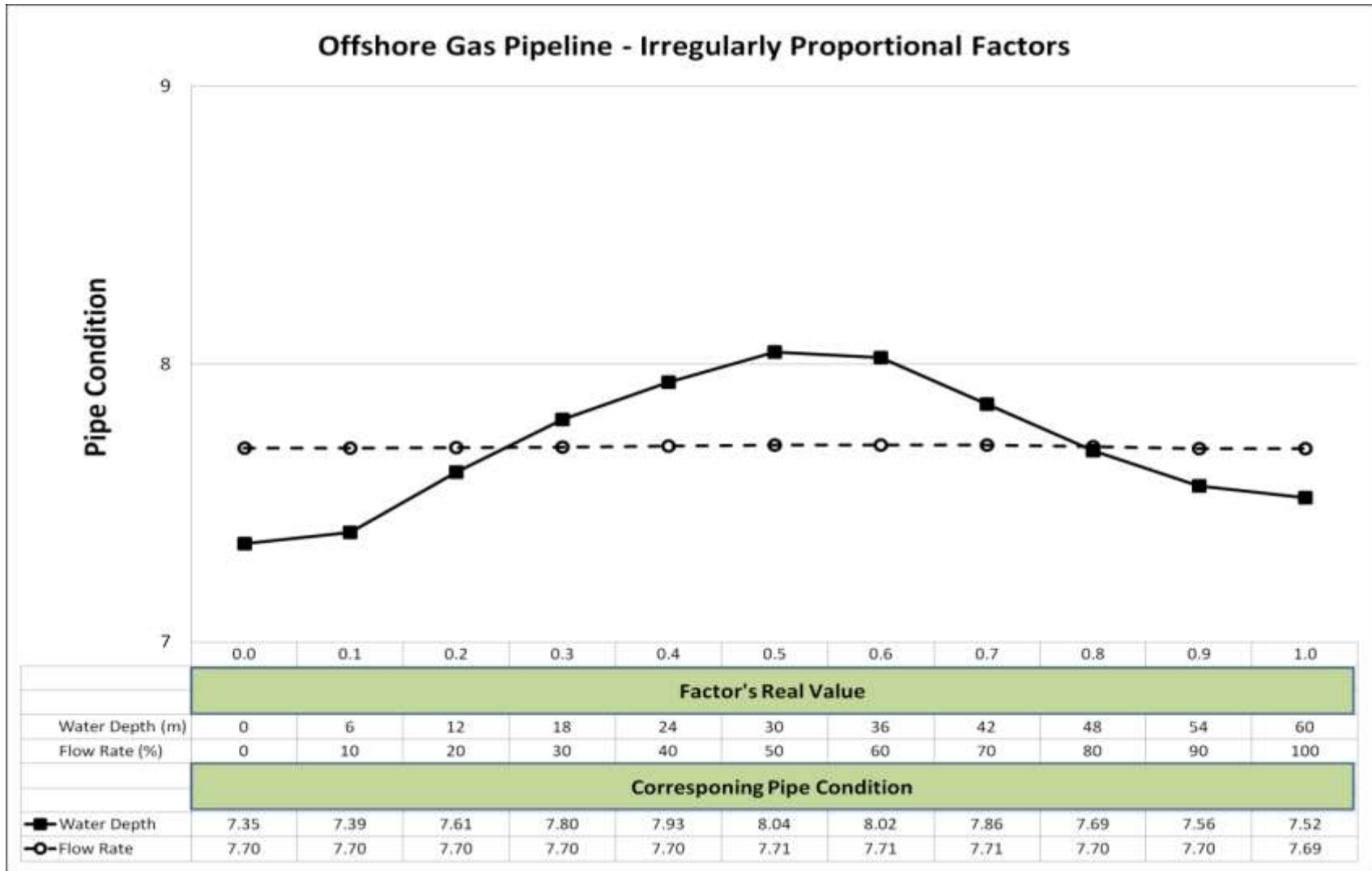


Figure 5 - 20: Irregularly Proportional Factors.

The results show that all the factors are sensitive to value change but with different degrees of sensitivity according to their ANP weights as shown in figures 5-18, 5-19 and 5-20. The factors *Age*, *Metal Loss*, *Crossings*, *Marine Route Existence*, and *Operating Pressure* all show the same trend, in which increasing their values would decrease the pipeline condition. While on the other hand, the factors *Diameter*, *Coating Condition* and *Cathodic Protection Effectiveness* show an opposite trend, that is increasing their values increase the pipeline condition. The reason behind that is that the pipeline coating condition and cathodic protection are protective measures for the pipeline where improving them prolong the pipeline life and protects it from degradation for longer periods. Whereas the diameter, i.e. size, which also increases the pipeline condition due to the possible larger SDR (Standard Dimension Ratio). This affects the structural performance of the pipeline and decreases its vulnerability to external impact. Therefore, increasing the values of *Diameter*, *Coating Condition* and *Cathodic Protection Effectiveness* would definitely increase the overall pipeline condition.

In regards with irregularly proportional factors which include Water Depth and Flow Rate as shown in Fig. 5-20, the pipeline condition demonstrated an increasing and decreasing trends with variability of change percentages for Water Depth. It is because the offshore pipelines experience high external loading of water pressure in deep waters. This leads to increased chances of collapse from external force buckle. On the other hand, shallow water pipelines are easily affected by external parties and weather conditions which may create sea currents. These currents may impose buckling forces on offshore pipelines as well. According to the current research, the offshore gas pipelines need to be placed 24 to 36 meters below water surface in order for these pipeline to be away from shallow water currents and in the same time not to be exposed to deep water pressure (Muhlbauer, 2004). Furthermore, the Flow

Rate factor displayed a stable trend which may be due to having the lowest relative weight, 0.008, of all factors. Nevertheless, it is a necessity to point out that flow rates influence the pipeline health integrity since low flow rates could increase the chances of liquid or solid dropout and accumulation in low places of the pipeline, whereas high flow rates may lead to pipeline erosion (Muhlbauer, 2004). Hence, determining the suitable flow rate is significant.

Table 5-13 demonstrates the ANP weights versus the difference in condition resulting for the changing the factors' values from lowest to highest. It can be seen that *Cathodic Protection Effectiveness* has the highest change in condition (Δ Condition = 2.24) which responds to the highest global weight (0.211) among all factors. The second highest condition difference (Δ Condition = 1.59) happened with *Metal Loss* which has a global weight of 0.180. Follows that is *Coating Condition* which has a condition difference of 1.28 and a global weight of 0.166.

According to the developed sensitivity analysis charts and Table 5-13, it can be observed that *Cathodic Protection* and *Coating Condition* have the highest positive effect on the pipe condition. They compose together 37.7% of contributing strength. Similarly, *Diameter* has a positive effect on the pipe condition but it is the lowest among the factors affecting the pipe condition positively. On the other hand, *Metal Loss* and *Operating pressure* have the highest negative effect on the pipe condition while *Crossings* have the lowest negative effect. The *Water Depth* and *Flow Rate* have a changing effect as shown in the sensitivity analysis charts and thresholds presented earlier.

It is noticed that the factors related to corrosion, *Metal Loss*, *Coating Condition* and *Cathodic Protection*, have the greatest effect of the pipe condition either positively or negatively. However, other factors including Age, Diameter, Crossings, Marine Route Existence, Water

Depth, Corrosive Impurities, Operating Pressure and Flow Rate, are still essential for pipe condition prediction as they form together around 44.3% in their condition contributing strength.

Table 5 - 13: Sensitivity Analysis (ANP Global Weights Vs Condition Difference).

Factor		Global Weight	Max. Condition	Min. Condition	Δ Condition
A1	Age	0.040	7.84	7.62	0.22
A2	Diameter	0.014	7.75	7.68	0.07
A3	Metal Loss	0.180	8.13	6.54	1.59
A4	Coating Condition	0.166	7.71	6.43	1.28
B1	Crossings -	0.029	7.71	7.55	0.16
B2	Cathodic Protection	0.211	8.04	5.80	2.24
B3	Marine Route Existence	0.095	7.92	7.24	0.68
B4	Water Depth	0.112	8.04	7.35	0.69
C1	Corrosive Impurities	0.031	7.73	7.66	0.07
C2	Operating Pressure	0.114	8.24	7.48	0.76
C3	Flow Rate	0.008	7.71	7.69	0.02
Total		1.000			

Finally, the ANP global weights mentioned in Table 5-13 were developed from the feedback of professionals in the oil and gas industry in Qatar and Saudi Arabia. These weights have a great effect on the final output of the model when changing the entered factors' values. Also, these weights can be updated in the developed model to reflect different conditions but still affect the model output. The larger ANP weight of the factor, the larger its effect on the final output (i.e. the bigger the difference in condition) when changing the factor's value.

5.7 Development of Pipeline Deterioration Curve

A relation between the condition rating and *Age* factor was built based on the developed model. The purpose of building this relation is to predict the pipe condition based on different physical, external and operational factors. It is important to express graphically the combined effect of all the factors on the pipeline condition. As a result, a deterioration curves was built for the developed model as shown in following figure. This deterioration curve gives a clearer knowledge of the interrelationships between the pipeline future conditions and the studied factors. Fig. 5-21 shows a polynomial relation of fifth degree between the overall pipe condition and Age. The vertical axis represents the predicted pipe condition while the horizontal axis represents the Age factor.

