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A condition assessment model for oil and gas pipelines using integrated simulation and analytic network process

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Even though they are safe and economical transportation means of gas and oil products around the world, pipelines can be subject to failure and degradation generating hazardous consequences and irreparable environmental damages. Therefore, gas and oil pipelines need to be effectively monitored and assessed for optimal and safe operation. Many models have been developed in the last decade to predict pipeline failures and conditions. However, most of these models used corrosion features as the sole factor to assess the condition of pipelines. Therefore, the objective of this paper was to develop a condition assessment model of oil and gas pipelines that considers several factors besides corrosion. The proposed model, which uses both analytic network process and Monte Carlo simulation, considers the uncertainty of the factors affecting pipeline condition and the interdependency relationships between them. The performance of the model was tested on an existing offshore gas pipeline in Qatar and was found to be satisfactory. The model will help pipeline operators to assess the condition of oil and gas pipelines and hence prioritise their inspections and rehabilitation requirements.

Keywords: oil and gas pipelines; condition assessment; analytic network process; Monte Carlo simulation

Introduction

Pipelines, which are the backbone of the oil and gas industry, transport millions of dollars of various product types in different environments (i.e. offshore or onshore). The first oil pipeline, which was built in 1879 in Pennsylvania, was 109 miles long and 6 inches in diameter (Kennedy, 1993). At present, more than 60 countries have pipeline networks exceeding 2000 km in length. The USA has the longest pipeline network followed by Russia (Goodland, 2005).

Because they have lower rate of accidents than railways and highways, pipelines represent the safest way to transport petroleum products. However, pipeline accidents can cause catastrophic environmental damage due to oil spillage as well as economic losses due to production interruption (Dey, 2001). According to the Conservation of Clean Air and Water in Europe (CONCAWE) report (Davis, Dubois, Gambardella, & Uhlig, 2010), oil pipeline failures may be due to the following factors: mechanical, operational, corrosion, natural hazards and third-party activity.

In order to maintain pipeline in a safe condition, frequent inspections are mandatory. Several inspection techniques have been developed in the last decade, such as magnetic flux leakage (MFL) and ultrasound. These techniques provide the pipeline industry with accurate and effective tools to detect pipeline anomalies that could lead to failure. Pipeline inspection techniques, especially in line inspection (ILI), clearly detect and/or predict oil pipeline anomalies. However, they are costly and time-consuming. ILI costs vary with the type of inspection, the length and diameter of the pipeline to be inspected, and the type of information processing and reporting required after the inspection (Byrd, McCoy, & Wint, 2004). Low-esolution magnetic flux inspection cost varies between \$600 and \$1200 per mile. However, the cost varies between \$1500 and \$4000 per mile if high resolution or specialty pigs are used (Byrd et al., 2004). Most of the developed models are not considered comprehensive because they consider only one or two factors such as corrosion and third-party activity. Therefore, there is a need for the development of a more comprehensive condition assessment model for oil and gas pipelines.

This research is intended to include other factors/criteria besides corrosion (e.g. operating pressure, diameter and crossings) in the pipeline condition assessment process through questionnaires and to account for the inherited uncertainty in the respondents' view of the criteria weights. The interdependency relationships among influential criteria can create dynamics in the form of cause and effect relationships, which can severely affect the pipeline condition assessment. In order to address these

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issues, the presented research thoroughly identified the main criteria that affect the condition of oil and gas pipelines based on experts' responses to questionnaires. To address the interdependency and uncertainty among criteria, analytic network process (ANP) and Monte Carlo simulation were utilised, respectively. The main objectives of the present study were to (1) identify and study the critical factors affecting the condition of oil and gas pipelines and (2) design a condition assessment model for such pipelines.

Literature review

Significant efforts have been carried out in the last decade to assess the condition of oil and gas pipelines condition and to predict their failure type and their remaining life. Noor, Yahaya, Ozman, and Othman (2010) and Noor, Ozman, and Yahaya (2011) used a semi-probabilistic and deterministic methodologies to predict the remaining strength of submarine pipelines subjected to internal corrosion. Bersani, Citro, Gagliardi, Sacile, and Tomasoni (2010) developed a risk assessment model using historical data from the USA Department of Transportation (DOT) to predict the failure caused by third-party activity. Historical failure data were also used to develop a tool to predict the class of each spillage in oil pipelines using statistical analysis classification and regression tree (Bertolini & Bevilacqua, 2006). Li, Yu, Zeng, Li, and Liang (2009) presented a methodology to predict the corrosion and the remaining life of underground pipelines using a mechanically based probabilistic model that considers the effect of randomness in pipeline corrosion. Monte Carlo simulation technique was used to calculate the remaining life and its cumulative distribution function.

Singh and Markeset (2009) presented a fuzzy logic methodology for the establishment of a risk-based inspection programme for pipelines using estimated corrosion rates. Peng, Zhang, and Chen (2009) developed a fuzzy neural network model, which is based on failure tree and fuzzy computing, to predict the rate of failure of long-distance oil and gas pipelines. Dawotola, VanGelder, and Vrijling (2009, 2011) proposed a combined analytic hierarchy process (AHP) and multi criteria decision analysis model for the design, construction, inspection and maintenance of oil and gas pipelines that proposes an optimal selection strategy based on the probability and consequence of failure.

The AHP was also used by Dey (2001) to develop a model to help decision-makers select a suitable type of inspection or monitoring technique for pipelines. Kumar and Taheri (2007) used a neuro-fuzzy expert system for pipeline condition assessment. Hallen, Caleyo, and Gonzalez (2003) presented a probabilistic analysis framework to evaluate the condition of a corroding pipeline and the evolution of its probability of failure over time. Sinha and Pandey (2002) developed a simulation-based probabilistic fuzzy neural network model to estimate the failure probability of ageing oil and gas pipelines subject to corrosion. Ahammed (1998) presented a probabilistic approach to assess the remaining service life of a pressurised pipeline containing active corrosion defects.

The aforementioned models were either subjective or did not cover all failure causes of oil and gas pipelines. The subjectivity was because the developed models depended only on experts' opinion without consideration of historical data. In other words, they lack the objectivity in predicting all failure types of pipelines. As a result, Senouci, El-Abbasy, Elwakil, Abdrabou, and Zayed (2013) developed regression and artificial neural network (ANN) models to predict possible failure types or causes for oil and gas pipelines. The models took into consideration the prediction of failure types other than corrosion, such as mechanical, third-party activity, natural hazard and operational failures. To overcome subjectivity, the models were built based on historical data collected from a report prepared by CONCAWE in 2010 (Davis et al., 2010). The report covers 38 years of spillage data on European cross-country oil pipelines with particular focus on spillage volume, clean-up and recovery, environmental consequences and incident causes. Later, Senouci, El-Abbasy, and Zayed (in press) developed another model for the same purpose using the fuzzy logic technique and compared its results with those obtained using the previously built regression and ANN models. The results showed that the developed fuzzy-based model outperformed the regression and ANN models with respect to model validity.

Despite the attempts made to predict the failure type of oil pipelines considering causes other than corrosion, there is still a lack in developing pipeline condition assessment models considering factors other than corrosion. For instance, the models developed by Senouci et al. (2013) and Senouci et al. (in press) predict the expected failure type of pipelines, but do not assess the actual condition of such pipelines. On the other hand, the developed condition assessment models mainly addressed factors that cause corrosion or third-party damage failures. Few studies considered other factors besides corrosion and third-party damage, but they did not address the 'interdependency' between different factors' relations and the 'uncertainty' of factors' severity weights.

AHP and ANP

ANP was introduced by Saaty (1996) to overcome the limitations of AHP regarding the assumption of independence between criteria. The AHP establishes decision models through a process that contains both qualitative and quantitative factors. It decomposes a decision problem from a top overall goal to a set of manageable clusters, sub-clusters and so on down to the final level, which usually contains scenarios or alternatives. The clusters or sub-clusters can be attributes, criteria, activities, objectives and etc. The AHP uses pair-wise comparison to assign weights to the elements at the cluster and sub-cluster levels, and finally calculates 'global' weights for the assessment that takes place at the final level. Each pair-wise comparison measures the relative importance or strength of the elements within a cluster by using a ratio scale.

