DATA ACQUISITION AND ANALYSIS FOR OFFSHORE GAS PIPELINES CONDITION ASSESSMENT MODEL

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ABSTRACT: Condition assessment of offshore gas pipelines is a significant component in pipeline operations and maintenance. They are used to ensure better decisions for repair and/or replacement and reduce failure possibilities. Therefore, it is valuable to have effective condition assessment of pipelines to prevent failure incidents. Furthermore, current practices of assessing gas pipelines condition can be considered simplified for the intended purpose and mainly depend on experts' opinions in interpreting inspection data where the process is influenced by the human subjectivity and reasoning uncertainty. This will surely lead to decisions lacking thorough and extensive review of the most influential aspects on pipelines condition. The research presented in this paper identifies the most influential factors that affect offshore gas pipelines condition, which are classified into three categories: (1) Physical; (2) External; and (3) Operational. The presented data is collected by conducting interviews and distributing a structured questionnaire among experts and professionals in the Oil and Gas industry in the Gulf region. This data forms the basis used to develop a new evidential reasoning-based methodology in which integrated Analytic Network Process (ANP), Fuzzy Set Theory and Evidential Reasoning (ER) are utilized to develop a meticulous condition assessment model that accounts for interdependency, subjectivity and uncertainty. The model is found to deliver satisfactory outcomes based on real life data.

1. INTRODUCTION

Pipelines are considered as the basic transportation tool for oil and gas products worldwide. They transport various types of products that are worth billions of dollars either offshore or onshore. Also, oil and natural gas is being transported between continents by large diameter pipelines. (Hopkins 2007). These pipelines are much safer and economical than usual methods, like railroads or ships, for transporting crude oil, natural gas, and refined oil products. Despite that, a pipeline accident can cause environmental disasters and economical losses.

The energy worldwide demand is causing the oil and gas industry to increase with time and the fact that the oil and gas pipelines carry hazardous products and operate in various environments leads to the importance of constructing safe and sound pipelines network. Also, regular inspections and maintenance must be provided to ensure the pipelines structural safety and prevent any future failures. 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). Several inspection practices are developed recently such as

Magnetic Flux Leakage (MFL) and Ultrasound (UT) to maintain the safety of operated pipelines. These inspection techniques provide accurate and effective tools to detect any defects in the pipelines that could cause any future failure. Another inspection is the In Line Inspection (ILI) which can detect oil and gas pipeline anomalies. However, regular or periodical inspections are time consuming and cost millions of dollars every year.

This paper discusses the data acquisition and analysis for condition assessment of offshore gas pipelines. Based on the data collected in this research, a model is developed to predict the offshore gas pipeline condition.

Therefore, the research presented in this paper aims to fulfill the following objectives:

1) Identify and study the critical factors affecting the condition of offshore gas pipelines.
2) Acquire, analyze and prepare the available required data for offshore gas pipeline condition assessment model development and implementation.
3) Develop a deterioration curve for offshore gas pipelines in Qatar based on the developed methodology.

