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Research Article

Decision Analysis Framework for Risk Management of Crude Oil Pipeline System

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A model is constructed for risk management of crude pipeline subject to rupture on the basis of a methodology that incorporates structured expert judgment and analytic hierarchy process (AHP). The risk model calculates frequency of failure and their probable consequences for different segments of crude pipeline, considering various failure mechanisms. Specifically, structured expert judgment is used to provide frequency of failure assessments for identified failure mechanisms of the pipeline. In addition, AHP approach is utilized to obtain relative failure likelihood for attributes of failure mechanisms with very low probability of occurrence. Finally, the expected cost of failure for a given pipeline segment is estimated by combining its frequency of failure and the consequences of failure, estimated in terms of historical costs of failure from the pipeline operator's database. A real-world case study of a crude pipeline is used to demonstrate the application of the proposed methodology.

1. Introduction

1.1. Background

Pipelines carry products that are very vital to the sustenance of national economies and remain a reliable means of transporting water, oil, and gas in the world. They are generally perceived as safe with limited number of failures recorded over their service life. However, like any other engineering assets, pipelines are subject to different degrees of failure and degradation. When it occurs, pipeline rupture can be fatal and very disastrous. It is therefore important that they are effectively monitored for optimal operation while reducing failures to acceptable safety limit.

Integrity maintenance of pipelines is a major challenge of service companies, especially those involved in the transmission of oil and gas. Two major factors have been the driving force behind this challenge. These are the need to minimize costs of operation and doing

it without compromising on risk. The huge impact of pipeline failure on operational costs has necessitated the development of more effective risk management strategies to help mitigate potential risks. Ideally, most pipeline operators ensure that during design stage, safety provisions are created to comply with theoretical minimum failure rate for the pipeline. Quantitative risk assessment has been a valuable tool to operators in minimizing risk as well as complying with minimum safety requirement for engineering structures. In quantitative risk assessment, an attempt is made to numerically determine the probabilities of rupture caused by various failure mechanisms and the likely consequences of failure in terms of economic loss, human hazards, and degradation of the environment.

Quantitative risk assessment (QRA) of pipeline networks is complex and can sometimes be laborious due to the differences in the system networks. According to Huipeng [1], one approach to simplify QRA process is the use of hierarchical approach. Hierarchical approaches such as fault tree analysis, event tree analysis, and failure mode event analysis have found applications in risk assessment for complex structures as explained in Dhillon and Singh [2]. However, such methodologies are data intensive. The rupture of pipelines occurs in most countries rarely, and as such, the data of failures are often insufficient to carry out a thorough hierarchical approach. Also, when failure data are gathered, the classifications may not cover all the known failure mechanisms and attributes.

In this paper, a systematic approach to risk ranking and risk management of rupture of crude pipelines is presented and applied to a case study. The pipeline is divided into three different segments, and the level of risk for each segment was determined. The proposed methodology involves a combination of two well-known techniques: AHP and Cooke's classical model for expert elicitation in the context of pipeline maintenance decision support. Developed by Saaty [3], AHP fundamentally works by using opinions of experts in developing priorities for alternatives and the criteria used to judge the alternatives in a system. The classical model proposed by Cooke [4] is a structured expert judgment-based approach. The model is able to provide rational probability assessments and has been successfully applied to over forty-five expert elicitation case studies covering both academic and industrial areas by Cooke and Goossens [5].

In the proposed methodology, the classical model was used to obtain frequency of failure due to rupture for an existing crude pipeline system. Five failure mechanisms were considered. These are external interference, corrosion, structural defects, operational errors and other minor failures. Four of the failure mechanisms are further subdivided into *attributes* as follows:

(i) external interference (sabotage and mechanical damage),

(ii) corrosion (internal and external corrosion),

(iii) structural defects (construction defect and material defect),

(iv) operational errors (equipment failure and human error).

Analytic hierarchy process is then used to rank segments of pipeline riskwise by obtaining relative proportion of *attributes* with respect to the failure mechanisms. The motivation for AHP was due to the realization that experts find it more difficult to estimate the frequency of failure of failure attributes with generally low probability of occurrence. In essence, it was proposed to conduct pairwise ranking of the attributes using AHP. In addition, failure costs for each failure mechanism/attribute was estimated on the basis of historical failure expenditure data obtained from the pipeline company. On the account of

the frequency of failure and failure costs, the expected cost of failure due to rupture on each of the pipeline segment is then calculated.

The unique feature of the approach is that two known methodologies are combined to achieve quantitative risk assessment of pipeline assets. One of the benefits of the approach is that the level of subjectivity in AHP is reasonably reduced, since the classical model entails performance-based calibration of the experts. In other words, experts' inputs are utilized on the basis of the consistency of the experts during elicitation process. The risk assessment results include quantitative estimate of frequency of failure instead of relative ranks expected from a stand-alone AHP. The fact that AHP's output are ranks and not probability can be seen as a major setback to its application in risk analysis. By combining quantitative estimates from classical model with relative ranking from AHP, frequencies of failure of pipeline segments can be estimated, taking uncertainty into consideration.