The AHP involves calculating the consistency ratio (CR) to measure how consistent the judgements have been relative to large samples of purely random judgements. If the CR is much in excess of 0.1, the judgements are untrustworthy because they are too close to randomness and the exercise is valueless or must be repeated (Saaty, 1996). A suitable example that shows the main features of the AHP is a model that was built to assess water main conditions by Al-Barqawi and Zayed (2006, 2008). Nevertheless, AHP models assume unidirectional relationships between clusters of different decision levels and between clusters. It is not appropriate for models specifying interdependent relationships to use AHP. The ANP was then developed to enhance the tool's analytical power (Cheng & Li, 2004). It is a generic form of AHP that allows for more complex interdependent relationships among elements. As shown in Figure 1 (Cheng & Li, 2004), interdependence can occur in the following forms:

(1) Uncorrelated elements (i.e. criteria within the same cluster) are connected.
(2) Uncorrelated levels (i.e. different hierarchal levels) are connected.
(3) Dependence of two hierarchal levels is two-way (i.e. bi-directional).

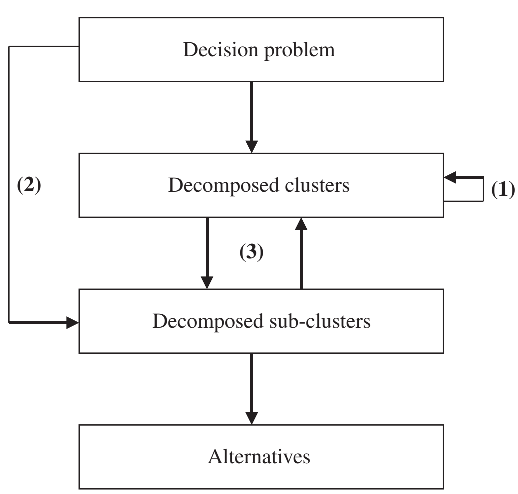

Figure 1. Interdependencies in ANP.

With interdependent influences, the system that consists of cluster and sub-cluster matrices must translate to a supermatrix. This can be achieved by entering the local priority vectors in the supermatrix to obtain global priorities (Cheng & Li, 2004). A supermatrix is developed by incorporating interdependencies through the addition of feedback loops into the model. The supermatrix adjusts the relative importance weights in individual matrices to form a new overall matrix with the eigenvectors of the adjusted relative importance weights. Four main steps are involved in ANP computation as follows (Sarkis, 1999):

(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 supermatrix.
(3) Adjust the values in the supermatrix so that it can achieve column stochastic.
(4) Raise the supermatrix to various powers until weights have converged and remained stable.

Factors affecting oil and gas pipeline condition assessment

The condition assessment factors related to corrosion or third-party features are insufficient to build an accurate model. Therefore, it is essential to identify other factors affecting pipeline condition. The identification process included three major steps. The first step consisted of conducting several interviews with experts in the operation of oil and gas pipelines in Qatar to identify the factors that could impact pipeline condition. The authors prepared a preliminary list of factors from a literature review (API Standard 1160, 2001; Bersani et al., 2010; Muhlbauer, 2004). Finally, a comparison was made between the factors identified from the previous two steps. Both lists of factors were found to be almost the same. Subsequently, the selected factors were divided into three main groups: physical, external and operational as shown in Figure 2.

The physical factors comprise general pipe characteristics such as age, wall thickness, diameter and applied coating condition. The external factors deal with the surrounding environmental condition for the pipeline while the operational factors deal with the adapted operational strategies for the pipelines. It should be noted that the external factors group was further classified based on the pipeline location: onshore-above ground, onshore-underground and offshore pipelines as shown in Figure 2. However, the physical and operational factors groups are applicable for all locations.

Research methodology

The developed methodology, which is shown in Figure 3, started by performing a brief literature review to search for

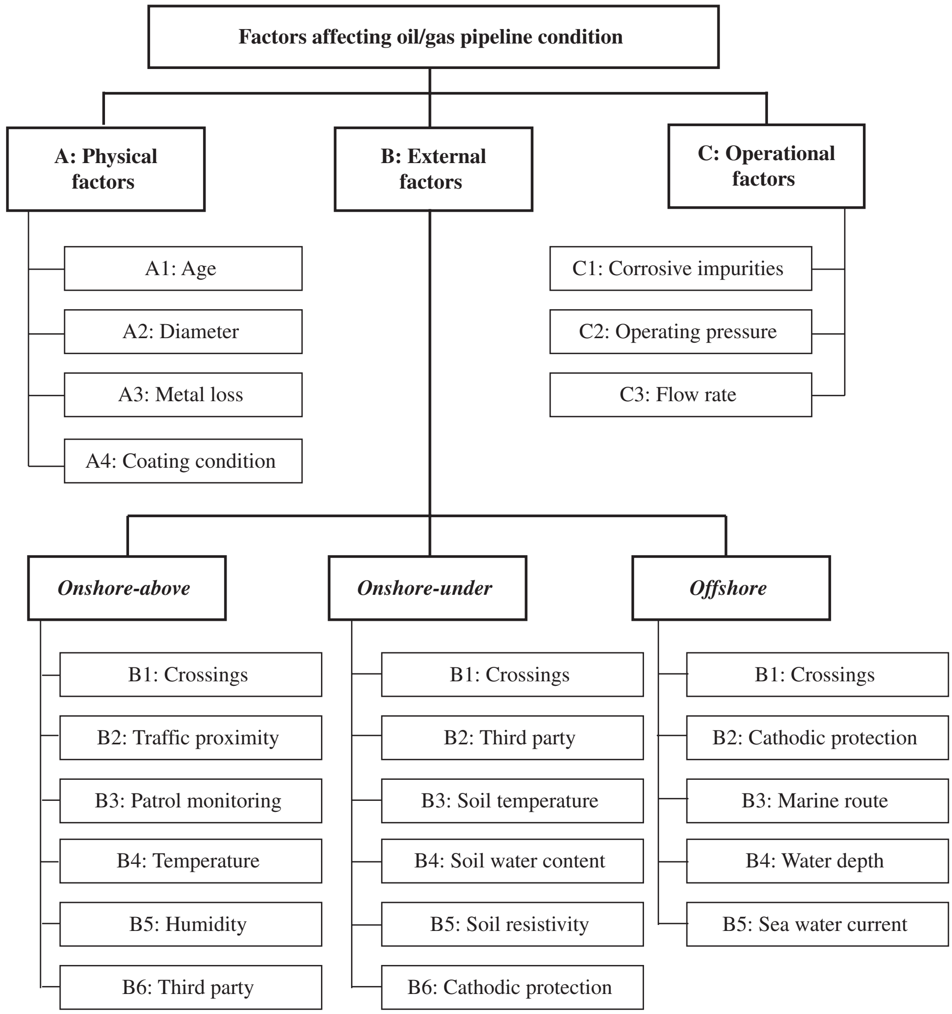

Figure 2. Hierarchy of factors affecting oil/gas pipeline condition.

the different methods and studies used by researchers for oil and gas pipelines condition assessment. The ANP and Monte Carlo simulation techniques are utilised in this research.

The ANP is one of the most widely applied methods in multi-criteria decision making (MCDM) systems which is used in this study to determine the criteria's weight of importance. The ANP approach offers several advantages over other techniques (Sarkis & Sundarraj, 2002). ANP is not as complicated as other MCDM techniques. It has the ability to mix quantitative and qualitative factors into a decision. Unlike other MCDM techniques, ANP provides inner and outer dependencies between criteria and deals with the complex relationship between these criteria covering all element interactions to make accurate predictions.

To determine pipeline condition, a decision should be made to use either a deterministic or probabilistic approach. The choice is usually based on whether the input parameters are deterministic or not. The decision was to use the probabilistic approach with Monte Carlo simulation because the parameters of our model are uncertain. Monte Carlo simulation is a powerful tool that accounts for and quantifies the uncertainty inherited in respondents' weighting of criteria. It is used in this study to determine the pipeline condition through a number of iterations.