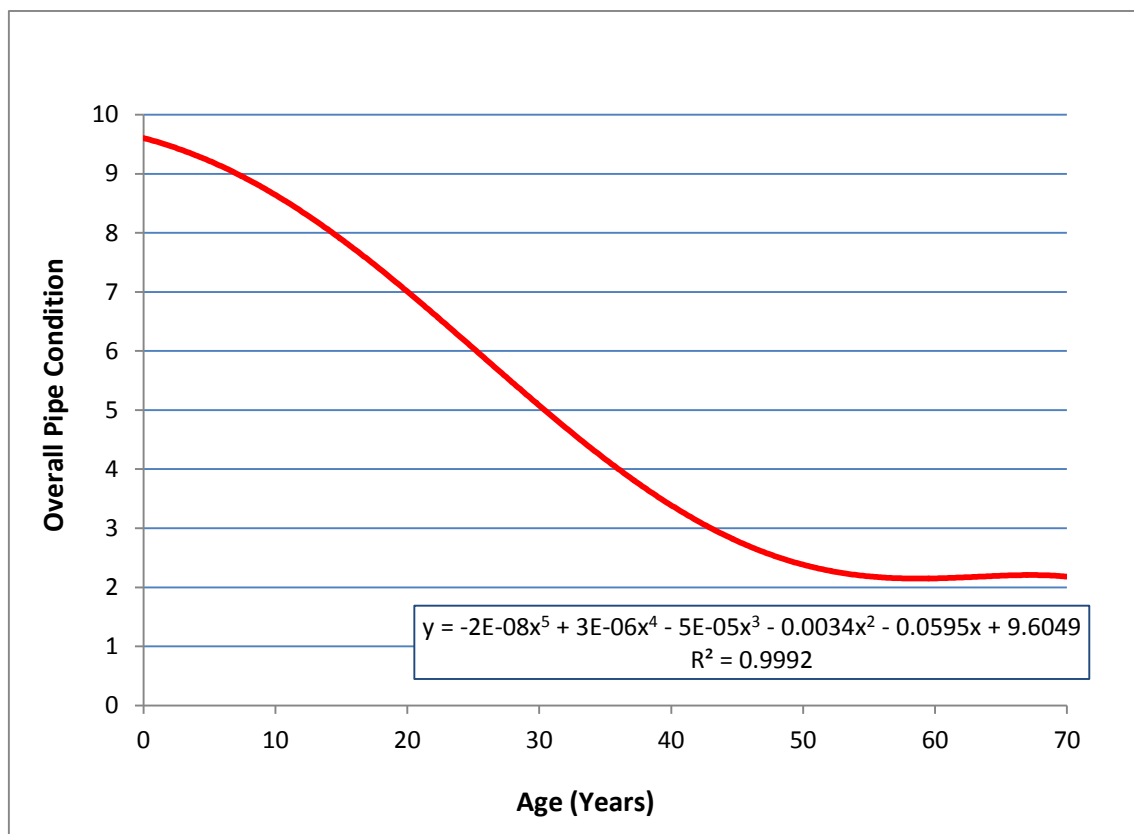


Figure 5 - 21: Predicted Deterioration Curve for Offshore Gas Pipeline.

It is noticed that the previous figure shows an inverse relation between the pipe condition and Age. Commonly, the effect of aging on the pipe condition is of negative nature. The pipe condition decreases as age increases. Also, this deterioration curve is built to study the effect of time on the pipe condition taking into consideration other factors' degradation. For example, the Metal Loss would definitely increase over time which in return decreases the pipe condition. The same thing is applied to the rest of the factors where their values is changing simultaneously from their best possible effect on the pipe condition to their worst. On the other hand, the Diameter and Number of Crossings are kept constant at average condition values which are 20 inches and 3 crossings, respectively.

5.8 Condition Assessment Scale

According to literature, there is no standard condition assessment scale (condition rating scale and its associated rehabilitation works). Pipeline operators use approximations and experts' opinions to determine the condition and required rehabilitation or inspection for an existing pipeline. It is recommended for pipeline operators to build their own condition rating scale which suits the environmental and operational status that accompanies a functional pipeline. Additionally, converting all condition rating into a numerical scale such as "0" to "10" scale, which was used in the proposed condition rating scale, is also recommended. The condition assessment scale proposed in this section is adapted from El-Abbasy et al. (2014a) who suggested an assessment scale for oil and gas pipelines using a scale from "0" to "10", where "0" indicates that the pipeline is at its worst condition and "10" at its best condition.

5.8.1 Proposed Condition Rating Scale

Since there is no standard condition scale was found for offshore gas pipelines, this research propose its own condition rating scale. This scale was developed from the data collected from

the received questionnaires where experts were asked to assign gas pipeline condition index in the last part. Table 5-14 illustrates the linguistic terms and the numeric values for the proposed condition rating scale for offshore gas pipelines.

Table 5 - 14: Proposed Condition Rating Scale.

Linguistic Scale	Numeric Scale
Excellent	9 -- 10
V. Good	7 -- 9
Good	5 -- 7
Fair	3 -- 5
Critical	0 -- 3

The developed condition rating scale will provide a framework for gas pipeline operators to decide and perform the required action to maintain their pipelines. For example, if the reported corrosion resulted in 26 to 55% of metal loss of the original wall thickness and the loss of coating condition ranged from 35 to 50% of the original. Then, the condition of the gas pipeline is considered "Good" and the suggested action to be taken is to schedule for re-coating and cathodic protection rehabilitation in the next 3 to 5 years. Also, the pipeline will be re-assessed after 5 years. Along with the previous, the pipeline operator may suggest regular annual maintenance for the considered pipeline to be observed continuously. That may come in handy if the operator noticed signs of any type of pipeline failure.

It is important to note that this proposed condition rating scale is a preliminary suggestion and many researches may suggest other alternatives. The choice of a suitable condition rating scale relays on the pipeline operators and depends whether this scale is designed for their working environment or not. For example, pipeline operators in Qatar cannot use a condition

rating scale that was proposed for rating pipelines in UK. Table 5-15 demonstrates the suggested required actions to be taken associated with each offshore gas pipeline condition.

A condition rating scale is proposed in this chapter to provide a framework for professional in the oil and gas industry in Qatar to plan for the required inspection and rehabilitation works for offshore gas pipelines. The developed scale is of interest to oil and gas pipelines operators in order to prioritize future inspection and rehabilitation planning for existing offshore gas pipelines.

5.9 Summary

The current research designed a condition assessment model using the integration of Fuzzy Logic, Analytical Network Process (ANP) and Evidential Reasoning (ER). Eleven factors within three main categories (physical, external and operational) were studied to check their effect on offshore gas pipelines condition in Qatar. A detailed literature review was performed about oil and gas pipelines and previous condition assessment attempts. In the literature review section, a detailed explanation was presented for the techniques used in developing the current model. A structured questionnaire was distributed among professionals in the oil and gas industry in Qatar to collect their feedback on the chosen factors. From the received questionnaires, the factors thresholds were developed and fuzzy logic was applied. The ANP global weights of the studied factors were calculated and a new condition assessment scale was proposed, as shown in the next chapter, to prioritize pipe inspection and rehabilitation planning. The Evidential Reasoning algorithm was used to develop the model by integrating the fuzzified factors' thresholds and the global ANP weights on these factors. A set of historical inspection data received from a pipeline operator in Qatar was used to validate the model prediction power.

Table 5 - 15: Numeric and Linguistic Scale for Condition Rating of Offshore Gas Pipelines.

Numerical Scale	Linguistic Scale	Criteria Description	Action Required
9 – 10	Excellent	<ul style="list-style-type: none"> ➤ Corrosion: <i>Almost no signs (0 – 17 % Metal Loss).</i> ➤ Cathodic Protection: <i>Very good (> 951 mV).</i> ➤ Coating Condition: <i>Almost new (< 15 % coat loss).</i> 	<ul style="list-style-type: none"> ➤ <i>Re-assess in 15 years.</i> ➤ <i>Regular annual maintenance.</i>
7 – 9	V. Good	<ul style="list-style-type: none"> ➤ Corrosion: <i>Few signs (9 – 35 % Metal Loss).</i> ➤ Cathodic Protection: <i>Good & within acceptable limits (850 – 1000 mV).</i> ➤ Coating Condition: <i>Few signs of damage (15 – 35 % coat loss).</i> 	<ul style="list-style-type: none"> ➤ <i>Re-assess in 10 years.</i> ➤ <i>Regular annual maintenance.</i> ➤ <i>Schedule for CP rehabilitation within the next 5-10 years.</i>
5 – 7	Good	<ul style="list-style-type: none"> ➤ Corrosion: <i>Average signs (26 – 55 % Metal Loss).</i> ➤ Cathodic Protection: <i>Adequate (751 – 900 mV).</i> ➤ Coating Condition: <i>Small damage but still intact (35 – 50% coat loss).</i> 	<ul style="list-style-type: none"> ➤ <i>Re-assess in 5 years.</i> ➤ <i>Regular annual maintenance.</i> ➤ <i>Schedule for CP rehabilitation & Re-coating within the next 3-5 years.</i>
3 – 5	Fair	<ul style="list-style-type: none"> ➤ Corrosion: <i>Significant signs (46 – 74 % Metal Loss).</i> ➤ Cathodic Protection: <i>Inadequate but acceptable (676 – 800 mV).</i> ➤ Coating Condition: <i>Partial damage (45 – 75 % Coat Loss).</i> 	<ul style="list-style-type: none"> ➤ <i>Re-assess in 2 years.</i> ➤ <i>Regular annual maintenance.</i> ➤ <i>Schedule for rehabilitation and/or replacement within the next 1-3 year.</i>
0 – 3	Critical	<ul style="list-style-type: none"> ➤ Corrosion: <i>Severe signs, close to failure (66 – 100 % Metal Loss).</i> ➤ Cathodic Protection: <i>Critical (< 700 mV).</i> ➤ Coating Condition: <i>Significant damage (> 60 % Coat Loss).</i> 	<ul style="list-style-type: none"> ➤ <i>Schedule for immediate rehabilitation &/or replacement.</i>

After building the model, a sensitivity analysis was performed to check the effect of changing the factors' values individually. Then, a deterioration curve was plotted in order to check the aging effect on the pipe condition as well as degradation of other factors.