The remainder of the paper is classified into four sections. Section 2 introduces and explains the proposed classical-AHP methodology. Section 3 presents a case study of cross-country crude pipeline to illustrate the proposed methodology. Section 4 applies the frequency of failure and failure costs hitherto obtained in the model to provide risk management philosophy of pipeline segments, and Section 5 draws the conclusion. The risk-based ranking of pipeline segments is valuable to oil and gas companies in prioritizing inspection and maintenance activities of pipelines, ranking causes of failure by severity of impact and in budget allocation to maintenance activities. The results could also prove valuable in arriving at a design, redesign, construction, and monitoring decision for existing and new pipelines.

2. The Classical-AHP Methodology

In the following sections, a description of analytic hierarchy process and structured expert judgment techniques will be provided in other to provide good background for the application of the proposed methodology in quantitative risk assessment of crude pipelines.

2.1. Failure Frequency Calculation Using Structured Expert Judgment (The Classical Model)

The classical model is a formal method for deriving the requisite weights for a linear pool of individual experts. It is a structured expert judgment elicitation approach that involves treating expert judgments as scientific data in a formal decision process. The basic procedures in the classical model are pre-elicitation, elicitation, and post-elicitation. The processes that comprise each step are summarized in Figure 1 below.

A major part of the classical model is the requirement that experts should provide information only on quantities which are measurable and familiar to the experts. That is, the quantities for which the experts have to provide information should be verifiable by experiments. The expert's uncertainty distribution is combined using performance-based weighting derived from their responses to the seed variables. The purpose of the seed variables in the model can be classified into three, namely, (i) to quantify experts' performance as subjective probability assessors, (ii) to enable performance-optimized combinations of experts' distributions, and (iii) to evaluate and validate the combination of expert judgments.

The tool used for carrying out structured expert judgment in classical model is the so-called expert calibration software, EXCALIBUR. The software is open access and available through the Risk and Environmental Modeling (REM) group of Delft University of Technology, website: http://risk2.ewi.tudelft.nl. It runs on a windows program that processes

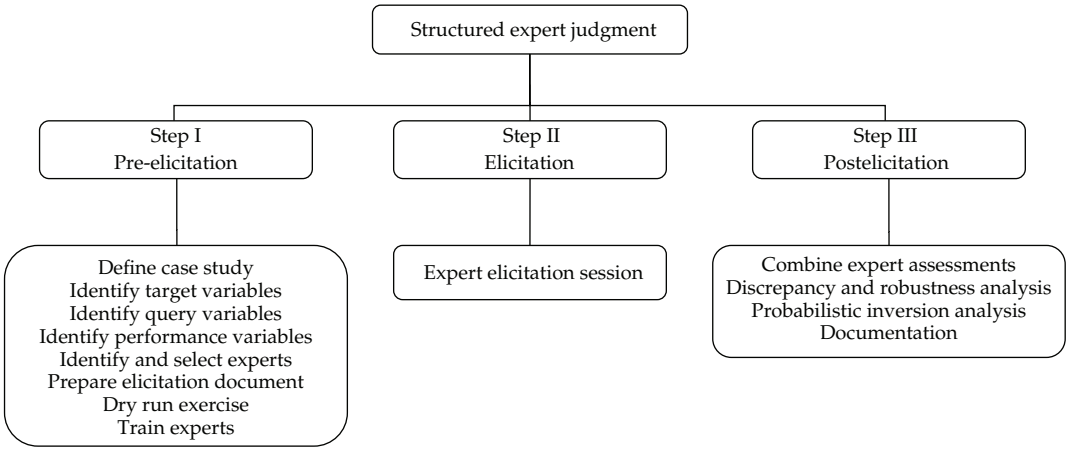

Figure 1: Expert judgment steps.