Monte Carlo simulation provides the following advantages over deterministic ('single-point estimate') analysis (Monte Carlo Simulation, 2013):

- *Probabilistic results*. The results show not only possible outcomes but also their likelihood.
- *Sensitivity analysis*. With just few cases, a deterministic analysis cannot show which variables impact the outcomes the most. On the other hand, Monte Carlo simulation can easily show which inputs have the biggest impact on bottom-line results.

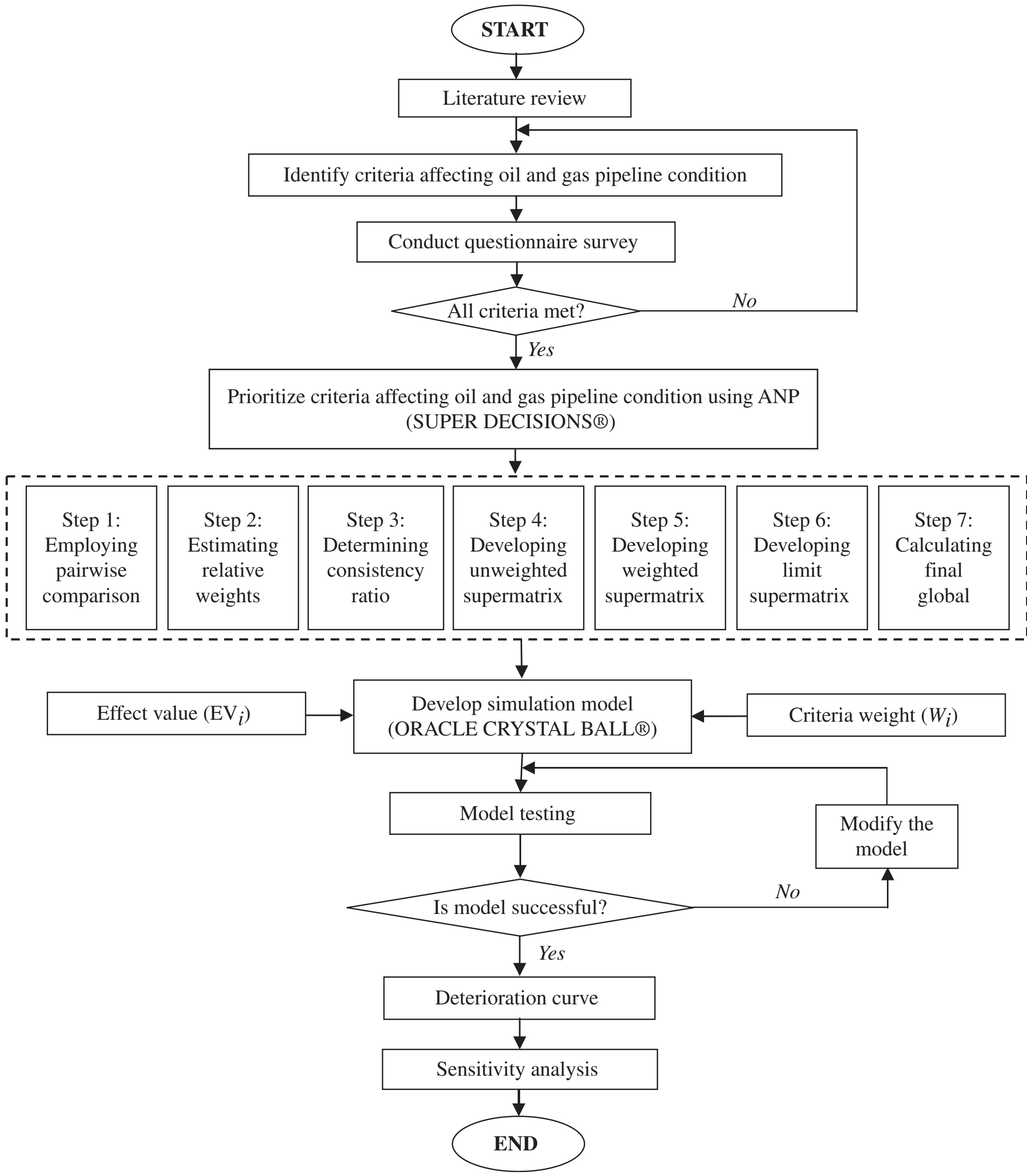

Figure 3. Research methodology.

- *Scenario analysis*. In deterministic models, it is very difficult to model different combinations of values for different inputs to see the effects of truly different scenarios. Using Monte Carlo simulation, it is easy to see exactly which inputs had which values together when certain outcomes occurred. This is invaluable for pursuing further analysis.
- *Correlation of inputs*. In Monte Carlo simulation, it is possible to model interdependent relationships between input variables.

A major disadvantage of Monte Carlo simulation is that increasing the number of iterations increases the number of generated random numbers and the computer processing time.

The criteria needed to increase the efficiency of the assessment process were determined as explained in the previous section. A structured questionnaire survey was then conducted with oil and gas pipeline engineers and operators. The survey was used as a tool to rank the criteria affecting the condition of oil and gas pipelines. In addition, the survey was also used to assign the attribute effect value of each factor on the pipeline condition. A condition rating scale for the pipeline was also defined from the survey. The relative weights of criteria were determined from the received surveys using the ANP technique. The obtained criteria weights along with the determined attribute effect values were then used as input in the developed condition assessment model of oil and gas pipelines.

The condition assessment model was then tested using actual inspection data of an existing gas pipeline in Qatar. A deterioration curve was then constructed with respect to different pipeline ages. Finally, a sensitivity analysis was carried out to examine the effect of changing the weight of importance for each assessment criterion on the model's output. It is worth noting that none of the existing research studies have integrated Monte Carlo simulation and ANP, i.e. interdependencies and uncertainties. This integration considered factors' interdependency (using ANP), made decisions under uncertainty (using simulation) and handled decisions involving large number of variables (using integrated simulation/ANP).

Model development

The proposed simulation model for oil and gas pipeline condition assessment provides the overall condition for either a pipeline segment or a whole pipeline using the following equation:

$$\mathrm{OPC}_j = \sum_{i=1}^{n} \mathrm{EV}_i \times W_i, \qquad (1)$$

where OPC_j is the overall pipeline condition for segment j, EV_i is the attribute effect value for criterion i, W_i is the final global weight of criterion i and n is the number of criterion. It is worth noting that OPC_j, EV_i and W_i are random variables.

The final global weights of criteria are determined using ANP as illustrated in the data analysis and model implementation sections. The pipeline attribute effect value ranges from 0 to 10 for each criterion where 0 indicates pipeline's worst eligibility for this criterion and 10 the best. The model was developed using the Oracle® Crystal Ball software (Oracle Corporation, Redwood Shores, CA, USA). The Monte Carlo method was used to randomly generate input variables and accordingly assess the value(s) of outputs. Four steps were used in order to build the proposed simulation model for the present research:

(1) The criteria and sub-criteria affecting oil and gas pipeline condition assessment were identified and analysed. The final global weights (W_i) of criteria and sub-criteria were obtained from the questionnaires received and their probability distributions were fitted.
(2) The attribute effect value (EV_i) for each criterion was determined using a value from 0 to 10 and its probability distribution was fitted based on the collected data.
(3) Equation (1) was used to determine the overall pipeline condition (OPC_j).
(4) The developed model in step 3 was simulated for several iterations using Monte Carlo simulation in order to assess the pipeline condition.

Data collection

A list of the most influential factors that affect the condition of pipelines was first prepared from the open-ended questionnaires (unstructured) that were completed by experts. The list was then compared with what is available in the literature. A structured questionnaire was also designed and sent to a sample of 55 experts in the integrity management of oil and gas pipelines. Out of the 55 questionnaires sent, 28 completed questionnaires were received out of which only 25 were taken into consideration, which represents 45.5% of the total sample. The respondents were asset managers, inspection managers, operation managers and onshore/offshore inspection engineers. It should be noted that 22 of the respondents were inspection/operation managers with a technical experience of more than 20 years. It should also be noted that the surveys were mainly collected from the Middle-East region, mostly from Qatar and Saudi Arabia. The structured questionnaire was divided into the following three parts.