CHAPTER SIX: CONDITION ASSESSMENT AUTOMATED

TOOL

6.1 Introduction

Technology and software advancements promote the existence of automation tools to overcome time obstacles and facilitate the application of the various methodologies that are being developed nowadays. These methodologies, which may be time consuming if not automated, can and will assist practitioners in multiple fields of industry in predicting and ranking the condition of existing offshore gas pipelines in Qatar and similar regions in less time and reduced cost.

This chapter illustrates the implementation of the developed fuzzy-based condition assessment methodology for offshore gas pipelines in Qatar described in the previous chapters. The methodology is automated via third party software, Microsoft Excel, which provided the necessary functions to perform such a task. The automated tool sets on four main pillars: 1) Inputs, 2) Fuzzification, 3) Defuzzification & Outputs and 4) Graphical Representation.

6.2 Automated Fuzzy-based Tool Framework

The proposed automation of the developed methodology is called Automated Fuzzy-based Condition Evaluator. It employs the fundamentals of three techniques; Analytic Network Process (ANP), Evidential Reasoning (ER) and Fuzzy Set Theory (FST). The automated tool will assist professionals in oil and gas industry to predict the condition rating of existing offshore gas pipelines based on the data which the model will request from the user as follows.

The Fuzzy-based Condition Evaluator provides two options for the users in regards of the factors' priorities. The user may decide whether to use the default ANP weights generated during the course of this thesis or generate their own customized weights. The automated tool then will require the information related to priorities and the data related to factors which will be counted for in the pipeline condition prediction. The results will include a condition rating value that ranges from "0" to "10" where 0 indicates that the considered pipeline is in "Critical" condition, and 10 expresses "Excellent" condition.

The flowchart shown in Fig. 6-1 epitomizes the functions of the proposed automated tool model where the procedure is detailed in the next section. This automation employs MS Excel in order to facilitate the application of the developed fuzzy-based methodology. Also, another type of software is used in the process, SuperDecisions, which is used as an extra option for the users to re-calculate their own ANP priorities or weights.

6.3 Fuzzy-based Condition Evaluator Process

The first page the user will face when starting the automated tool file is the welcome page, Fig. 6-2, which displays the most influential factors, classified into three main categories; physical, external and operational. These factors contribute in the condition prediction performed by the developed fuzzy-based model. In case of facing any difficulty in understanding any of the factors, the user can press the question mark button which will lead them to another page containing a brief description about all contributing factors as shown in Fig. 6-3. The automated tool contains "Next" and "Back" buttons which will enable the user to navigate through the automated tool file and proceed from one stage to another.

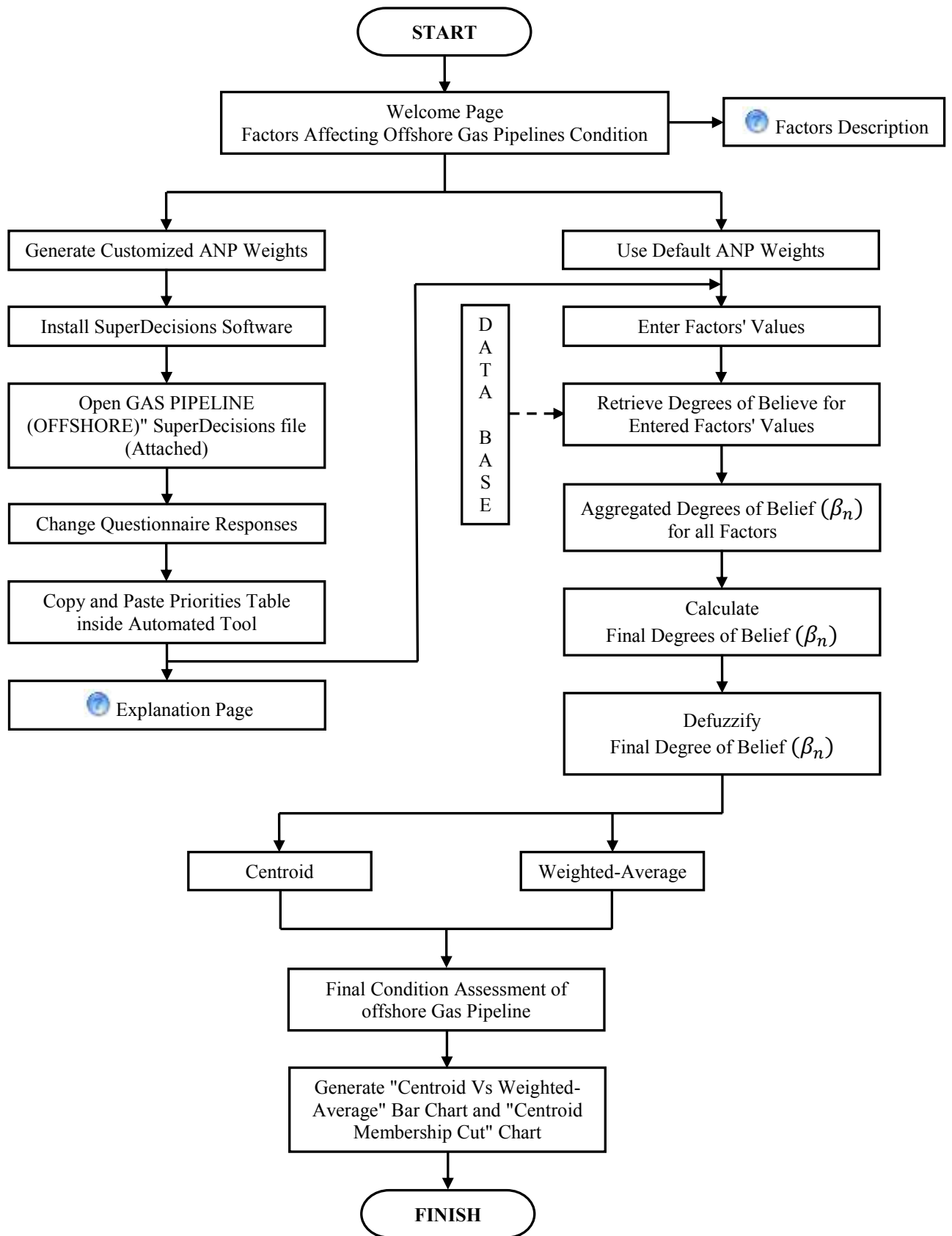


Figure 6 - 1: Flowchart of the Condition Assessment Automated Tool System.

As mentioned earlier, this automated tool was designed using MS Excel software and includes the functions and information required to automate the developed methodology. Many excel sheets were programmed to quickly retrieve the necessary information as response to the data entered by the user.

The user then is forced back to the welcome page where they will press the Next button which leads the user to the Weights selection page, Fig. 6-4. This page will inquire them to decide whether to advance using the shown default ANP weights or to generate their own customized weights. The default ANP weights were generated in the data collection phase by distributing a structured questionnaire among professionals in the oil and gas industry in Qatar and similar regions such as Saudi Arabia. The interested reader may refer to Data Collection chapter for more details.