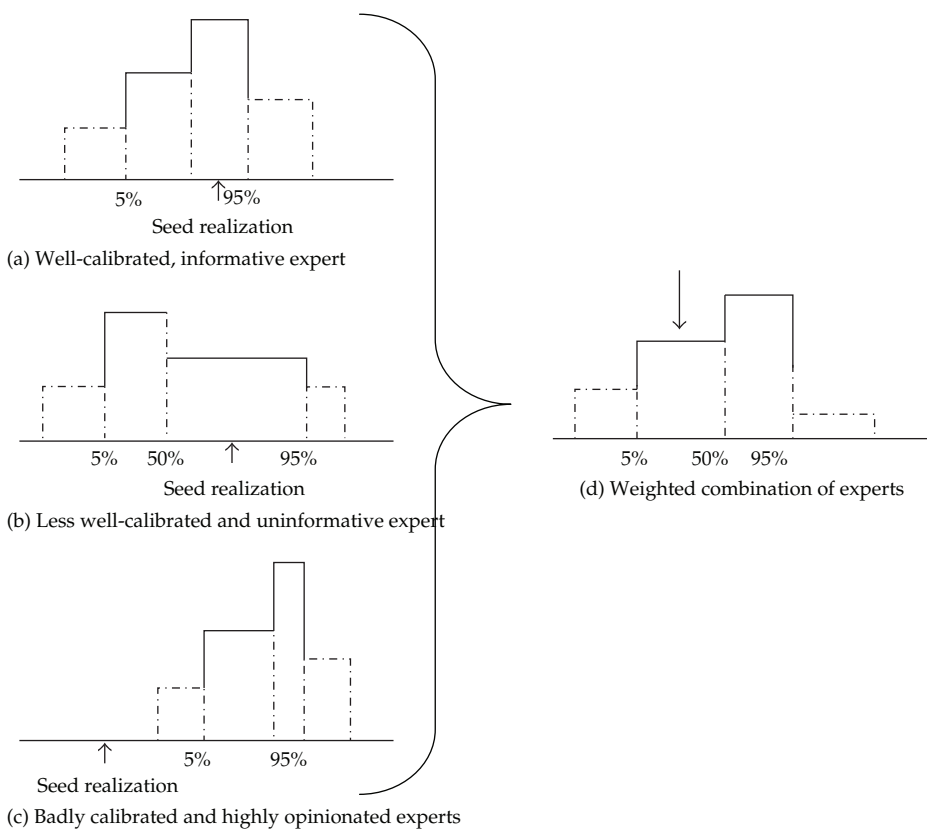

Figure 2: Experts calibration and information: Figures (a–c) show how experts are calibrated on the basis of responses to seed questions at given quantiles. Figure (d) shows the performance-based weighted combination of opinions of experts (a–c) on the target items.

parametric and quantile estimates for continuous uncertain quantities into final experts weights on the basis of the classical model. In addition to processing experts structured judgment, EXCALIBUR supports robustness and discrepancy analysis on the results. Robustness analysis shows how sensitive the results are to choice of expert and choice of calibration variables, and discrepancy analysis shows how the experts differ from the decision maker.

In the software, calibration and information scores are combined to derive performance-based weighted combinations of uncertainty distributions of each expert. Information is the degree to which the distribution provided by the expert is concentrated. In the classical model, the amount of concentration is commonly measured by the uniform and log-uniform distributions. Calibration measures the degree to which the actual measured values correspond statistically with the experts assessments. The weights of the classical model are derived from experts' calibration and information scores, as measured on seed variables. Figure 2 is a schematic chart that shows how calibration and information are defined for different experts.

2.2. Failure Likelihood Estimate Using Analytic Hierarchy Process

Analytic hierarchy process is used in the methodology to rank the *attributes* of failure mechanisms according to the likelihood of failure for different segments of the pipeline. The outcome is a relative scale which gives a rational basis for risk-based decision making. Analytic hierarchy process has found applications in diverse industries. For example, Quresh and Harrison [6] applied AHP in Riparian revegetation policy selections for a small watershed in Australia. Similarly, Cagno et al. [7] utilised AHP as an elicitation method of expert opinion to determine the a priori distribution of gas pipeline failures, and Dey [8] applied AHP in benchmarking project management practices of Caribbean organizations. The building blocks of analytic hierarchy process are briefly explained below.

2.3. Procedures for Analytic Hierarchy Process

The first step of analytic hierarchy process is problem formulation, which involves the ultimate goal for the analysis. In the risk ranking of pipeline, the goal will be selection of pipeline segments with the highest likelihood of rupture due to different failure mechanisms and attributes. Once the goal has been defined, the failure mechanisms are then identified. The *failure mechanisms* are further divided into *attributes*. The *failure mechanisms* and *attributes* will be in the first and second level hierarchy, respectively, in the AHP value tree.

Secondly, the decision alternatives are selected. The identification of decision alternatives is a very important procedure in analytic hierarchy process. As a matter of fact, the conclusion on the decision alternatives is the outcome of the AHP. For example, the decision maker or an expert could be asked to conduct pairwise assessments of failure mechanisms/attributes of pipeline rupture for a set of pipeline segments. In this case, pipeline segments will be the decision alternatives, and the goal will be to compare these pipeline segments in terms of failure, and to rank them on the basis of the perceived likelihood of rupture.