Part 1: Criteria's weights determination

The main objective of this part is to identify the importance of each criterion in the assessment process using a pair-wise comparison method. This comparison was conducted on three levels as follows:

(1) Comparison between main criteria with respect to oil/gas pipeline condition.
(2) Comparison between sub-criteria within each main criterion.
(3) Comparison between main criteria with respect to each other.

It is worth noting that the third level creates an inner interdependency. The three levels can also be illustrated as shown in Figure 4(a). The pair-wise comparison for each level was designed in a very simple way such that each respondent decides based on his/her own experience the degree of importance of each criterion (X) or (Y) over the other(s) with respect to the goal under consideration. The degree of importance was scaled according to Saaty's scale (1996) from 1 to 9. An assigned value of '1' indicates that there is no significant importance of a criterion over the other, while a value of '9' indicates that there is an absolute importance for a criterion over the other.

For example, if we are considering 'level one' comparison, as shown in Table 1(a), and the respondent sees that the 'physical factors' has a very strong importance over the 'external factors' with respect to 'oil/gas pipeline condition', he/she should just check the appropriate box that shows such comparison. The same method is repeated for the 'operational factors'. It can be observed that one more comparison is not listed in the

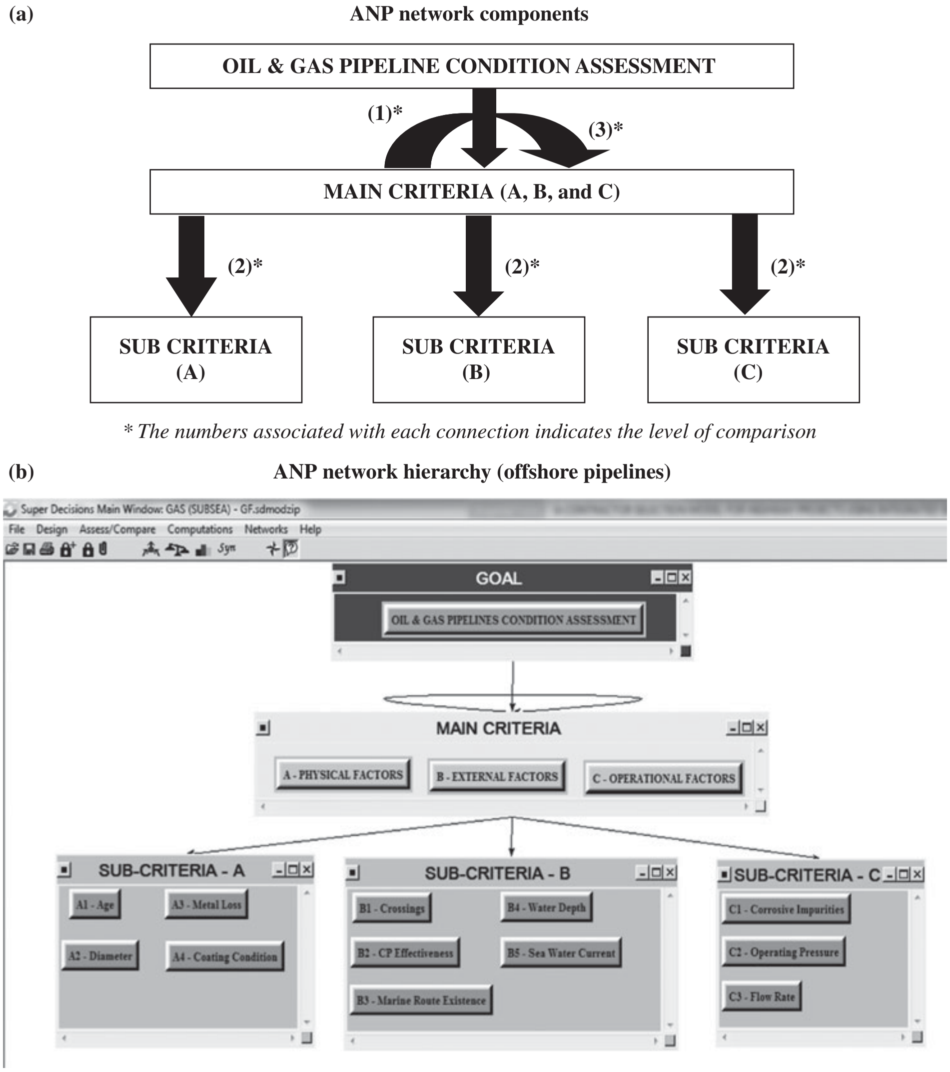

Figure 4. ANP network for oil and gas pipeline condition assessment.

table, i.e. 'external with operational'. This comparison is determined using the comparisons already made between the 'physical factors' and the 'external factors' as well as between the 'physical factors' and 'operational factors' as shown in Table 1(a). In other words, this table is also used to determine the comparison between other main criteria and sub-criteria.

Part 2: Attribute effect value determination

Each sub-factor has various attributes with different effects on oil/gas pipelines condition. For example, the 'metal loss' sub-factor has attributes that can vary in value from 0% to 100% of the wall thickness. These attributes do not have the same effect on the pipeline condition. Therefore, in this part of the questionnaire, the expert was requested to assign the attribute effect value for each value range category of each sub-factor using a scale from 0 to 10, where '0' represents the lowest attribute value and '10' represents the highest attribute value. A sample for this part of questionnaire is shown in Table 1(b).

Part 3: Overall pipeline condition identification

As no standard condition rating scale was found in the literature for oil and gas pipelines, this last part of the questionnaire was intended to develop a preliminary condition rating scale. The experts were asked to suggest a condition rating scale from '0' to '10', where '0' indicates that the pipeline is at its worst condition and '10' at its best condition. Experts were asked to suggest a suitable linguistic term to describe the pipeline condition associated with each scale. In addition, experts were asked to identify the required action to be taken for each numeric and linguistic category, as shown in Table 1(c).

Table 1. Questionnaire form sample.

(a) Part 1: Criteria's weights determination

Oil/gas pipeline condition

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	Criterion (Y)
Physical factors	√									External factors
		√								Operational factors

(b) Part 2: Attribute effect value determination

Main factor	Sub-factors	Unit of measure	Qualitative description (parameters)	Quantitative value range	Effect value on pipeline condition (0–10)
Physical	Pipeline age	(Years)	Old	(36)–(50)	(0)–(3)
			Medium	(16)–(35)	(4)–(7)
			New	(0)–(15)	(8)–(10)

(c) Part 3: Overall pipeline condition identification

	Qualitative description						Action required						
Overall pipeline condition (0–10)	Excellent	Very good	Good	Moderate	Critical	Others	No action	Cleaning	Inspection	Lining	Rehabilitation	Replacement	Others
10	√						√						
9		√						√					
8		√						√	√				

Finally, in order to test the model, a full inspection data for an existing gas pipeline in Qatar were collected as described later in the Model testing section.

Data analysis and model implementation

Weight (W_i) determination for criteria and sub-criteria

The steps of ANP process were followed in order to determine the final global weights of assessment criteria using the data collected from questionnaires. The implementation of the ANP process, for each of the 25 responses received, is briefly described using the following steps.

Step 1: Employing the pair-wise comparisons

The elements of each level of network hierarchy are rated using the pair-wise comparison according to Saaty's scale of measurement mentioned earlier. A sample of the pair-wise comparison questionnaire is shown in Table 1(a). After all elements are compared with the priority scale pair by pair, a paired comparison matrix is developed.

Step 2: Estimating relative weights

After the pair-wise comparison matrix is developed, a vector of priorities in the matrix is calculated and then normalised to a sum of 1.00 or 100%. This is done by dividing the elements of each column of the matrix by the sum of that column (i.e. normalising the 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.

Step 3: Determining CR

As humans are sometimes inconsistent in answering questions, CR is used to validate the results and measure the consistency in the pair-wise comparison process. Saaty (1994) has set acceptable CR values for different sizes of matrices as follows: (1) CR $\leq$ 0.05 for a 3 $\times$ 3 matrix, (2) CR $\leq$ 0.08 for a 4 $\times$ 4 matrix and (3) CR $\leq$ 0.1 for larger matrices. The CR values were calculated for all matrices, which showed that all of them were consistent.