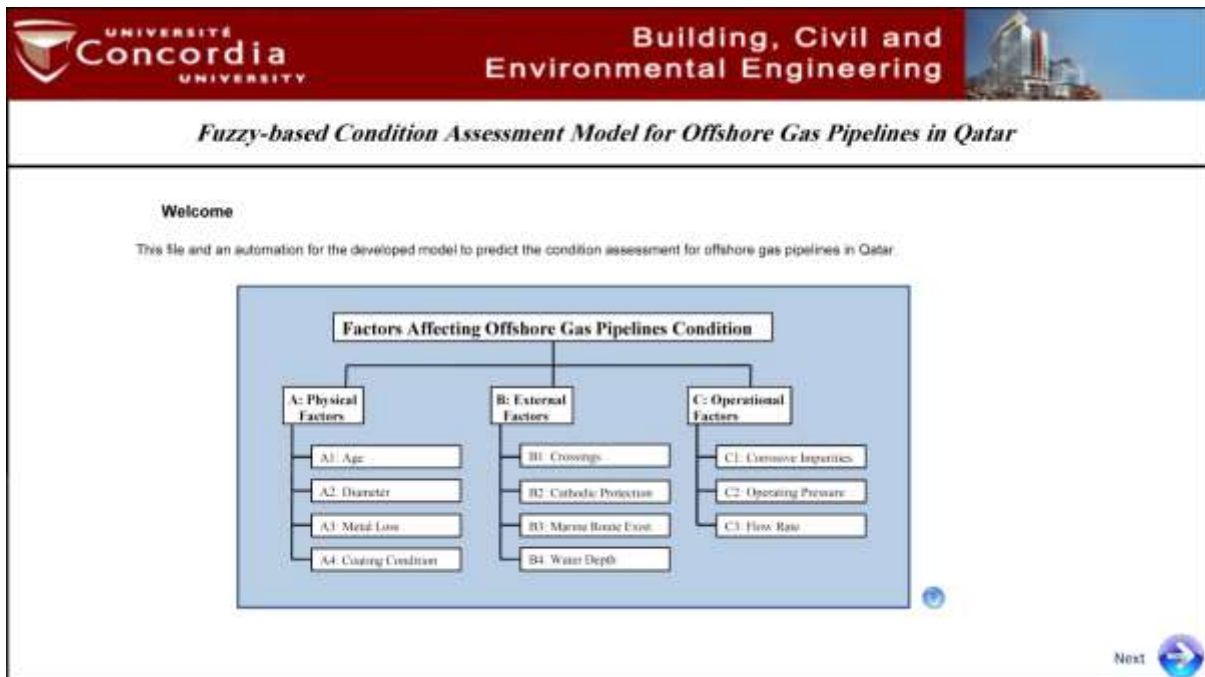


Figure 6 - 2: Welcome Page and Contributing Factors.

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Fuzzy-based Condition Assessment Model for Offshore Gas Pipelines in Qatar

Factor		Explanation
Physical	Age	Refers to pipe Age. Effect of degradation increases with time.
	Diameter	The smaller pipe diameter, the more it is affected by degradation
	Metal Loss	Indicates the loss in pipe wall thickness.
	Coating Condition	Quality of pipe interior/ exterior coating.
External	Crossings	Number of pipelines crossing over or under the considered pipe.
	Cathodic Protection Effectiveness	Power used to control corrosion of pipe metal surface.
	Marine Route Existence	Existence of marine routes over the studied pipe.
	Water Depth	Depth of pipe from water surface.
Operational	Corrosive Impurities	Percentage of corrosive impurities in transported product.
	Operating Pressure	Pipe Operating pressure as a percentage of designed pressure.
	Flow Rate	Pipe flow rate as percentage of designed flow rate.

[Back](#)

Figure 6 - 3: Contributing Factors Description.

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Fuzzy-based Condition Assessment Model for Offshore Gas Pipelines in Qatar

Please choose one of the following options:

1- Use default weights (See table below)
 2- Generate customized weights

Category	Global Weight	Factor	Local Weight	Global Weight
A Physical Factors	0.400	A1 Age	0.100	0.040
		A2 Diameter	0.034	0.014
		A3 Metal Loss	0.450	0.180
		A4 Coating Condition	0.416	0.166
B External Factors	0.447	B1 Crossings	0.054	0.029
		B2 Cathodic Protection	0.472	0.211
		B3 Marine Route Existence	0.213	0.095
		B4 Water Depth	0.251	0.112
C Operational Factors	0.153	C1 Corrosive Impurities	0.199	0.031
		C2 Operating Pressure	0.746	0.114
		C3 Flow Rate	0.055	0.008
Total	1.000		3.000	1.000

[Back](#)

Figure 6 - 4: ANP Weights Selection (Default Vs Customized).

In case the user chose to generate their own weights, the automated tool will display the page shown in Fig. 6-5 where the user will be asked to install the SuperDecisions software. After that, the user will open the pre-arranged SuperDecisions file attached with the automated tool. It will guide the user through the process of generating the customized ANP weights as shown in figures 6-5 through 6-8. During this process, the user will be asked to change the questionnaire responses in the pre-arranged SuperDecisions file as shown in the figure below.

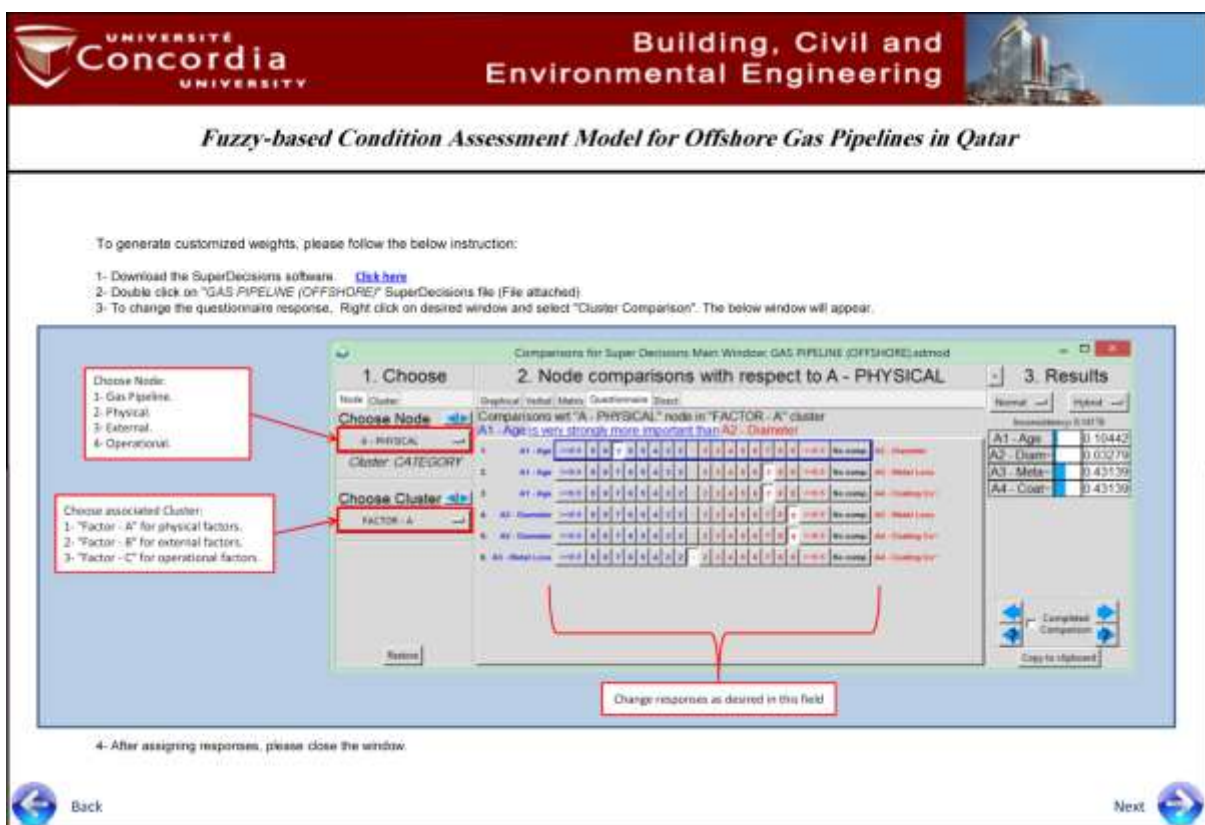


Figure 6 - 5: Generate Customized Weights - SuperDecisions File.

If no previous knowledge of SuperDecisions software existed, instructions are presented to direct the user. After changing the questionnaire responses, the SuperDecisions will calculate the re-distributed priorities for the contributing factors and their main categories as shown in Fig. 6-6.