The next step is the development of hierarchy (value tree). The value tree connects together the goal of the risk assessment, the failure mechanisms and attributes, and the decision variables. In the value tree for risk ranking of crude pipeline, the goal (*pipeline selection*) is connected to the first level hierarchy (*failure mechanisms*). The first level hierarchy is then connected to the decision variables (*pipeline segments*) via the second level hierarchy (*attributes*).

Table 1: Scale of decision preference for comparing two failure attributes.

Judgment	Explanation	Score
Equally	Two attributes have equal likelihood of rupture	1
Moderately	The likelihood of rupture due to one attribute is slightly more than the other attribute	3
Strongly	The likelihood of rupture due to one attribute is strongly more than the other attribute	5
Very strongly	The likelihood of rupture due to one attribute is very strongly more than the other attribute	7
Extremely	The likelihood of rupture due to one attribute is extremely more than the other attribute	9
Intermediate judgment	The intermediate values are used when compromise is needed	2, 4, 6, 8

Thirdly, all necessary information pertaining to the pipeline segments will be collected and recorded. To aid in the classification of the segments, the required features could be divided into physical data, construction data, operational data, inspection data, and failure history. The necessary information on the pipeline/segments should be documented and made available to the experts before pairwise ranking exercise.

Finally, a training session should be organized to familiarize experts with the elicitation procedures. During the elicitation, the experts rank each pair of attribute on the basis of scale proposed by Saaty [3]. Table 1 below gives an explanation of the scale for comparing two attributes. For example, if two criteria are judged to have the same level of risk, the pairwise comparison score will be 1. A score of 9 is given if one criterion is assumed to be extremely stronger than the other. Intermediate judgments of 2, 4, 6, and 8 are selected when a conclusion cannot be reached from the scores of 1, 3, 5, and 7 as defined in Table 1. The responses are consolidated in a preference matrix and synthesized to obtain the weightages.

2.3.1. Consistency Check

AHP provides the possibility of checking the logical consistency of the pairwise matrix by calculating the consistency ratio (CR). The acceptable value for CR is 0.1 maximum, indicating deviations from nonrandom entries of less than an order of magnitude. Factors that affect consistency ratio include homogeneity of attributes of the decision variables, sparseness of the attributes, and the level of knowledge of experts participating in the pairwise ranking of attributes.

Given a weight vector,

$$\vec{w} = \begin{bmatrix} w_1 \\ w_2 \\ w_n \end{bmatrix}. \tag{2.1}$$

Obtained from a decision matrix,

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{1n} \\ a_{21} & a_{22} & a_{2n} \\ a_{n1} & a_{n2} & a_{nn} \end{bmatrix}. \tag{2.2}$$

The consistency of the decision matrix is calculated as follows: multiply matrix A by the weight vector $\vec{w}$ to give vector,

$$\vec{B} = \vec{A} \cdot \vec{w} = \begin{bmatrix} b_1 \\ b_2 \\ b_n \end{bmatrix}, \tag{2.3}$$

where

$$\begin{aligned} b_1 &= a_{11}w_1 + a_{12}w_2 + a_{1n}w_n, \\ b_2 &= a_{21}w_1 + a_{22}w_2 + a_{2n}w_n, \\ b_n &= a_{n1}w_1 + a_{n2}w_2 + a_{nn}w_n. \end{aligned} \tag{2.4}$$

Divide each element of vector, $\vec{B}$ with the corresponding element in the weight vector $\vec{w}$ to give a new vector

$$c = \begin{bmatrix} b_1/w_1 \\ b_2/w_2 \\ b_n/w_n \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_n \end{bmatrix}, \tag{2.5}$$

$\lambda_{\max}$ is the average of the elements of vector $\vec{c}$:

$$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n} c_i. \tag{2.6}$$

Consistency Index is then calculated using,

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1}, \tag{2.7}$$

where n is order of the decision matrix and $\lambda_{\max}$ is obtained from (2.6) above.

Using (2.7), consistency ratio is calculated as

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}, \tag{2.8}$$

where RI is the random index and its value is obtained from Table 2 below.

Other measures of consistency have been defined. For example, Mustajoki J and Hämäläinen [9] give a consistency measure (CM) of between 0 to 1 using the multiattribute value theory inherent in their Web-HIPRE software. According to their work, a CM of 0.2 is considered acceptable.

Table 2: Random index table.

n	3	4	5	6	7	8	9	>9
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Consistency measure is calculated using

$$\mathrm{CM} = \frac{2}{n(n-1)} \sum_{i>j} \frac{\overline{r}(i,j) - \underline{r}(i,j)}{(1+\overline{r}(i,j))(1+\underline{r}(i,j))}, \tag{2.9}$$

where $\overline{r}(i,j) = \max a(i,k)a(k,j)$, $k \in \{1,\ldots,n\}$ is the extended bound of the comparison matrix element $a(i,j)$, and $\underline{r}(i,j)$ is the inverse of $\overline{r}(i,j)$.