Step 4: Developing the unweighted supermatrix

With interdependent influence, the system consisting of cluster and sub-cluster matrices is translated into a two-dimensional supermatrix. The unweighted portion of the supermatrix, which is shown in Table 2 for one of the questionnaire responses for 'offshore oil pipelines', is constructed from the priorities (relative weights) derived from the different pair-wise comparisons that were done in the previous steps. The nodes, which are grouped by the clusters they belong to, are the labels of rows and columns of the supermatrix. The entire supermatrix is not presented due to paper-size limitations. Therefore, only the main criteria part in the column side is presented against main

Table 2. Portions of various types of supermatrix (offshore oil pipelines).

	Unweighted supermatrix				Weighted supermatrix				Limit supermatrix			
		Main criteria				Main criteria				Main criteria		
With respect to	Goal	A	B	C	Goal	A	B	C	Goal	A	B	C
Goal	0	0	0	0	0	0	0	0	0	0	0	0
Main criteria												
A	0.778	0	0.875	0.167	0.778	0	0.438	0.083	0.212	0.212	0.212	0.212
B	0.111	0.875	0	0.833	0.111	0.438	0	0.417	0.232	0.232	0.232	0.232
C	0.111	0.125	0.125	0	0.111	0.063	0.063	0	0.056	0.056	0.056	0.056
Sub-criteria (A)												
A1	0	0.093	0	0	0	0.047	0	0	0.020	0.020	0.020	0.020
A2	0	0.036	0	0	0	0.018	0	0	0.008	0.008	0.008	0.008
A3	0	0.435	0	0	0	0.218	0	0	0.092	0.092	0.092	0.092
A4	0	0.435	0	0	0	0.218	0	0	0.092	0.092	0.092	0.092
Sub-criteria (B)												
B1	0	0	0.043	0	0	0	0.021	0	0.010	0.010	0.010	0.010
B2	0	0	0.368	0	0	0	0.184	0	0.085	0.085	0.085	0.085
B3	0	0	0.197	0	0	0	0.098	0	0.046	0.046	0.046	0.046
B4	0	0	0.197	0	0	0	0.098	0	0.046	0.046	0.046	0.046
B5	0	0	0.197	0	0	0	0.098	0	0.046	0.046	0.046	0.046
Sub-criteria (C)												
C1	0	0	0	0.265	0	0	0	0.133	0.015	0.015	0.015	0.015
C2	0	0	0	0.063	0	0	0	0.031	0.004	0.004	0.004	0.004
C3	0	0	0	0.672	0	0	0	0.336	0.037	0.037	0.037	0.037

and sub-criteria in the row-side part of the matrix as shown in Table 2.

Step 5: Developing the weighted supermatrix

The weighted supermatrix is obtained by dividing each entry in each row in the unweighted supermatrix by the total summation of its relative intersecting column. For example, the summation of column B in Table 2, unweighted supermatrix, is equal to 2.00 and the corresponding entry in row C is 0.125; therefore, dividing those values by each other results in the weighted value of this entry gives 0.063. This value is entered into the intersecting cell of row C and column B in the Table 2, weighted supermatrix. Similarly, the other corresponding values of the weighted supermatrix are determined as shown in Table 2. The summation of each column in the weighted supermatrix is 1.0. It should be noted that the 'goal' values in the weighted supermatrix remained the same as their summation in the unweighted supermatrix is equal to 1.0.

Step 6: Developing the limit supermatrix

After entering the sub-matrices into the supermatrix and completing the column to determine the weighted supermatrix, it is then raised to sufficient large power until convergence occurs in order to obtain the limit supermatrix as shown in Table 2. The reason for that is, to capture overall influence (dominance), all transitivities of different length must be considered. These are represented by the corresponding power of the supermatrix. For each such matrix, the influence of an element (criterion) on all others is obtained by taking the sum of its corresponding row. When this is done for all criteria, a vector of influence from that matrix is obtained. The sum of these vectors gives the overall influence (Figueira, Greco, & Ehrgott, 2005). It is noted that the number in all columns of limit supermatrix in Table 2 are identical due to convergence. As a reminder, the results shown in Table 2 are for only one of the responses received. Therefore, the limiting power value was different for each response as the pair-wise comparisons were not identical for the received responses which lead to different unweighted and weighted supermatrices.

Step 7: Calculating final global weights

From the limit supermatrix, the final weights can be obtained by proportioning the elements of each cluster. For example, as shown in Table 2, the cluster of 'main criteria' has the physical, external and operational factors with values of 0.212, 0.232 and 0.056, respectively, which results in a total value of 0.50. Therefore, their final weights were calculated by dividing each of these values by 0.50. The same procedure was followed with each sub-criteria cluster to obtain the local weight which was then multiplied by the final weights of each corresponding main criteria in order to obtain the global weight. The average main and sub-criteria's final local and global weights are shown in Table 3 for the collected data from questionnaire responses.

For instance, as shown in Table 3, the average global weight for the main criterion 'physical factors' was 0.4, and the average local weight of the sub-criterion 'metal loss' was 0.459. Therefore, by multiplying those two values by each other (i.e. 0.4×0.459), the final global weight for the 'metal loss' factor was determined, i.e. 0.184 (18.4%). The final weights listed in Table 3 are applicable to both oil and gas pipelines except for the operational factors. It can be observed that more weight is assigned to the 'flow rate' sub-factor in the oil pipeline than in the gas, while the opposite is for the 'operating pressure' sub-factor.

Super Decisions® software (Creative Decisions Foundation, Pittsburgh, PA, USA) was used to facilitate the application of the above-discussed steps. Simply, the network's components and relations were identified as shown in Figure 4(b). The pair-wise comparisons for each level were then entered. The model can be used for assessing more than one pipeline at a time.

Probability fitting for weights of criteria and sub-criteria

Table 4 summarises the statistical information for the different distributions selected for each criterion. Statistical tests, such as the chi-squared, the Anderson–Darling (A–D) and the Kolmogorov–Smirnov (K–S) tests, were performed to check whether the fitted distributions are statistically sound based on the maximum *P*-value for each criterion's distributions. Tables 3 and 4 highlight that for 'onshore-above ground' pipelines, A3 (metal loss), A4 (coating condition) and B6 (third party) are the most important criteria, with mean weight values of 0.184, 0.164 and 0.113, respectively. The mean weight values of A3, A4 and B6 form 0.461 (46.1%) of the total weight of all criteria.

For the 'onshore-underground' pipelines, the criterion B6 (cathodic protection) received a higher weight (0.145) than the criterion B2 (third party) in the same category. This resulted in a combined total weight of all criteria of 0.493 (49.3%) along with criteria A3 and A4. For the 'offshore' pipelines, 'cathodic protection' received a higher weight (0.189) than that for the 'onshore-underground' pipelines forming a combined total weight of all criteria of 0.537 (53.7%) along with criteria A3 and A4. It can be noticed that the only difference between the oil and gas pipelines factors' weight distribution was in criteria C2 (operating pressure) and C3 (flow rate), the latter being more important for oil pipelines and vice versa

Table 3. Average final local and global weights for main and sub-criteria.

Main criteria	Global weight (%)	Sub-criteria	Local weight (%)	Global weight (%)
(A) Physical factors	40.0	A1: Age	9.9	4.0
		A2: Diameter	3.4	1.3
		A3: Metal loss	45.9	18.4
		A4: Coating condition	40.8	16.3
(B) External factors	44.7	Onshore (above)		
		B1: Crossings	4.0	1.8
		B2: Traffic proximity	18.5	8.3
		B3: Patrol monitoring	20.9	9.3
		B4: Temperature	16.0	7.1
		B5: Humidity	15.5	6.9
		B6: Third party	25.1	11.3
		Onshore (under)		
		B1: Crossings	4.1	1.9
		B2: Third party	22.5	10.2
		B3: Soil temperature	12.5	5.6
		B4: Soil water content	11.5	5.0
		B5: Soil resistivity	16.8	7.5
		B6: Cathodic protection	32.6	14.5
		Offshore		
		B1: Crossings	5.2	2.3
		B2: Cathodic protection	42.2	18.9
		B3: Marine route	17.4	7.8
		B4: Water depth	17.9	8.0
		B5: Sea water current	17.3	7.7
(C) Operational factors	15.3	C1: Corrosive impurities	22.2[a]/19.9[b]	3.3[a]/3.1[b]
		C2: Operating pressure	5.2[a]/74.6[b]	0.8[a]/11.4[b]
		C3: Flow rate	72.6.0[a]/5.5b	11.2.0[a]/0.8[b]

[a] Oil pipelines.
[b] Gas pipelines.

for gas pipelines. Finally, criterion A2 (diameter) was found to be the least important criterion with a weight of 0.014 (1.4%).