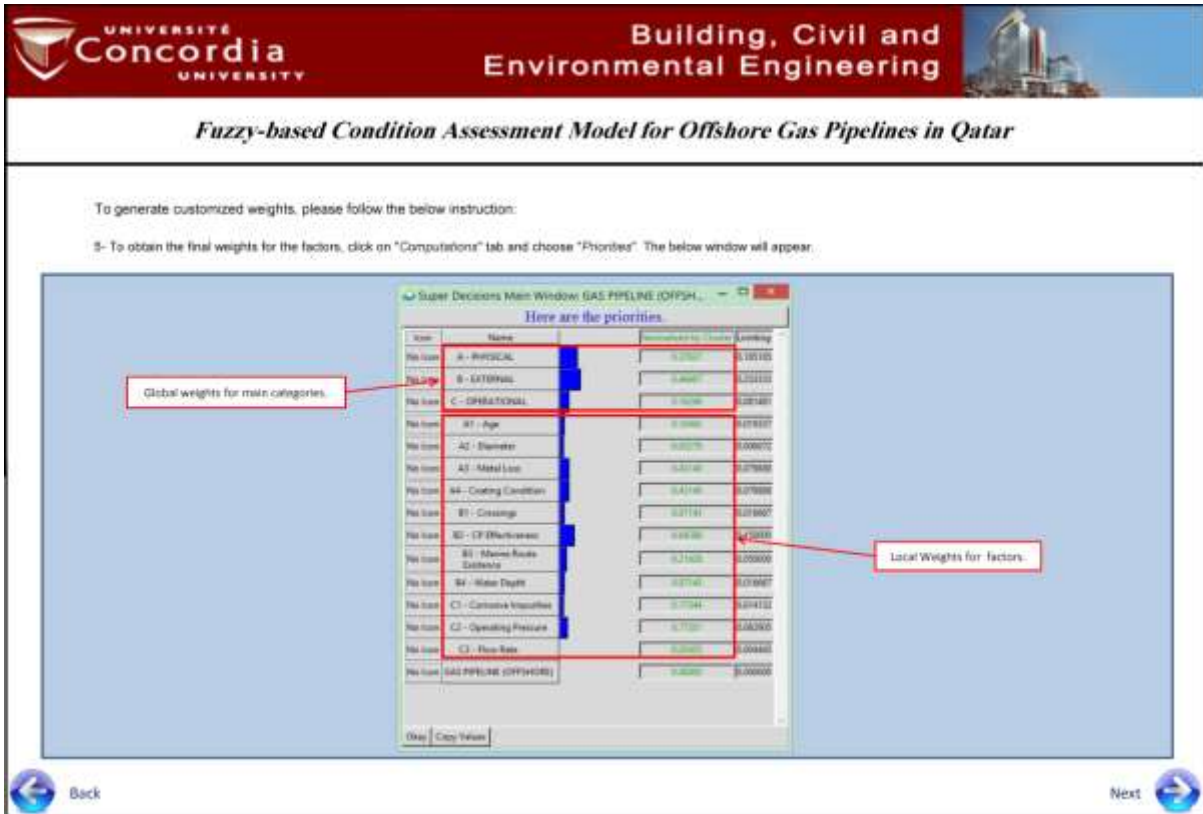


Figure 6 - 6: Generate Customized Weights - Priorities Table Explanation.

Later on and as shown in Fig 6-7, the user will be asked to copy the priorities table into the assigned space in the automated tool where it will be automatically recognized for the calculations of the final global weights for the factors and their main categories. Fig. 6-8, is an extra explanation page that exhibits the transference occurring when copying the priorities table into the designated space. After generating the customized weights, the user is imposed to the final page of the tool, Fig. 6-9. This page displays the user-generated ANP weights that will be used in the final pipeline condition prediction. In the last step, the user will be asked to enter the factors' values such as pipeline age, diameter and so on. Factors that have limits for their values like Cathodic Protection Effectiveness which uses a unit other than percentage (%), their values can be determined from a drop down list that appears when selecting this factor value's square (green colored).



Fuzzy-based Condition Assessment Model for Offshore Gas Pipelines in Qatar

To generate customized weights, please follow the below instruction:

- 6- To obtain the final weights for the factors, click on "Computations" tab and choose "Printers". The below window will appear.
- 7- Press "Copy Values" button shown at the window's left bottom. Then right click on RED square and choose "Paste" where shown below.

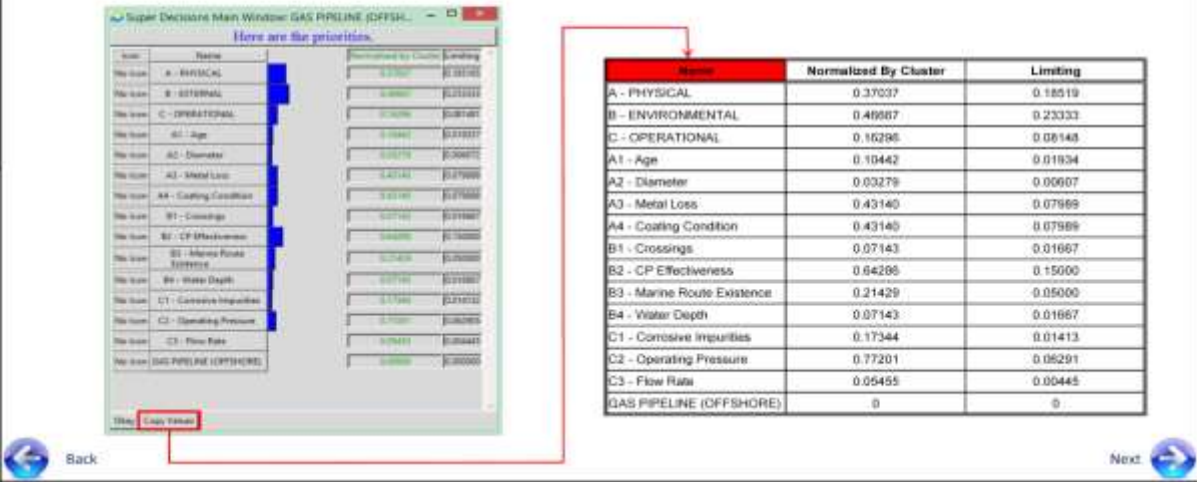


Figure 6 - 7: Generate Customized Weights - Final ANP Weights (1).



Fuzzy-based Condition Assessment Model for Offshore Gas Pipelines in Qatar

The purpose of Steps 6 & 7 is to transform the weights from SuperDecisions file into this automated tool to obtain the final global weights for the factors as shown below.

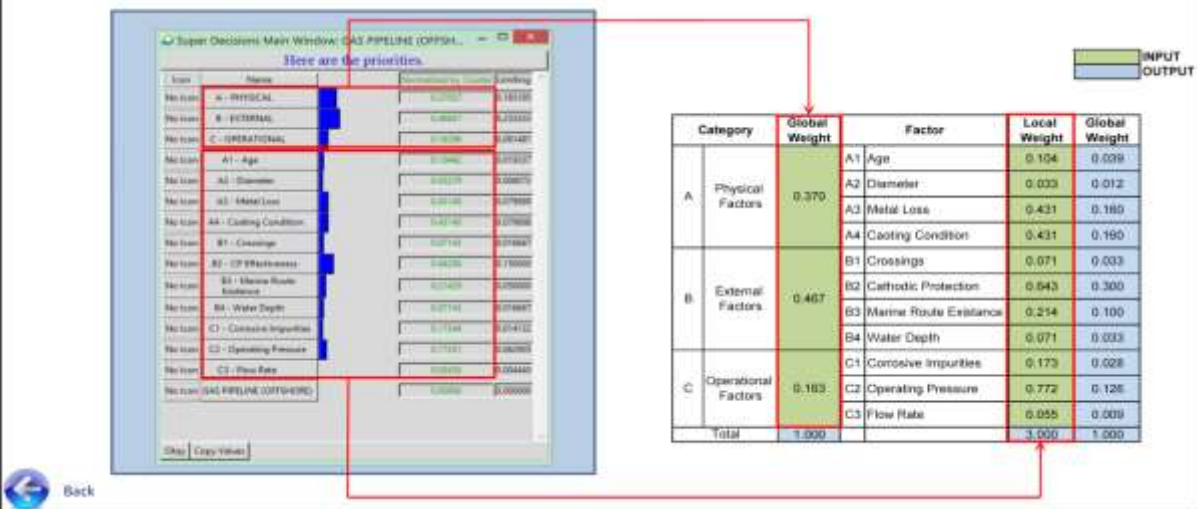


Figure 6 - 8: Generate Customized Weights - Final ANP Weights (2)

It is important to note that the fuzzified membership functions developed earlier for the contributing factors (inputs) and final evaluation (output) are inserted into the automation file as a Data Base along with the programmed sheets to calculate the Centroid and Weighted-Average of the final evaluation of the model. Therefore, the automated tool will detect the associated degrees of belief as soon as the factor's value is determined. This process is repeated for the rest of the contributing factors. After assigning the degrees of belief for all the factors, the tool will combine them using the newly generated ANP weights and the ER algorithm discussed earlier. The aggregation of all belief degrees is executed in the tool's background and does not appear for the user.

Finally, the products of the automated tool can be outlined in two points as follows:

- 1) The final pipeline evaluation as crisp value using two defuzzification methods; Centroid and Weighted-Average (blue colored squares).
- 2) Graphical representation of the final evaluation which includes:
 - a) Centroid's Membership cut and defuzzified value of the final degrees of belief.
 - b) Bar chart displays the comparison between Centroid and Weighted-Average defuzzification results.

Fig. 6-10 shows the page displayed when choosing to use the default ANP weights (red colored squares) generated in this research. In this case, the user will only be obliged to enter the factors' values in the green colored squares. The results will be the same as in Fig. 6-9 which are the final evaluation defuzzified values, their graphical representation and comparison.



Fuzzy-based Condition Assessment Model for Offshore Gas Pipelines in Qatar

INPUT
OUTPUT

Please Enter Value.