2. BACKGROUND

In the recent years, many researches have been carried out to assess infrastructure systems including oil and 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 pipelines' condition rating and their probabilities of future failure. Ren et al. (2012) applied back propagation neural network to predict the corrosion rate of natural gas pipelines. These studies are conducted to develop condition assessments and failure prediction models in order to predict the pipeline condition based on available pipeline data. However, these models were subjective and focused on one type of failure only such as corrosion or third-party failures. In other words, they lack the objectivity in predicting the different failure types and condition of pipelines. Hence, there was a need to develop a more comprehensive condition assessment model for oil and gas pipelines. Therefore, Senouci et al. (2014a) developed a regression and artificial neural network (ANN) models to predict possible failure types for oil and gas pipelines. The model took into consideration the prediction of failure types beside corrosion, such as mechanical, third party, natural hazard, and operational failures. Later, Senouci et al. (2014b) developed another model for the same purpose using fuzzy logic technique which outperformed the regression and ANN techniques. El-Abbasy et al. (2014a) developed a model that assesses the condition of oil and gas pipelines based on several factors including corrosion using both ANP and Monte-Carlo simulation. Consequently, oil and gas pipelines condition prediction models using regression analysis and ANN techniques were developed by El-Abbasy et al. (2014b) and El-Abbasy (2014c), respectively. Zhang et al. (2020) proposed the use of Hidden Markov Models (HMM) for pipeline damage detection utilizing piezoelectric transducers. This method focuses on detecting negative pressure waves generated by leaks, providing a promising approach for early leak detection. Oshingbesan (2022) explored the application of machine learning models for leak detection in natural gas pipelines. The study demonstrated that intelligent models could effectively detect small leaks using basic operational parameters, offering a promising approach to pipeline monitoring. Feo et al. (2022) developed a three-dimensional, three-phase fluid flow numerical model to predict the migration of contaminants resulting from hydrocarbon releases in onshore pipelines. This model aids in minimizing environmental contamination by providing accurate predictions of oil migration trajectories. A recent study by Katser et al. (2023) introduced a method for oil pipeline defect detection using Magnetic Flux Leakage (MFL) data preprocessing combined with a Convolutional Neural Network (CNN) approach. This technique enhances the accuracy of identifying pipeline anomalies.

The data collected in this journal paper is the basis of the developed evidential reasoning-based model by Mosleh et al. (2016) to assess the condition of offshore gas pipeline.

2.1 Analytic Network Process (ANP) and Applicataion

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. In this research, the ANP was chosen over the AHP and other multi-criteria methods because it explicitly accounts for interdependence amonf factors, which are common in pipeline systems. Unlike regression based models, ANP allows expert judgement to guide prioritization while maintaining a structured analytical framework.

3. RESEARCH METHODOLOGY

The presented research methodology, Figure 1, is initiated by performing a comprehensive literature review that involves studying the current practices related to this research, studying the different techniques to be used to develop the condition assessment model, and categorizing and identifying the factors affecting offshore gas pipelines. Consequently, data collection is carried to determine the identified factors' weight of importance throughout interviews and distributed questionnaires. Later on, the ANP module is developed to prioritize the criteria affecting offshore gas pipeline condition which is later integrated with two other modules: FST and ER modules. After that, a condition assessment model for offshore gas pipelines is developed by utilizing and integrating the ANP, FST, and ER modules. Each module is built to serve a specific function. The ANP module, which is the main focus in this journal paper, is first used to determine the factors' mean final global weights. Then the FST module is used to assign the fuzzy thresholds and membership functions for the main model's inputs and output and the ER module is used to determine the degrees of belief for the main model's output which is then defuzzified using the FST module. The developed model is then validated by applying it on existing pipelines in Qatar. Finally, a deterioration curve is plotted in order to check the aging effect on the pipe condition as well as degradation of other factors.