Attributes effect value (EV_i) determination

In order to determine the pipeline's attribute effect value for each criterion, the results obtained from 'part 2' of the questionnaire distributed, shown in Table 1(b), are to be applied. The average range of each criterion's attribute actual quantitative value and its corresponding attribute effect value was calculated as shown in Table 5. In addition, the statistical characteristics of the attribute effect values of the factors used in the model implementation are shown in Table 6.

Overall pipeline condition (OPC_j) determination

The last part of the model implementation is to determine the overall pipeline condition. This is done by applying Equation (1) for all pipelines or pipeline's segments under study simultaneously using the developed simulation model. The model simply runs by multiplying each pipeline's attribute effect value for each criterion by the final global weight of the corresponding criterion, which is obtained from the ANP implementation. The results of these multiplications are then added up to determine the overall pipeline condition for each pipeline or pipeline's segment. This process is repeated for 1000 iterations (simulations) and the parameters of the stopping criterion were set to 5% accuracy ($\epsilon = 0.05$) with 99% confidence level ($\alpha = 0.01$). It shows the robustness of Monte Carlo simulation algorithm where in each iteration a random final global weight is chosen based on the probability distribution defined for each criterion.

This randomness ensures that uncertainty is considered and the mean value of the overall pipeline condition (OPC_j) obtained throughout the iterations is the final condition value for each pipeline. Finally, based on the condition value, the operator can decide on what actions can be taken towards the pipe with the aid of the results obtained from 'part 3' of the questionnaire (see Table 1(c)) as shown in Table 7. However, the required action shown in Table 7 is considered as preliminary to guide the pipeline operator towards the expected final actual action. The determination of the final actual action requires a further analysis of the pipeline condition, which is outside the scope of this study.

Table 4. Summary of statistical analysis results for criteria weights.

						χ^2 test		A–D test		K–S test	
Criterion	Distribution	Mean weight (μ)	Standard deviation (σ)	Variance (σ^2)	Standard error (ε)	Test value	*P*-value	Test value	*P*-value	Test value	*P*-value
A1	Uniform	0.040	0.003	1.1E-05	0.002	26.800	0.001	2.073	0.042	0.250	0.050
A2	Normal	0.014	0.001	9.4E-07	0.001	1.200	0.549	0.788	0.034	0.154	0.126
A3	Normal	0.184	0.030	0.001	0.001	1.200	0.549	0.855	0.023	0.219	0.001
A4	Weibull	0.164	0.032	0.001	0.004	8.400	0.004	1.242	0.036	0.246	0.019
Onshore (above)											
B1	Gamma	0.018	0.004	1.6E-05	0.003	18.800	0.001	1.235	0.036	0.213	0.069
B2	Max extreme	0.083	0.034	0.001	0.003	4.000	0.135	0.789	0.038	0.155	0.117
B3	Uniform	0.093	0.037	0.001	0.002	5.200	0.074	1.218	0.163	0.293	0.012
B4	Min extreme	0.071	0.042	0.002	0.001	3.600	0.165	1.324	0.001	0.206	0.001
B5	Uniform	0.069	0.015	2.0E-04	0.001	20.800	0.001	1.818	0.061	0.265	0.032
B6	Logistic	0.113	0.053	0.003	0.001	2.800	0.247	1.493	0.001	0.193	0.001
Onshore (under)											
B1	Lognormal	0.019	0.007	4.2E-05	0.004	19.200	0.001	1.805	0.001	0.276	0.001
B2	Min extreme	0.102	0.049	0.002	0.003	12.400	0.002	1.174	0.001	0.184	0.023
B3	Uniform	0.056	0.028	0.001	0.002	3.200	0.202	1.636	0.082	0.258	0.041
B4	Gamma	0.050	0.029	0.001	0.004	5.200	0.023	3.775	0.001	0.331	0.001
B5	Logistic	0.075	0.038	0.001	0.004	4.400	0.111	1.343	0.001	0.183	0.001
B6	Uniform	0.145	0.033	0.001	0.002	8.000	0.018	0.762	0.370	0.215	0.133
Offshore											
B1	Max extreme	0.023	0.008	5.9E-05	0.001	6.400	0.041	1.545	0.001	0.199	0.001
B2	Uniform	0.189	0.040	0.002	0.002	15.200	0.001	2.279	0.030	0.346	0.001
B3	Uniform	0.077	0.033	0.001	0.002	6.800	0.033	0.893	0.287	0.212	0.144
B4	Logistic	0.080	0.031	0.001	0.003	9.200	0.010	1.153	0.001	0.160	0.036
B5	Uniform	0.077	0.034	0.001	0.001	7.200	0.027	1.787	0.065	0.257	0.041
Oil pipeline											
C1	Gamma	0.033	0.009	7.5E-05	0.001	13.200	0.001	1.268	0.028	0.221	0.044
C2	Gamma	0.008	0.003	6.3E-06	0.002	10.800	0.001	1.584	0.029	0.206	0.161
C3	Logistic	0.112	0.035	0.001	0.003	8.000	0.018	0.960	0.001	0.221	0.001
Gas pipeline											
C1	Normal	0.031	0.011	1.0E-04	0.003	8.000	0.018	1.950	0.001	0.301	0.001
C2	Gamma	0.114	0.031	0.001	0.002	8.000	0.005	1.521	0.011	0.217	0.051
C3	Max Extreme	0.008	0.002	5.7E-06	0.004	4.000	0.135	0.685	0.072	0.149	0.156

Table 5. Average attributes effect value.

Sub-factor	Qualitative description	Attribute quantitative value range	Attribute effect value on pipeline condition	Sub-factor	Qualitative description	Attribute quantitative value range	Attribute effect value on pipeline condition
Age (years)	Old	36–55	0–3	Soil water content (%)	High	56–100	0–3
	Medium	16–35	4–7		Medium	26–55	4–7
	New	0–15	8–10		Low	0–25	8–10
Diameter (inches)	Large	27–48	8–10	Soil resistivity (Ohm-cm)	High	>15,000	9–10
	Medium	14–26	4–7		Medium	1001–15,000	3–8
	Small	1–12	0–3		Low	0–1000	0–2
Metal loss (%)	Low	0–25	8–10	Cathodic protection (mV)	Poor	−600–700	0–3
	Medium	26–65	4–7		Fair	− 701–900	4–7
	High	66–100	0–3		Good	−901–1300	8–10
Coating condition (%)	Good	76–100	8–10	Marine route existence (%)	High	66–100	0–3
	Fair	36–75	4–7		Medium	36–65	4–6
	Poor	0–35	0–3		Low	0–35	7–10
Traffic proximity (m)	Close	0–3	0–4	Water depth (m)	Deep	41–60	4–6
	Medium	4–6	5–7		Medium	11–40	7–10
	Far	7–14	8–10		Shallow	0–10	0–3
Patrol monitoring (%)	High	71–100	8–10	Sea water current (m/sec)	High	NA	NA
	Medium	31–70	4–7		Medium	NA	NA
	Low	0–30	0–3		Low	NA	NA
Temperature (% of design)	High	76–100	0–4	Crossings (#)	Numerous	>5	0–2
	Medium	36–75	7–10		Medium	3–5	3–7
	Low	0–35	0–3		Few	0–2	8–10
Humidity (%)	High	71–100	0–3	Corrosive impurities (%)	High	61–100	0–3
	Medium	31–70	4–7		Medium	26–60	4–7
	Low	0–30	8–10		Low	0–25	8–10
Third party involvement (%)	High	71–100	0–3	Operating pressure (% of design)	High	76–100	0–3
	Medium	31–70	4–7		Medium	41–75	4–7
	Low	0–30	8–10		Low	0–40	8–10
Soil temperature (% of design)	High	76–100	0–4	Flow rate (% of design)	High	81–100	0–3
	Medium	36–75	7–10		Medium	56–80	8–10
	Low	0–35	0–3		Low	0–55	4–6

Table 6. Summary of statistical analysis results for attributes effect value.