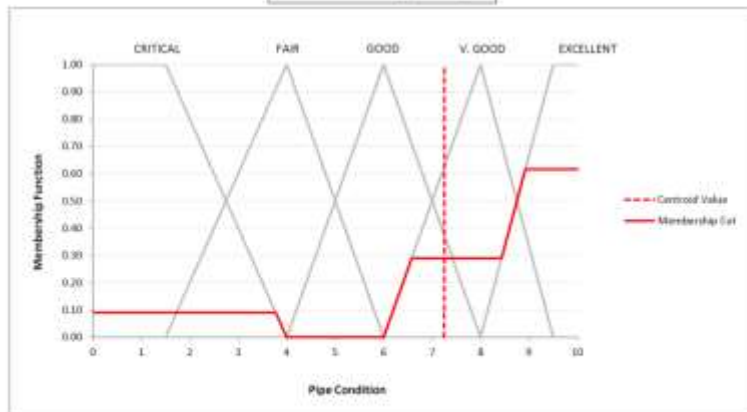
Local Weights	
Physical	0.104
	0.033
	0.431
	0.431
Total	1.000
External	0.071
	0.643
	0.214
	0.071
Total	1.000
Operational	0.173
	0.772
	0.055
Total	1.000
Total	3.000

Factor	Global Weights
Age (Years)	0.039
Diameter (Inches)	0.012
Metal Loss (%)	0.180
Coating Condition (%)	0.180
Crossing (#)	0.033
Cathodic Protection Effectiveness (mV)	0.300
Marine Route Existence (%)	0.100
Water Depth (m)	0.033
Corrosive Impurities (%)	0.028
Operating Pressure (% of Design)	0.126
Flow Rate (% of Design)	0.009
Total	1.000

Input Factor
6
12
18.10
99.80
0
1040
14.50
28
15.00
90.00
91.00

Final Evaluation	
By Weighted-Average	8.33 /10
By Centroid	7.25 /10

Final Evaluation (Centroid)



Final Evaluation Chart (Weighted-Average Vs Centroid)

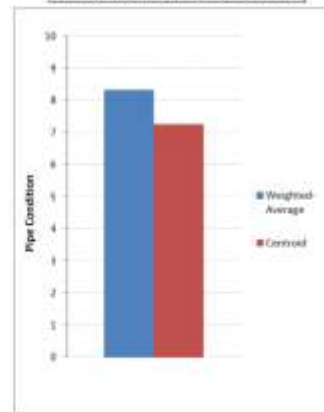


Figure 6 - 9: Generate Customized Weights - Final Report.

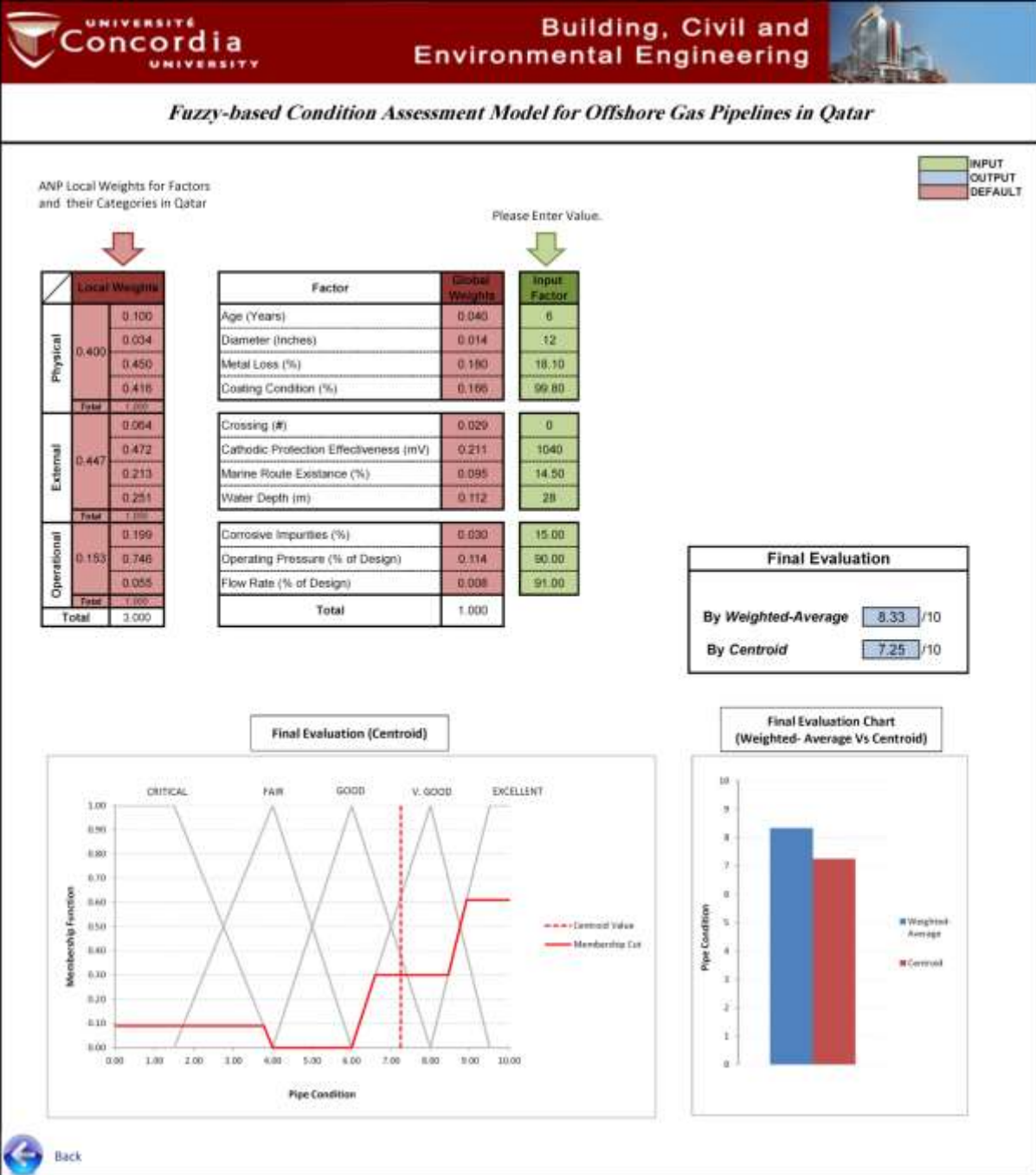


Figure 6 - 10: Use Default Weights - Final Report.

6.4 Summary

An automation tool used for condition rating prediction is proposed. This tool is based on the developed condition assessment methodology which utilizes FST, ANP and HER to evaluate

an existing offshore gas pipeline. It could be beneficial for professionals in oil and gas industry to predict pipelines condition and assist in planning for future inspection and rehabilitation works. This automated tool could be enhanced further to be more user friendly and accommodate new functions to provide an augmented solid platform for future extension of this research.

CHAPTER SEVEN: SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

7.1 Summary and Conclusion

The current research resulted in the development of a new numerical and linguistic assessment scale for offshore gas pipelines. This scale comprises five grades, Excellent, Very Good, Good, Fair and Critical. The details and characteristics of each grade were described earlier in details. The new condition assessment scale could serve as a framework for pipeline operators to plan future rehabilitation works for existing pipelines. The developed model in this research is based on expert's feedback and historical inspection reports gathered mainly from Qatar. Hence, this model can be described to be best suited for Qatar and similar regions. On the other hand, the proposed methodology can be updated to apply for different regions.

This research presented a condition assessment model for offshore gas pipelines in Qatar using the integration of three techniques which are Analytic Network Process (ANP), Fuzzy Sets Theory (FST) and Evidential Reasoning (ER). First, a comprehensive literature review was conducted on the three techniques implemented in this study. This literature review also contained the types, design and material of oil and gas pipelines used in Qatar. Based on literature review, eleven factors were identified as the most influential criteria that affect offshore gas pipelines in the studied region. The data needed to perform this research was collected from two sources, experts' feedback through a structured questionnaire and historical data from previous inspections in Qatar.

The proposed methodology focused on obtaining a comprehensive evaluation of the offshore gas pipelines based on multi-criteria and not just the corrosion related ones. Also, the interdependency between these criteria along with uncertainty of the respondent's view were addressed through using ANP and HER, respectively. The use of fuzzy logic came in handy to quantify the respondents' feedback. Many defuzzification methods were introduced and a comparison was made between two common methods, Centroid and Weighted-Average, to convert the final degrees of belief into a crisp value.

The developed model was tested with historical inspection data to demonstrate the accuracy and usefulness of the new methodology in predicting of offshore gas pipeline condition. The received inspection reports data were prepared and organized to validate the model. The average validity percent (AVP) of this model was 97.6% and the root mean squared error (RMSE) ranged between 0.241 and 0.250 which clearly demonstrates the accuracy in predicting the condition of offshore gas pipelines in Qatar. An extra criteria used to validate the model is the Fit Index which ranged between 836.32 and 839.18. Since the fit index values are very close to 1000, the model was considered fit for the predetermined objectives. A sensitivity analysis was conducted to examine the impact of each factor individually on the overall pipeline condition. It was found that Cathodic Protection and Metal Loss were the most positively and negatively influencing factors, respectively. However, the factors of diameter and crossings had the lowest positive and negative effect on offshore gas pipeline condition.