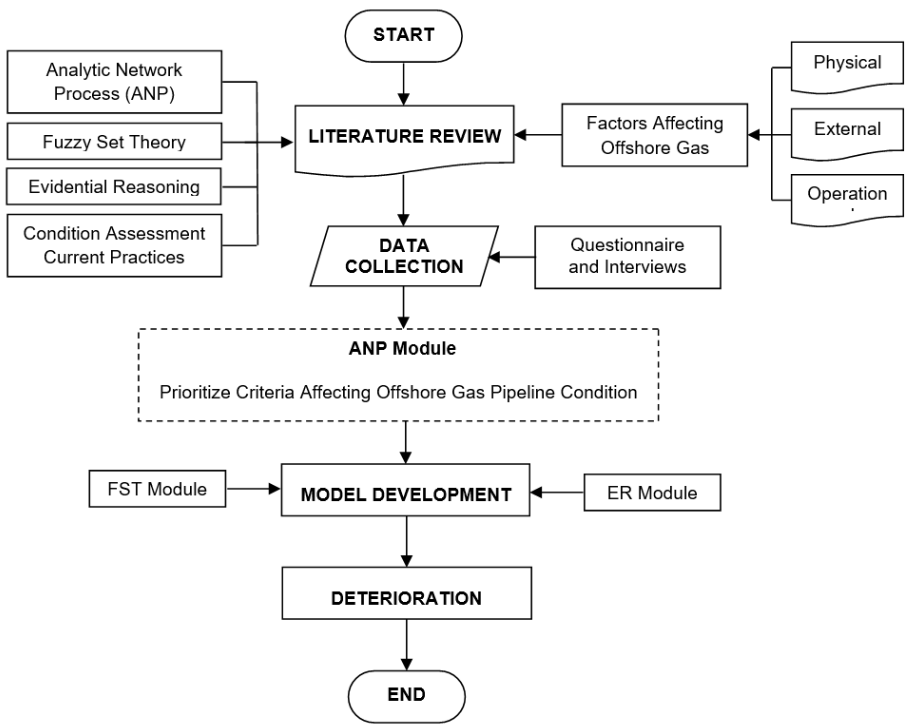

Figure 1: Research Methodology.

4. FACTORS AFFECTING OFFSHORE GAS PIPELINE CONDITION ASSESSMENT

As mentioned earlier, several previous studies are carried to predict the pipelines' condition rating and their probabilities of future failure. However, such studies focused mainly on factors that are related to corrosion or third party (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 a more accurate assessment model. The identification process started by conducting interviews with experts in oil and gas industry and extensive literature review where two separate lists of factors are prepared. Later on, the two factors' list, from literature and from interviews, are compared to each other to come up with a comprehensive list of the most important factors affecting offshore gas pipeline condition. The identified factors are divided into three main groups, namely, Physical, External, and Operational (Mosleh 2014).

4.1 Physical Factors

The physical factors comprise general pipe characteristics such as age, diameter, wall thickness, and applied coating condition.

1) Age: Pipeline usually degrades as it ages, resulting in a pipeline condition decrease.
2) 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.
3) Metal Loss: The pipeline condition decreases when the metal loss as a percentage of the wall thickness increases.
4) Coating Condition: Well-maintained applied coating enhances the pipeline condition.

4.2 External Factors

The external factors deal with the surrounding environmental condition of the pipeline such as number of crossings of other pipelines, the applied cathodic protection, existence of marine routes and the water depth.

1) Crossings: As the number of pipelines crossing over or under the considered pipeline increases, the pipeline becomes less stable, and its condition eventually decreases.
2) Cathodic Protection: It is essential to protect a pipeline against corrosion. As the protection potential decreases, the pipeline condition decreases due to the absence of corrosion resistance.
3) Marine Route Existence: Existence of marine routes near the considered pipeline may lead to third party damage.
4) Water Depth: Pipeline depth under the water greatly affects the pipeline condition. Offshore pipelines experience high external loading of water pressure in deep waters which leads to increased chances of collapse from external force buckle. On the other hand, shallow water pipelines are easily affected by third parties and weather conditions which may create sea currents (Muhlbauer, 2004).

4.3 Operational Factors

The operational factors deal with the adapted operational strategies of these pipeline such as existence of corrosive impurities, the operating pressure and the flow rate.

1) Corrosive Impurities: The existence of high level of corrosive impurities in the transported product severely affect the inner pipe wall resulting in internal corrosion.
2) 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.
3) Flow Rate: This influences 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.

5. DATA COLLECTION

5.1 Structured Questionnaire

A structured questionnaire is distributed among professionals, engineers and managers, in the oil and gas industry in Qatar and similar regions such as Saudi Arabia. This method is used to gather the feedback of practitioners and specialists regarding the most influential factors affecting the condition of offshore gas pipelines in Qatar, their main categories. This questionnaire contains a small introduction about the conducted research along with the most influential factors affecting offshore gas pipelines in Qatar. In addition, it includes pair-wise comparisons between the factors and their main categories. This questionnaire is adapted from a questionnaire designed by El-Abbasy et al. (2014a).

5.2 Pair-wise Comparison between Factors.

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

1) Comparison among 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.