Sub-factor	Qualitative description	Range	Statistical parameters			
			Mean EV (μ)	Variance (σ^2)	Standard deviation (σ)	Standard error (ε)
Age	Old	Min	0.000	0.000	0.000	0.000
		Max	3.080	0.660	0.812	0.163
	Medium	Min	4.040	0.660	0.812	0.163
		Max	6.760	0.273	0.523	0.105
	New	Min	7.760	0.273	0.523	0.105
		Max	10.000	0.000	0.000	0.000
Diameter	Small	Min	0.000	0.000	0.000	0.000
		Max	3.000	0.000	0.000	0.000
	Medium	Min	4.000	0.000	0.000	0.000
		Max	6.830	0.150	0.388	0.081
	Large	Min	7.830	0.150	0.388	0.081
		Max	10.000	0.000	0.000	0.000
Metal loss	High	Min	0.000	0.000	0.000	0.000
		Max	3.040	0.911	0.955	0.195
	Medium	Min	4.040	0.911	0.955	0.195
		Max	7.500	0.609	0.780	0.159
	Low	Min	8.500	0.609	0.780	0.159
		Max	10.000	0.000	0.000	0.000
Coating condition	Poor	Min	0.000	0.000	0.000	0.000
		Max	3.480	1.260	1.123	0.225
	Fair	Min	4.480	1.260	1.123	0.225
		Max	7.000	0.000	0.000	0.000
	Good	Min	8.000	0.000	0.000	0.000
		Max	10.000	0.000	0.000	0.000
Crossings	Numerous	Min	0.000	0.000	0.000	0.000
		Max	2.440	0.261	0.511	0.121
	Medium	Min	3.440	0.261	0.511	0.121
		Max	7.110	0.105	0.323	0.076
	Few	Min	8.110	0.105	0.323	0.076
		Max	10.000	0.000	0.000	0.000
Cathodic protection	Poor	Min	0.000	0.000	0.000	0.000
		Max	3.048	0.148	0.384	0.084
	Fair	Min	4.048	0.148	0.384	0.084
		Max	7.000	0.100	0.316	0.069
	Good	Min	8.000	0.100	0.316	0.069
		Max	10.000	0.000	0.000	0.000
Operating pressure	High	Min	0.000	0.000	0.000	0.000
		Max	3.050	0.682	0.826	0.185
	Medium	Min	4.050	0.682	0.826	0.185
		Max	7.050	0.050	0.224	0.050
	Low	Min	8.050	0.050	0.224	0.050
		Max	10.000	0.000	0.000	0.000

Table 7. Overall pipeline condition numeric and linguistic scale.

Overall pipeline condition	Qualitative description	Required action
10	Excellent	No action
9	Excellent	Cleaning
8	Very good	Cleaning + inspection
7	Good	Cleaning + inspection
6	Good	Inspection + lining
5	Moderate	Inspection + lining
4	Moderate	Lining + rehabilitation
3	Critical	Rehabilitation
2	Very critical	Replacement
1	Partial failure	Replacement
0	Full failure	Replacement

Model testing

A full inspection data for an existing 12-inch diameter gas pipeline in Qatar were collected for testing the developed model. The pipe was constructed in 1990 with a total length of 211 km (77 km offshore and 134 km onshore). In Qatar, the inspections of offshore pipelines usually take place externally and internally for the whole pipeline length. The inspection time intervals vary from 6 months for ageing pipelines to 10 years for relatively new pipelines. The inspection data collected were only for the offshore segment. Two inspection data-sets carried in 1996 and 2004 were received. The data included reports and excel sheets obtained from MFL for the internal inspection. While for the external inspection, remotely operated vehicle and cathodic protection-monitoring system reports were used. Both internal and external inspections, which were performed in the years 1996 and 2004, cover the whole length of the offshore pipeline.

The main objective was to assess the condition of this pipeline for each inspection year using the developed model and compare it with the actual expert assessment. In addition, the model was used to forecast the deterioration curve for this pipeline. The expert condition assessment for the year 2012 was 8 on a scale of 10, i.e. the actual pipeline condition can be considered in a very good condition according to the linguistic condition scale shown in Table 7. It is worth to mention that the pipeline condition assessment ‘8’ given by the expert was based on a fact that rehabilitations were carried on the pipeline before the year 2012.

Based on the provided inspections data, it was found that not all the criteria identified in this research were present. Hence, only the matching criteria, namely age, diameter, metal loss, coating condition, cathodic protection, crossings and operating pressure were taken into consideration. As a result, the final global weights of the new updated criteria were adjusted to keep the summation of weights equal to 100%. In addition, it was found that some of the selected criteria were not constant across the whole pipe length. For example, the metal loss depth could be high in a certain sector of the pipeline and low in another. The same applies for the coating condition, cathodic protection and crossings. Consequently, it was suggested that it would be more accurate to divide the pipeline into several segments and then assess the condition of each segment individually. Subsequently, the overall condition for the whole pipe length can be determined by calculating the average condition of the total segments. Based on the previous discussion, the pipeline was divided into 770 100-m-length segments. The steps involved in the testing process are summarised as follows:

(1) The main characteristics for each pipeline segment were determined based on the selected criteria and sub-criteria.
(2) The pipeline segment’s attribute effect value was obtained for each selection criteria according to the values given in Table 5.
(3) The pipeline segment’s attribute effect value obtained along with the previously defined weight distributions of the selecting criteria were inputted into the model to obtain each pipeline segment’s condition.

The above steps were applied for both sets of inspections received. For a better explanation, the attributes actual quantitative value for each criterion for a sample of five segments was extracted from the inspection data as shown in Table 8. Those values were converted to attributes effect value based on Table 5 and inputted into the developed model along with the previously defined weight distributions of the selecting criteria to obtain each pipeline segment’s condition. Finally, the overall pipeline condition will be determined by calculating the average conditions obtained for the 770 segments.

The overall pipeline conditions obtained using the developed model for the year 1996 and 2004 were 8.18 and 7.63, respectively. Furthermore, the overall pipeline condition for the year 2012 was predicted by changing the age of the pipe factor. In addition, the metal loss, coating condition and cathodic protection factors were also changed proportionally – based on the historical inspection data received – as inputs while keeping the other factors constant (i.e. diameter, crossings and operating pressure).

The predicted overall pipeline condition for the year 2012 was found to be 6.90 on a scale of 10. This can be considered as a satisfactory result when compared with the approximate evaluation given by the expert which was 8.0, i.e. 86% accuracy. However, this per cent accuracy does not take into consideration any kind of repair or replacement that may have taken place on the pipeline under study. As mentioned earlier, the pipeline condition assessment of ‘8’ that was given by the expert was based

Table 8. Sample of inspection data for model testing.