Additionally, a relation between the Age factor and the pipe condition was built to predict the deterioration of the pipe along its age based on the presented methodology. In addition, a new condition assessment scale was proposed as a guideline for pipeline operators to help in

planning for future inspections and rehabilitation works. The last step of this research was to automate the designed model. This automated tool will assist professionals in oil and gas industry to predict the condition rating of existing offshore gas pipelines based on the data requested from the user.

Finally, the model is expected to provide the engineers in oil and gas industry and pipeline operators with a platform designed solely to predict and assess the condition of offshore gas pipelines in Qatar and similar environments. Also, this model can assist in planning and prioritizing their future inspections and rehabilitation works.

7.2 Research Contributions

The current research contributions included a comprehensive evaluation methodology to assess offshore gas pipelines that are affected by various factors. The following developments resulted from the proposed methodology:

- 1) Develop a hierarchy of various factors that affect offshore gas pipeline condition in Qatar.
- 2) Develop a condition assessment model for offshore gas pipelines in Qatar considering uncertainty and subjectivity using the integration of three main techniques, Fuzzy Set Theory (FST), Analytic Network Process (ANP), and Hierarchical Evidential Reasoning (HER).
- 3) Design a condition assessment scale.
- 4) Build a deterioration curve to predict future conditions of the considered pipeline.
- 5) Design an automated tool for the developed condition assessment model.

7.3 Research Limitations

The presented research work introduced a new methodology to help pipeline operators in evaluating and predicting the condition of offshore gas pipelines in Qatar. In order to deploy the developed model in a pipeline operating company, the following should be considered:

- 1) Only eleven factors within three categories were considered in developing this model while other factors could be used to provide a more comprehensive picture about the offshore gas pipeline condition such as Sea Water Current. In order to perform this, a reliable information system concerning physical, external and operational factors should be included in the developed model.
- 2) The data collected from experts' feedback was based on a random sample of 25 professionals which can be considered a small number. Also, experts with more diverse backgrounds could be reached.
- 3) The developed model eliminated ignorance in order to a full degree of membership, equal to 1, for each entered factor's value.

7.4 Future Recommendations

Recommended future work of the current research can be divided into two section which are described as follows:

❖ *Potential Enhancements of current research:*

- a) Historical inspection data with various pipe conditions, to cover all possibilities, could be used to further evaluate the model's prediction power. Other pipeline operators could be reached in Qatar and similar regions such as UAE and Saudi Arabia. This is because the data used to validate the developed model was limited to a certain pipe condition

that circles around Good and Very Good. So, data for pipelines that have worse conditions could be gathered and added to the validation process.

- b) The factor's hierarchy included 11 factors under three main categories. So, more factors could be incorporated to enhance the developed model such as structural related factors like Joint Type or Free Span and external factors like Surrounding Soil Type. These factors could be chosen based on the availability of gathered data in order to better validate the developed model.
- c) More experts can be encouraged to participate in the data collection part by answering the structured questionnaire. This could cover a wide variety of feedbacks and experiences. As mentioned in the Data Collection chapter, the developed model was based on 25 feedbacks of experienced professionals in the oil and gas industry in Qatar and Saudi Arabia. Also, they were gathered mainly from inspection and operation professionals. So, more professionals from different sectors in the industry and from different countries, that have an environment similar to that of Qatar's and Saudi Arabia, could be encouraged to participate.
- d) The developed model was designed to have zero ignorance. It can be enhanced and updated to account for ignorance in responses where a professional is not 100% sure that a pipeline is assessed under a certain pipe condition. Based on that, the new model will predict the pipeline condition with a degree of confidence and ignorance.

❖ *Hypothetical extension areas of current research:*

- a) Consolidate the developed model with web-GIS system so that the condition rating of offshore gas pipeline segments in an existing network can be assessed separately and automatically. A central database will be built to incorporate the existing pipeline network where each pipeline or segment would have a unique ID. Each pipeline history

such as inspection records, annual planned maintenance cost ... etc. will be shared in real time basis with authorized professionals across the organization or worldwide. This work history will be used for continuous condition assessing using the developed model. Then, these assessments are compared with the most recent ones to investigate each pipeline segment deterioration in any place of the network.

- b) Based on the combination of the developed model and web-GIS system, the pipeline network could be under continuous monitoring. As a result, a new methodology could be proposed to prioritize future inspection schedules of pipeline segments based on their condition. This methodology would process inspection reports data and assess the condition of all offshore gas pipelines in a network in order to generate an inspection schedule for the whole network on priority basis.
- c) The developed model can be the basis of a condition assessment software concerning not only offshore gas pipelines but exceeding that to oil pipelines either offshore or onshore (buried or above soil). This software will have options to assess oil or gas pipelines either offshore or onshore.
- d) Design condition prediction software in which historical inspection reports are imported and analyzed automatically. This requires a thorough literature review about the software and inspection types used in oil and gas industry in Qatar. The new software will be designed to automatically accommodate the inspection data without the need to refine it for the condition assessment model. As a result, time and money wasted on initial preparing of this data could be saved.

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APPENDIX (A)

APPENDIX (A)

SAMPLE PROFESSIONAL EXPERT QUESTIONNAIRE



CONDITION ASSESSMENT OF OFFSHORE GAS PIPELINES

Dear Sir/Madam

We would like to present our appreciation and thanks to you for taking part of your time to complete this questionnaire. This questionnaire aims to identify the degree of importance of the factors affecting the assessment of offshore gas pipelines' condition. This questionnaire is a part of the requirements for an academic research which is done under the supervision of Dr. Tarek Zayed at Concordia University to build a condition assessment model for offshore gas pipelines. The information in the questionnaire will be used for academic research with complete commitment for absolute confidential to your information. Based on literature review and interviews with experts, the main factors that were found to have an effect on the oil/gas pipelines' condition can be summarized as shown in Figure 1 below:

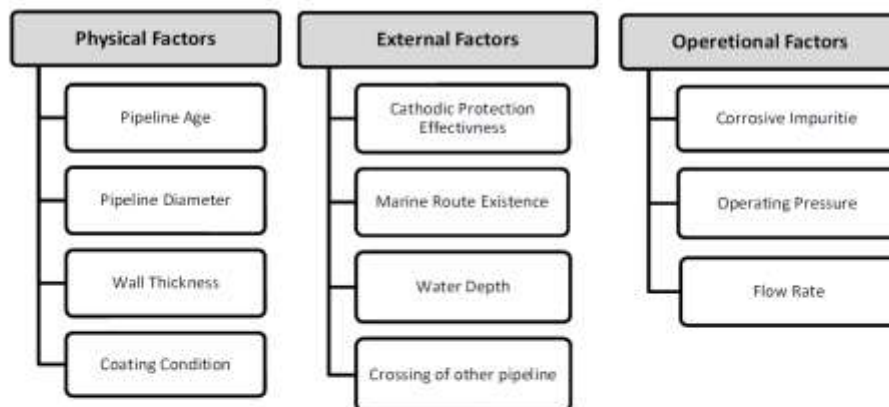


Figure 1: Factors Affecting the Condition of Offshore Gas Pipelines

After reviewing the main factors listed; please kindly fill in parts (1) to (4) of this questionnaire.

PART (1) : GENERAL INFORMATION

- 1) How do you describe your occupation ?
 - Organization Manager
 - Construction Manager
 - Project Manager
 - Others _____

- 2) Which best describes your working experience ?
 - Less than 5 years
 - 11 – 15 years
 - More than 20 years
 - 6 -10 years
 - 16 – 20 years

- 3) How do you describe your organization ?
 - Public Owner
 - International Agency
 - NGOs
 - Consultant
 - Implementing Agency
 - Others _____

- 4) What are the types of implemented projects through your organization ?
 - Residential Buildings
 - Public Buildings
 - Industrial Buildings
 - Infrastructure Projects
 - Environmental Projects
 - Others _____

PART (2): PAIRWISE COMPARISON BETWEEN FACTORS

In an attempt to determine the degree of importance of factors affecting the oil/gas pipelines' condition, please kindly fill the tables in the next pages by ticking (✓) in the appropriate box from your point of view.

Example:

In the table below, consider comparing "Pipeline Age" (Criterion X) with "Pipeline Diameter" (Criterion Y) with respect to the "Physical Factors".

PHYSICAL FACTORS											Criterion (Y)	Remarks
Criterion (X)	Degree of Importance									Criterion (Y)		
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		Criterion (Y)	Remarks
Pipeline Age											Pipeline Diameter	
											Wall Thickness	
											Coating Condition	

If you consider that "Pipeline Age" is more important than "Pipeline Diameter" and the degree of this importance is "Strong" then tick (✓) here.

If you consider both "Pipeline Age" and "Pipeline Diameter" have "Equal" importance; then tick (✓) here.

If you consider the "Pipeline Diameter" is more important than "Pipeline Age" and the degree of importance is "Absolute" then tick (✓) here.

The same procedure is then followed when comparing "Pipeline Age" with "Wall Thickness" and "Condition of Interior/Exterior Coating".

1) **Pair wise Comparison Between Factors' Categories with respect to Goal:**

With respect to "Gas Pipeline Condition" how important is criterion "X" or "Y" when compared to each other ?