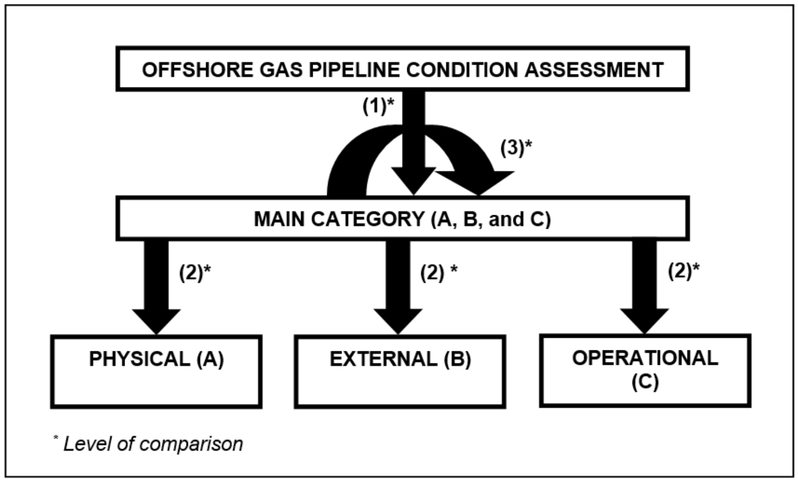

Figure 2: ANP Framework in Distributed Questionnaire.

The pair-wise comparison is designed in a very simple way such that each respondent decides based on his/her own experience the degree of importance of each factor (X) or (Y) over the other(s) with respect to the goal under consideration. Figure 2 which is 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 is 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 is included in this questionnaire to assure that the experts understand the pair-wise comparison and how to fill the questionnaire properly as shown in Figure 3.

Table 1: Acceptable CR Values.

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

5.3 Consistency Ratio

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 1.

5.4 Factors' Weights

The structured questionnaire is designed and distributed to 55 experts from various fields in the oil and gas industry. Only 28 questionnaires are received back and 25 of them are considered in this research (i.e. 45.5% response rate) as shown in Figure 4. The reason for excluding the remaining three questionnaires is that they are inconsistent according to the ANP methodology where the consistency ratio (CR) is calculated to validate each questionnaire response. The respondents are from different departments such as asset management, inspection and operation management, and others. The range of professional experience of the respondents varied from 5 to 20 years in the oil and gas industry. The surveys are mainly collected from Qatar and Saudi Arabia whom almost have similar weather and operating conditions.

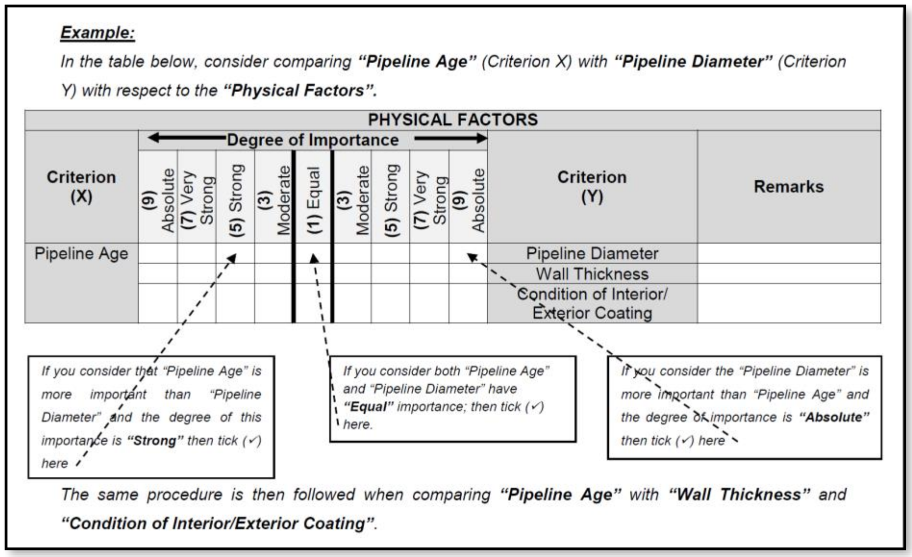

Figure 3: Pair-Wise Comparison.