	Attributes actual quantitative value							Attributes effect value							
Segment #	Age (years)	Diameter (inches)	Metal loss (%)	Coating condition (%)	Crossings (#)	Cathodic protection (mV)	Operating pressure (% of design)	Age	Diameter	Metal loss	Coating condition	Crossings	Cathodic protection	Operating pressure	Overall pipe segment condition
1	6	12	18.1	99.8	0	−1040	90	9	3	8	10	10	10	1	7.89
2	6	12	15.3	100	0	−1054	90	9	3	9	10	10	7	1	7.37
3	6	12	7.4	100	0	−1057	90	9	3	10	10	10	7	1	7.62
4	6	12	7.9	100	1	−1049	90	9	3	10	10	9	10	1	8.37
5	6	12	17.0	100	1	−1048	90	9	3	9	10	9	10	1	8.11

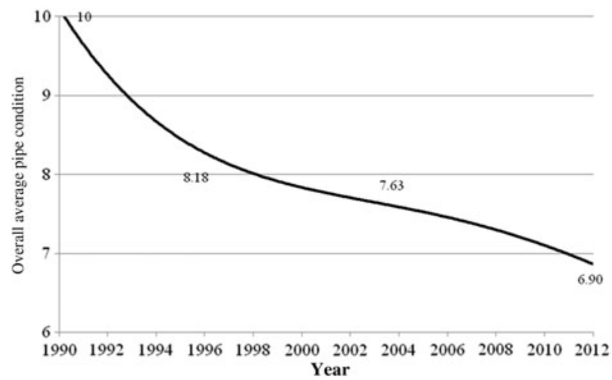

Figure 5. Predicted deterioration curve for 12-inch offshore gas pipeline.

on a fact that rehabilitations were carried on the pipeline prior the year 2012. Moreover, the obtained per cent accuracy percentage can be increased if more inspection data for other time intervals were received, which was unfortunately difficult to have. Based on the results obtained throughout the different inspections, a deterioration curve was built as shown in Figure 5 with respect to age.

Sensitivity analysis

As explained earlier, the ANP technique was used to calculate the final global weights of all criteria according to the questionnaires' responses received. Nevertheless, the final evaluator using the developed model may have different concerns regarding those weights. In addition, receiving only 25 responses out of 55 (i.e. 45.5% response rate) is considered insufficient. In other words, if more number of responses were received, the final global weights might be different from those obtained in this study.

To overcome this limitation, a sensitivity analysis was used to examine the effect of changing these weights on the model's results. For the tested 12-inch pipeline, the weights of the seven criteria were changed one at a time from 0 (i.e. the criterion is not considered in the assessment process) to 1 (i.e. the criterion is the only one considered in the assessment process). For instance, if the mean value of the final global weight of the 'metal loss' criterion is changed to 0.7 instead of the original average value of 0.184, as shown in Table 4, the weights of other criteria are set equal to the total mean weight of 0.3 ($1-0.7=0.3$). As a result, the mean values of these criteria are to be changed proportionally according to their average mean values shown in Table 4 to sum up to 0.3.

It should be noted that the standard deviations associated with the changed mean weight values were also updated. The mean weight changing procedure took place on a 10% interval (0, 0.1, 0.2, 0.3, etc.). Accordingly, the overall pipeline condition was calculated against each change for both years' inspection received (1996 and 2004) for the 12-inch pipeline and plotted as shown in Figure 6.

For the 1996 inspection, it can be observed that all the seven factors are sensitive to any change in their weights as shown in Figure 6(a). The factors of age, metal loss, coating condition, crossings and cathodic protection show that increasing their weight would increase the pipeline condition, as these factors were initially in a relatively good condition according to the inspection data. On the other hand, the factors of diameter and operating pressure show that increasing their weight would decrease the pipeline condition because the pipeline operating pressure was very high which in turn decreased the pipeline condition. A smaller diameter also decreases the pipeline condition due to the possible smaller Standard Dimension Ratio, which affects the structural performance of the pipeline and makes it more vulnerable to external impact. Therefore, giving more weight of importance to the diameter and operating pressure will decrease the overall pipeline condition.

The 2004 inspection's sensitivity analysis displays almost the same trends as those of 1996 except for the metal loss factor. As shown in Figure 6(b), the metal loss factor followed the same trend as that of the diameter and operating pressure. This is because the actual metal loss in the pipeline in year 2004 has increased when compared with that of year 1996. As a result, giving more importance for this factor will decrease the overall pipeline condition. Finally, it can be observed that the cathodic protection trend was the same as that of 1996; however, the curve was shifted slightly up, indicating that the potential values of the cathodic protection was enhanced in 2004.

Figure 6 illustrates that the 'diameter' and 'operating pressure' factors have the highest influence on the pipeline condition. However, this is not true as the diameter is relatively very small and the operating pressure is very high. Thus, giving those two factors a high mean weight of importance will dramatically drop the pipeline condition. The final average global weights shown in Table 3 can be used as a trend to determine the factors that have the highest influence on offshore pipeline condition. Table 3 shows that the metal loss, coating condition and cathodic protection have the highest influence on offshore pipeline condition as they represent 53.6% (i.e. $0.184 + 0.163 + 0.189$) of importance to determine pipeline condition.

Conclusions

This study presents a multi-criteria approach for the condition assessment of oil and gas pipelines considering uncertainties and interdependencies among criteria and sub-criteria. Twenty quantitative and qualitative criteria were identified to have a major impact on the condition of oil and gas pipelines. The identified criteria took into consideration whether the pipeline is onshore-above ground, onshore underground or offshore. The metal loss, coating condition, third party and cathodic protection had the highest impact when assessing the condition of offshore oil and gas pipelines. The ANP, which was used to rank and weigh the criteria according to their importance, allowed the consideration of the inner interdependencies between criteria. An integrated simulation/ANP model was developed to assess the condition of oil and gas pipelines. This integration provides three main benefits: (1) making decisions under uncertainty, (2) encompassing interdependencies among criteria and (3) handling decisions that involve large number of variables.

When tested on an existing offshore gas pipeline in Qatar, the developed model yielded conditions with a 86% accuracy when compared with those of the actual pipeline. The model also allowed the construction of a pipeline deterioration curve. Finally, a sensitivity analysis was

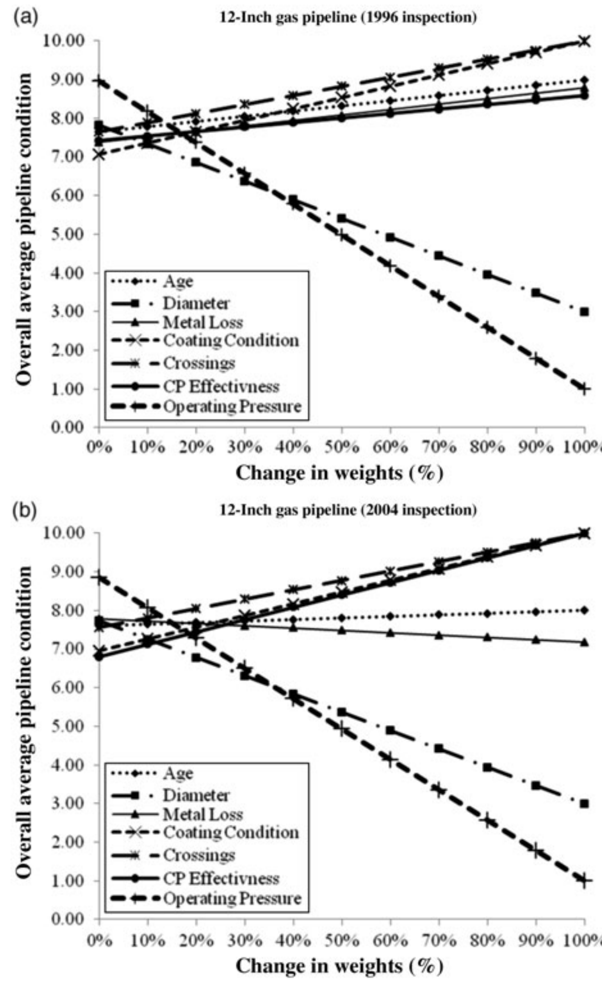

Figure 6. Sensitivity analysis.

carried to examine the effect of changing the criteria's weight of importance. It was found that all criteria were sensitive – with varying levels – to any change that could happen, which indicates that the final evaluator should be careful in assigning his/her own weights. In other words, the condition assessment that depends only on factors related to third party or corrosion is not sufficient. The model is considered satisfactory and can be expected to help pipeline operators to assess the condition of oil and gas pipelines accurately and hence prioritise their inspections and rehabilitation requirements.

The model has still two major limitations. First, the percentage of accuracy cannot be guaranteed as the model was tested only on a single pipeline due to the difficulty faced in getting sufficient data of different pipelines or even getting more inspection data for other time intervals for the studied pipeline. Second, the questionnaire response rate is relatively low. Although the sensitivity analysis overcame the latter limitation, more responses and pipelines' inspection data should be collected for future studies to enhance the model.

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