CM gives an indication of the size of the extended region formed by the set of local preferences, when $w_i \leq \overline{r}(i,j)w_j$ for all $i,j \in \{1,\ldots,n\}$.

2.3.2. Group Decision Making in AHP

The decision making process in analytic hierarchy process depends on the combination of individual responses of experts to arrive at a group decision. The two big issues in group decision making is how to aggregate individual judgments and how to construct a group choice from individual choices. For programmatic reasons of assignment, it is proposed to aggregate individual judgments using equal weights. Individual expert comparison is combined groupwise by finding the average of individual responses. The average of responses is consistent with the classical model discussed in Section 2.1.

2.3.3. Limitations of Analytic Hierarchy Process

As previously noted, subjectivity limits the outcome of AHP. The presence of subjectivity would introduce uncertainties into the decision making, which could affect the final outcome. In addition, analytic hierarchy process only gives direct qualitative outcomes or relative comparisons. Many researchers such as Cengiz et al. [10], Chang [11], and van Laarhoven and Pedrycz [12] have attempted to fuzzify the results of AHP in other to achieve quantitativeness and reduce subjectivity. However, Saaty and Tran [13] has demonstrated that such approaches are ineffective and capable of creating more uncertainties.

3. Decision Model Application

3.1. Background Information

The application of the proposed classical-AHP model for risk ranking and assessment is illustrated based on the case study of a crude oil pipeline owned by the Nigerian Petroleum Development Company (NPDC). Some figures of pipeline's failure data have been slightly modified for confidentiality reasons. The pipeline system was commissioned in 1989 and supply crude oil within the south western region of Nigeria. The pipeline is 24 inch in diameter, total

length 340 km, with design pressure and operating temperature of 100 bar and 26.8°C, respectively. The material of the pipeline is made from API5LX42 carbon steel, with a concrete type coating. It is basically located onshore but connects a compressor station located offshore.

In the analysis, the entire pipeline is classified into three segments (X1, X2, and X3), in line with its natural stretch. AHP-classical model is utilized to assess the risks related to the pipeline by arranging the segments of pipeline into a hierarchical ranking of risk. The aim of the analysis is to prioritize the most critical segments of pipeline to various failure mechanisms due to rupture. The analysis also takes into consideration the human, environmental, and financial consequences of accidents which may occur in any segment of pipeline.

In order to start the analysis, six pipeline experts from the company were invited and trained on the application of the model. Failure data sheet of each pipeline segment is made available to the experts. The failure data sheet contains information related to pipeline repair history, design parameters, inspection records, and current operating conditions. All the experts are familiar with the pipeline and pipeline segments under study. They participated in both structured expert judgment and AHP-based pairwise ranking of the pipeline segments. The procedure is explained separately below.

3.2. Estimation of Failure Frequency Using the Classical Model

Estimation of failure frequencies and uncertainties is carried out on the basis of the classical model. Five failure mechanisms were considered for each pipeline segment, namely, external interference, corrosion, structural defects, operational errors, and other minor failures. The failure mechanisms are actually the target variables in the classical model. In total, twenty eight variables were obtained, considering five target variables for each segment of the pipeline and ten seed variables that are used to calibrate the experts. The seed variables were obtained using generic equipment failure rates from literature and books to calibrate the experts. Initially, the experts were elicitated on the values of the seed variables. Thereafter, each of the experts was required to provide 5%, 50%, and 95% quantiles of the uncertainty distributions for the frequency of failure (*in kmyr*) by rupture due to the failure mechanisms for segment X1, X2, and X3 of the pipeline.

3.2.1. Expert Calibration

The experts' responses were processed using EXCALIBUR software. The outcome of expert calibration which is based on performance of the "seed" variables are displayed in Table 3. The optimal decision maker (ODM) is also computed. The ODM is obtained as the normalized weighted linear combination of the experts' distributions. In EXCALIBUR, the experts' distributions can be combined using either *global weight*, *item weight*, or *equal weight*. However, in this paper, *global weight* was used, because it possesses the best calibration and unnormalized weight—which is the combined score of the experts.

From Table 3, the calibration of the experts reveals that the best experts (in an increasing order) are experts 1, 6, and 4 with normalized weights of 0.248, 0.30, and 0.452 respectively. The other experts (2, 3, and 5) have very low calibration scores, and their individual weights are not considered in the optimal decision maker. Therefore, only experts 1, 6, and 4 form the decision maker. The calibration and information of the optimal decision maker is calculated on the basis of *global weight*, as discussed before. The outcome confirms the assertion that the ODM calculated on the basis of *global weight* (calibration = 0.474)

Table 3: Results of expert calibration and optimal decision maker.