It is noticed from Table 2 that the majority of questionnaire responses were from inspection and operation mangers 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. Also, the pair-wise comparisons in the distributed questionnaires showed similarity in responses. For example, an inspection manager at a local pipeline operator considered the physical factors of a pipeline are of very strong importance compared to the external and operational factors. This implied that the material, age and other physical characteristics of a pipeline greatly affect its condition. As for deeper evaluation of the pair-wise comparisons, the majority of the responses considered that the pipeline age is more important than its diameter when it comes to assessing a pipeline condition. However, this is not the case when comparing the age factor with the coating condition of the pipeline. This seemed reasonable since the coating condition is a protective measure for the pipeline against deterioration. All the responses followed the same pattern with some differences on the degree of importance.

Table 2: Questionnaire Respondents' Details.

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**

6. ACQUIRED DATA ANALYSIS

The following steps are applied in order to calculate the factors' global weights of the considered factors using ANP technique:

1. Conduct Pairwise Comparisons: Experts use Saaty’s 1-to-9 scale to compare elements at each hierarchy level, creating a pairwise comparison matrix.
2. Estimate Relative Weights: The matrix is normalized, and row averages provide the relative weights for each element.
3. Determine Consistency Ratio (CR): The CR is calculated to validate the reliability of comparisons, ensuring consistency in judgments.

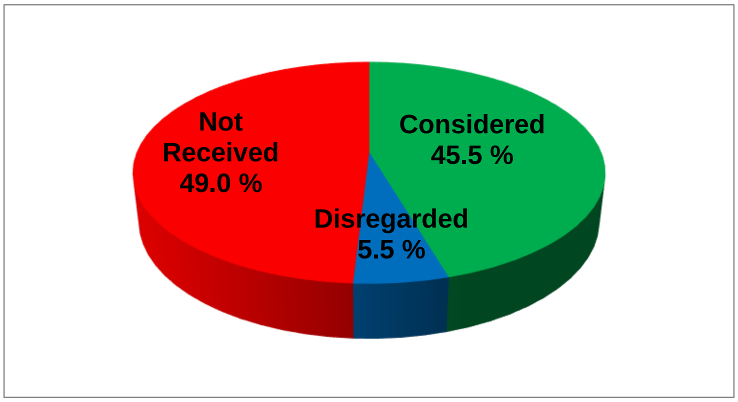

Figure 4: Distributed Questionnaires Summary

4. Develop the Unweighted Super-matrix: Verified comparisons are structured into a two-dimensional super-matrix, showing relationships among elements.
5. Develop the Weighted Super-matrix: Each column in the unweighted super-matrix is normalized so that its total equals 1.
6. Develop the Limit Super-matrix: The weighted super-matrix is raised to a high power until it stabilizes, yielding final local weights.
7. Calculate Final Global Weights: The mean local weights are adjusted to remove the intermediate category level, producing the final global weights, ensuring the sum of all factor weights is 1.

After calculating the mean local weights for all the responses, the final global weights are 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 3, to get the final global weight for "Age" the local weight value of "0.019" is 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 is repeated for the rest of the factors and for all questionnaire responses. Then, the mean values of the global weights for all the factors are calculated.

Table 3: Preliminary and Final Local Weights.

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

By implementing the above steps on each of the 25 responses received, the mean final global weights for the main factors and sub-factors are as shown in Table 4. It can be noticed from the mean final global

weights of the first two main factors (physical with 0.400 and external with 0.447) that they affect the offshore gas pipeline condition almost equally.
The operational main factor has a mean final global weight of 0.153 making it the least affecting. On the sub-factors level, "Cathodic Protection" and " Metal Loss" are the most important sub-factors affecting the offshore gas pipeline condition with mean final global weight values of 0.211 and 0.180, respectively. These two sub-factors are followed by the "Coating Condition" with a mean final global weight of 0.166. These three sub-factors are related to the protection level of the operated pipeline. Thus, they are considered having the highest priority due to the hot weather condition in Qatar and Saudi Arabia which greatly affect the pipelines' physical condition. The "Operating Pressure" and “Water Depth” have moderate effect on the pipeline. Finally, the rest of the factors have low priority or effect on the pipeline condition given that the “flow rate” was the least with a mean final global weight of 0.008.

7. DETERIORATION DATA ANALYSIS

After collecting the required data, a relation between the condition rating and Age factor is 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 is built for the developed model as shown in Figure 5.