GAS PIPELINE CONDITION										Criterion (Y)	Remarks
Criterion (X)	Degree of Importance										
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		
Physical Factors										External Factors	
										Operational Factors	

2) **Pair wise Comparison Between Factors with respect to their Categories:**

a) With respect to "Physical Factors" how important is criterion "X" or "Y" when compared to each other ?

PHYSICAL FACTORS										Criterion (Y)	Remarks
Criterion (X)	Degree of Importance										
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		
Pipeline Age										Pipeline Diameter	
										Wall Thickness	
										Coating Condition	

b) With respect to "External Factors" how important is criterion "X" or "Y" when compared to each other ?

EXTERNAL FACTORS										Criterion (Y)	Remarks
Criterion (X)	Degree of Importance										
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		
Crossing of Other Pipelines										Cathodic Protection Effectiveness	
										Marine Route Existence	
										Water Depth	

c) With respect to "Operational Factors" how important is criterion "X" or "Y" when compared to each other ?

OPERATIONAL FACTORS										Criterion (Y)	Remarks
Criterion (X)	Degree of Importance										
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		
Corrosive Impurities										Operating Pressure	
										Flow Rate	

3) Pair wise Comparison Between Factors' Categories with respect to Each OtherThemselves:

a) With respect to "**Physical Factors**" how important is criterion "X" or "Y" when compared to each other ?

PHYSICAL FACTORS										Criterion (Y)	Remarks
Criterion (X)	Degree of Importance										
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		
External Factors										Operational Factors	

b) With respect to "**External Factors**" how important is criterion "X" or "Y" when compared to each other ?

EXTERNAL FACTORS										Criterion (Y)	Remarks
Criterion (X)	Degree of Importance										
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		
Physical Factors										Operational Factors	

c) With respect to "**Operational Factors**" how important is criterion "X" or "Y" when compared to each other ?

OPERATIONAL FACTORS										Criterion (Y)	Remarks
Criterion (X)	Degree of Importance										
	(9) Absolute	(7) Very Strong	(5) Strong	(3) Moderate	(1) Equal	(3) Moderate	(5) Strong	(7) Very Strong	(9) Absolute		
Physical Factors										External Factors	

PART (3): DETERMINING THE SCORE OF FACTORS

In order to determine the condition index; it is required to determine the score of factors. As a result, please kindly fill the table below by identifying for each factor using a quantitative scale ranges from 0 to 10, where "0" represents the worst effect and "10" represents the highest effect on pipe condition.

Example:

In the table below, consider evaluating the "Pipeline Age" factor.

Main Factor	Sub-factors	Unit Of Measure (if applicable)	Qualitative Description (Parameters)	Quantitative Value Range (if applicable)	Quantitative Scale Range (0 – 10)
PHYSICAL	Pipeline Age	Years	Old	35 to 50 years	0 to 3
			Medium	15 to 35 years	4 to 7
			New	0 to 15 years	8 to 10

The "Unit of Measure" can be "Years"

The "Quantitative Value Range" can be "35 to 50 years", "15 to 35 years", and "0 to 15 years" for the "old", "Medium", and "New" parameters respectively.

The "Quantitative Scale Range" can be "0 to 3", "4 to 7", and "8 to 10" for the "old", "Medium", and "New" parameters respectively.

Main Factor	Sub-factors	Unit Of Measure <i>(if applicable)</i>	Qualitative Description (Parameters)	Quantitative Value Range <i>(if applicable)</i>	Quantitative Scale Range (0 – 10)
PHYSICAL	Pipeline Age		Old		
			Medium		
			New		
	Pipeline Diameter		Large		
			Medium		
			Small		
	Wall Thickness		Thick		
			Medium		
			Thin		
	Coating Condition		Good		
			Fair		
			Poor		
EXTERNAL	Cathodic Protection Effectiveness		Good		
			Fair		
			Poor		
	Marine Route Existence		High		
			Medium		
			Low		
	Water Depth		Deep		
			Medium		
			Shallow		
	Crossing of Other Pipelines		Numerous		
			Medium		
			Few		
OPERATIONAL	Corrosive Impurities		High		
			Medium		
			Low		
	Operating Pressure		High		
			Medium		
			Low		
	Flow Rate		High		
			Medium		
			Low		

PART (4): GAS PIPELINES CONDITION INDEX

Finally, it is required to develop a condition index for the gas pipelines from 0 to 10. Therefore, please kindly fill the table below by identifying the following:

- Pipe Condition index value range from 0 to 10
- Qualitative description for each index value range.
- Action required to be taken for each index range

Example:

In the table below, consider evaluating the "Pipe Condition Index Value Range" from (9 to 10)

Condition Index Value Range (0 – 10)	Qualitative Description						Action Required						
	Excellent	Very Good	Good	Moderate	Critical	Others	No Action	Cleaning	Inspection	Lining	Rehabilitation	Replacement	Others
9 to 10													

The "Qualitative Description" can be "Excellent", therefore tick (✓) here.

The "Action Required" can be "No Action", therefore tick (✓) here.

The same procedure can be followed with other ranges from your point of view, e.g. (8 to 9), (7 to 8),...etc.

Condition Index Value Range (0 – 10)	Qualitative Description						Action Required						
	Excellent	Very Good	Good	Moderate	Critical	Others	No Action	Cleaning	Inspection	Lining	Rehabilitation	Replacement	Others

APPENDIX (B)

APPENDIX (B)

PIPELINE PROTECTION, LEAK DETECTION AND MANUFACTURING

Pipelines Protection

Hopkins (2002) says that the pipelines are designed to be protected from the surrounding environment for the following reasons:

- 1) **External Corrosion:** In order to protect a steel pipe for the external corrosion, the pipe must be separated from humid environment like soil or water. There is no standard limit for the corrosion in the design books to allow for a maximum percentage of external corrosion in the pipe like increasing the wall thickness. This is called “corrosion allowance”. So, the external side pipeline is coated with special material like coat tar as a primary protection and a corrosion protection system is the secondary protection.

- 2) **Internal Corrosion:** Unlike the external corrosion, a corrosion allowance is considered to accommodate in service, predictable, corrosion which can be introduced at the design stage. On the other hand, it is more convenient to prevent the internal corrosion for happening in the first place. That is why the pipeline is treated before put to service. That is done by checking the pipeline quality, cleaning the line and mixing chemicals to accommodate any corrosion.

- 3) **External Damage:** Many precautions can be done to protect the pipeline for any damage that is caused by external reasons or third parties. These precautions may include

increasing the wall thickness of the pipeline, using a deeper cover, installing the pipelines away from possible interferences and conducting good communications with third parties including the general public and protective measures such as concrete casings.

Pipeline Operation and Leak Detection

With the advancement to technology in all fields, the newly installed pipelines existing in remote areas are operated automatically by computers at the headquarters of the pipeline company. The pipeline pressure, flow rate and many other parameters at various locations are monitored by these computers which also performs large numbers of computations and send the suitable commands along the pipelines network to control the valves and pumps operation. In some cases, manual operating is needed. These cases may include modifying the automatic operation when different batches of fuels are directed to different temporary storage tanks, or when the system must be shut down or restarted. Since the oil spill can cause big damage environmentally and economically, leak detection systems would be installed in the pipelines network to prevent leakage and to allow for a rapid response in case of a pipeline failure. (Hopkins, The Structural Integrity Of Oil And Gas Transmission, 2002)

There are various types of leak detection systems but the most used are the following:

- 1- **Simple Systems:** As the names suggests, this system involves a member of the staff working near the pipelines to regularly survey the pipelines and looking for any evidence of leakage such as smell, of different in coloration around the pipe. In addition, people living near the pipelines or just passing by can perform this task.

- 2- **Flow Balance:** This method is done by measuring the inputs and outputs of a pipeline. If the outputs are less than the inputs, the supervising staff will conclude a leakage incident.

- 3- **Acoustic Methods:** This method uses the noise as an indication of leakage incidents. The associated noise causes vibrations which have frequencies more than 20 kHz. Transducers can be attached a pipeline to locate the leak accurately by noting signal strength.

- 4- **Pipeline Modeling:** This method propose pipeline modeling to simulate the operating conditions of the pipeline and comparing the actual with the expected conditions all the time. The model which is a mathematical representation of the real life condition. This model is used to calculate the expected pressure; flows etc., and compare them with the actual values. If there is any discrepancy that may imply a leak, a leak alarms goes on. (Hopkins, The Structural Integrity Of Oil And Gas Transmission, 2002)

Pipelines Manufacturing

Pipelines manufacturing can be done using either seamless manufacturing or welded pipelines. Seamless pipelines are formed by drawing a heated solid bar of steel over a piercing rod while welded pipelines are created by rolling a flat steel plate and welding the seam longitudinally. Seamless pipelines are stronger than welded ones because they withstand more pressure since they don't have any seams that can create weak spots but welded pipelines are cheaper to manufacture. (Crestwood Tubulars, 2013). Qatar's pipelines operators use both types of pipelines, seamless and welded with different steel grades starting from grade A to X80. The following table shows the different steel grades and their yield strength. Pipelines with high steel grades are used for offshore pipelines because they have higher yield strength and can withstand more pressure. The problem is that they require special type of welding and they are easily affected by impurities such as H₂S (Mikhail, 2011).