Expert	Calibration	Relative information realization	Unnormalized weight	Normalized weight DM
1	0.036	2.968	0.106	0.248
2	0	3.738	0	0
3	0.001	2.201	0	0
4	0.101	1.906	0.193	0.452
5	0	2.553	0	
6	0.036	3.584	0.128	0.300
Global DM	0.474	1.606	0.761	
Item DM	0.290	1.853	0.537	
Equal DM	0.114	0.989	0.112	

Table 4: Robustness analysis of the experts.

Excluded expert	Information to background realization	Calibration	Information to original DM realization
1	1.323	0.550	0.285
2	1.606	0.474	0.001
3	1.082	0.474	0.052
4	2.426	0.244	0.824
5	1.199	0.474	0.038
6	1.238	0.474	0.278
None	1.606	0.474	0

possess the best calibration than *item weight*-based decision maker (calibration = 0.29) and *equal weight* based decision maker (calibration = 0.11). In addition, it is found that the ODM is better calibrated and its unnormalized weight dominates that of the best experts (1, 4, and 6). However, on the basis of relative information realization, it can be said that the decision maker is less informative than the best experts.

3.2.2. Robustness Analysis

Robustness analysis is performed on the seed variables and the experts. In the robustness analysis, the variables of interest are removed one at a time, and the analysis is repeated until all variables have been covered. The robustness analysis on the experts shown in Table 4 indicates that the calibration score for the experts range from 0.474 to 0.55. These scores are well above the calibration score of 0.29 and 0.114 obtained for the item weight DM (item DM) and equal weight DM (equal DM), respectively, in Table 3. Similarly, the robustness of the seed variables is analysed and found to range from 0.405 to 0.731 (Table 5). The initial calibration score obtained for the global DM in Table 3 was 0.474. The analysis confirms the robustness of both the experts and the seed variables, when calibration and information scores of the new decision makers (Tables 4 and 5) are compared with that of the original decision maker (Table 3).

Table 5: Robustness analysis of the seed items.

Excluded seed variable	Information to background realization	Calibration	Information to original DM realization
1	1.129	0.405	0.549
2	1.569	0.571	0.194
3	1.701	0.405	0.227
4	1.132	0.571	0.167
5	2.452	0.593	0.821
6	1.179	0.731	0.737
7	0.958	0.571	0.593
8	1.626	0.405	0.095
9	1.346	0.571	0.287
10	1.804	0.405	0.133
None	1.606	0.474	0

3.2.3. Resulting Solution

The resulting solution is the combined decision maker's distribution of values assessed by experts that contribute to the ODM. The DM optimization is achieved at a significance level of 0.0358, giving 96.4% acceptable level. The acceptance level is acceptable and the outcome of the structured expert judgment on the frequency of failure of the pipeline due to the identified failure mechanisms for the segments of the pipeline (X1, X2, and X3) is satisfactory. Detailed results of the calculation of failure frequencies are given in Table 6. The 50% uncertainty frequencies of failure for segments X1, X2, and X3 are 2.28E−3 *per kmyr*, 1.75E−3 *per kmyr*, and 1.73E−3 *per kmyr*, respectively.

The overall failure frequencies compare favourably with results reported in literatures. For example, Little [14] reported a value of 0.42E−3 *per kmyr* for frequency of failure in Western Europe petroleum pipelines, 0.3E−3 *per kmyr* for cross country oil pipelines in United Kingdom, and 0.53E−3 *per kmyr* for total failure of USA Department of Transportation's liquid pipelines. The difference between these values and the frequency of failure obtained for the case study could be due to factors such as difference in location and physical and process properties of the pipelines. These factors have been shown to have significant influence on frequency of failure of pipelines, according to Restrepo et al. [15].

From Table 6, using 50% quantile estimate, it appears that X1 is the most vulnerable among the three pipeline segments, having the highest frequency of failure, followed by X2 and then X3. However, it is interesting to note that X3 has the highest frequency of failure due to operational error. This can be explained partially by the fact that there are more control valves that involve manual operations in X3 compared to X1 and X2.

3.3. Relative Estimate of Failure Attributes

In this step, AHP is utilized to determine the likelihood of rupture due to the failure *attributes*. The six experts that participated in the study were provided with questionnaires that describe features of pipeline segments X1, X2, and X3. The questionnaires were formulated so as to select pipeline segment on the basis of risk of rupture, considering all the failure *attributes*

Table 6: Resulting solution for the decision maker.