Table 4: Final Local and Global Weights.

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

This deterioration curve gives a clearer knowledge of the interrelationships between the pipeline future conditions and the studied factors. Figure 5 shows a polynomial relation between the overall pipe condition and Age. The vertical axis represents the predicted pipe condition while the horizontal axis represents the Age factor.

This deterioration curve presents an inverse relation between the pipe condition and Age. Commonly, the effect of aging on the pipe condition is of negative nature where the pipe condition decreases as age increases. Also, this 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.

8. CONCLUSIONS

A The research presented in this journal paper discusses the acquisition and analysis of the data that is collected to develop a new condition assessment model for offshore gas pipelines using Analytic Network Process (ANP). Several factors are identified in this paper as the most influential factors affecting offshore gas pipeline which are classified into three categories (1) Physical; (2) External; and (3) Operational. The factors identification process is performed by conducting interviews and distributing a structured questionnaire that targets experts and professionals in the oil and gas industry. The collected responses are then analyzed to prioritize the affecting factors, i.e. calculate the factors' weights, in order to rank them from the highest to the lowest affecting factor. The developed ANP module is integrated later with two other modules; FST and ER modules; to develop the condition assessment model. This model accounts for interdependencies and multi-criteria decision analysis under various uncertainties. The developed model is validated using historical inspection data to test its accuracy and usefulness in predicting of offshore gas pipeline condition. The AVP of 97.6% and RMSE of 0.241 clearly demonstrates the model's robustness. Finally, the research findings presented in this paper are expected to useful to academics and practitioners in oil and gas industry in analyzing and assessing the condition of offshore gas pipelines. Also, the presented model can assist in planning and prioritizing the pipelines' future inspections and rehabilitation works.

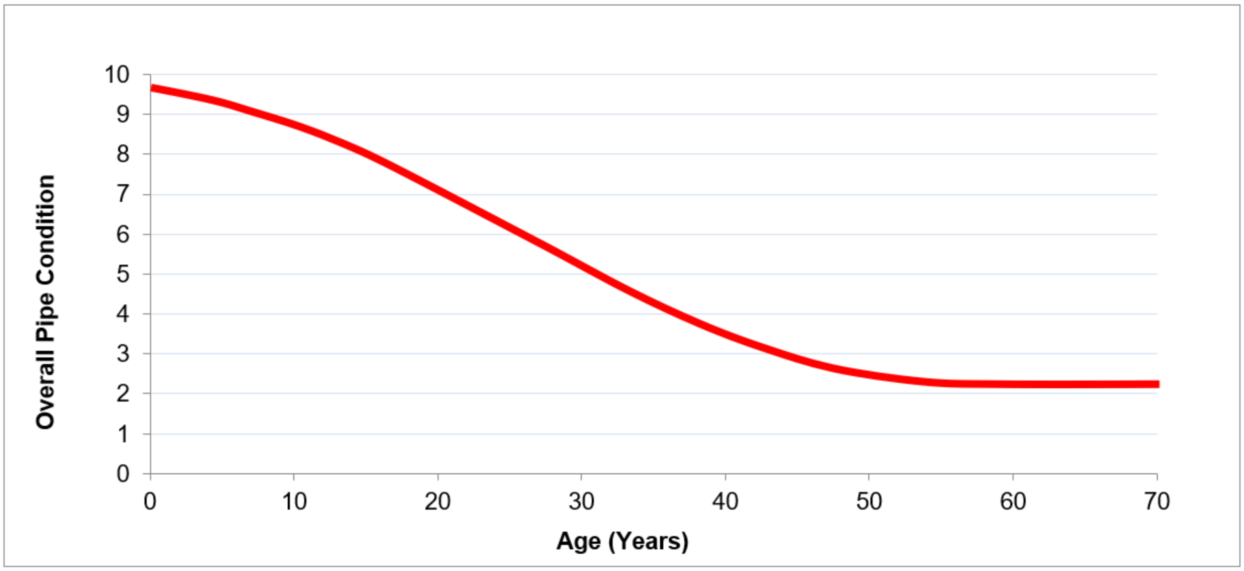

Figure 5: Deterioration Curve.

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