Item	5%	50%	95%	Failure mechanism
Segment X1				
1-X	0.00025	0.00132	0.00479	Ext. interference
2-X	9.29E−5	0.00045	0.00402	Corrosion
3-X	3.97E−5	0.00022	0.00064	Structural defects
4-X	5.37E−5	0.00016	0.00080	Operational error
5-X	2.37E−5	0.00013	0.00041	Other failures
	4.6E−4	2.28E−3	10.66E−3	Total failure
Segment X2				
1-Y	1.02E−4	0.00114	0.00332	Ext. interference
2-Y	3.20E−5	0.00022	0.00317	Corrosion
3-Y	1.64E−5	0.00016	0.00054	Structural defects
4-Y	2.14E−5	0.00012	0.00059	Operational error
5-Y	1.02E−5	0.00011	0.00033	Other failures
	1.82E−4	1.75E−3	7.95E−3	Total failure
Segment X3				
1-Z	8.20E−5	0.00122	0.00244	Ext. interference
2-Z	2.67E−5	0.00021	0.00241	Corrosion
3-Z	1.36E−5	0.00012	0.00040	Structural defects
4-Z	1.76E−5	0.00020	0.00048	Operational error
5-Z	6.97E−6	0.00008	0.00024	Other failures
	1.47E−4	1.73E−3	5.97E−3	Total failure

(sabotage, mechanical damage, internal corrosion, external corrosion, construction defect, material defect, equipment failure and human error, and minor failures).

3.4. Construction of Hierarchy

A hierarchy tree of the decision problem is constructed using Web-HIPRE software, version 1.22. The tree (Figure 3) contains information on the goal (selection of pipeline segment), criteria (failure mechanisms) and subcriteria (attributes). The decision alternatives are the three pipeline segments (X1, X2, and X3). The hierarchy tree structure provides the decision makers an overall view of the entire problem through the linking of the decision variables to the overall goal via the attributes and the criteria. The tree aids the decision maker in comparing elements that are on the same level of hierarchy.

3.5. Results of Pairwise Comparison

Individual expert opinion on the pairwise comparison of the *attributes* and the pipeline segments were separately collected and analysed using analytic hierarchy process. The outcome of the comparison is a pairwise matrix for the failure likelihood of the pipeline segments on the basis of the judgment of each expert. Initially, the outcome varied from one expert to another until a general session was held in other to establish a common consensus. For all the calculations, the average consistency matrix (CM) obtained from Web-HIPRE software range from 0 to 0.16. Thus, the logical consistency of the elicitation is acceptable.

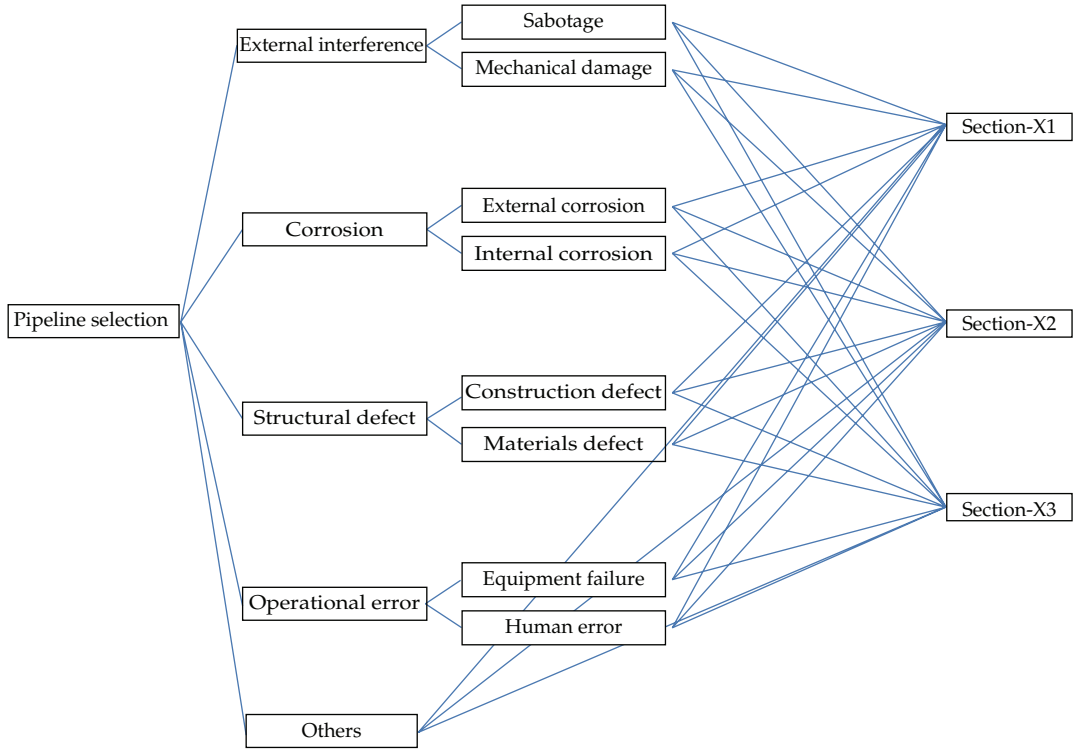

Figure 3: Hierarchical tree for the selection of pipeline segments on the basis of likelihood of rupture.

Results of pairwise comparison of *attributes* and pipeline segments shown in Table 7 indicate that sabotage contributes 52.5% to the likelihood of pipeline rupture. This was corroborated by the experts. External corrosion, with a percentage of 15.3% has the second highest likelihood of pipeline rupture. The other factors combined accounted for 32.2% of the failure likelihood. The overall failure likelihood for each pipeline segment was synthesized using Web-HIPRE software. The outcome reveals that X1, X2, and X3 have likelihood of failure of 48.8%, 31.6%, and 19.6%, respectively. The conclusion is that X1 is the more prone to rupture, and X3 is the least prone to rupture. The conclusion of AHP analysis is also in agreement with the conclusion from classical model in Table 6.

4. Risk Ranking and Risk Assessment of Pipeline

4.1. Inspection and Maintenance Strategy

Part of the risk management procedure is to formulate an appropriate inspection and maintenance strategy for pipelines. Broadly speaking, the selection of maintenance strategies for a given failure mechanism depends on a number of factors that include failure attributes, maintenance cost, failure history, level of risk, and acceptability of risk. Table 8 gives some possible strategies for the failure mechanisms and attributes identified for the pipeline under study. However, it should be noted that the selection of a particular inspection technique depends on the experience of pipeline operator.

Table 7: Pairwise ranking of failure criteria and likelihood.

Failure mechanisms	*Attributes*	Likelihood	Pipeline segment		
			X1	X2	X3
External interference	Sabotage	0.525	0.271	0.179	0.076
	Mechanical damage	0.081	0.051	0.019	0.011
Corrosion	External corrosion	0.153	0.093	0.041	0.018
	Internal corrosion	0.061	0.009	0.021	0.031
Structural defects	Construction defect	0.045	0.023	0.014	0.009
	Materials defects	0.021	0.006	0.007	0.008
Operational error	Equipment failure	0.050	0.009	0.018	0.024
	Human error	0.019	0.003	0.007	0.009
Others	Others	0.044	0.023	0.011	0.010
Overall			0.488	0.316	0.196

Table 8: Maintenance strategy for pipeline failures.

Failure mechanism	Attributes	Maintenance strategy
External interference	Sabotage	Patrolling
	Mechanical damage	Pipeline marking/improved right of Way
Corrosion	External corrosion	Pipe coating
	Internal corrosion	Intelligent pigging survey
Structural defects	Construction defect	Reconstruction/replacement
	Materials defects	Replacement of pipelines
Operational error	Equipment failure	Replacement of faulty equipment
	Human error	Operator training

4.2. Expected Failure Cost

For each pipeline segment, severity of failure was estimated from historical failure costs from database of the pipeline company. The failure costs obtained from the database could not be used directly due to proprietary reasons. The original data was slightly adjusted, and estimates were used in the risk calculations. However, the determination of cost of failure is based on the category of failure. In the Nigerian context, the category of failure in US dollars includes small failure (less than $50,000), medium failure (between $50,000 and up to $200,000), large failure (between $200,000 and $500,000), and catastrophic failure (more than $1 million).

4.3. Risk Ranking of Pipeline Segments

In Table 9, pipeline segments X1, X2, and X3 are ranked on the basis of level of risk. The result of frequency of failure (Table 6) shows X1 as the most vulnerable among the three segments, followed by X2 and then X3. However, when failure costs are taken into account and the expected cost of failure is calculated (Table 9) for 50% uncertainty measure of frequency of failure, the trend changed. The system with highest risk remains X1 but X3 now ranked higher based on expected level of risk than X2.

Table 9: Expected failure cost for pipeline segment X1, X2, and X3.

Pipeline segment	Frequency of failure *(per kmyr)* 5%	50%	95%	Failure cost ('$000)	Expected cost of failure *('$000 per kmyr)*	Risk ranking
X1	4.6*E*−4	2.28*E*−3	10.66*E*−3	5,100	11.6	1
X2	1.82*E*−4	1.75*E*−3	7.95*E*−3	2,095	3.67	3
X3	1.47*E*−4	1.73*E*−3	5.97*E*−3	2,425	4.20	2

In Table 10, the ranking obtained from AHP result in Table 7 is combined with severity of failure to calculate the expected failure cost for each pipeline segment at 50% uncertainty measure of frequency of failure. The expected failure cost calculation shows that the allocation of equal maintenance resources to the three segments will be a less effective maintenance strategy, since they differ in expected cost of failure.

5. Conclusions

A decision-based model has been presented for risk ranking and risk assessment management of crude oil pipelines. The model uses structured expert judgment and analytic hierarchy process to predict the frequency of failure and severity of failure for a given pipeline. The work hopes to contribute to the process of prioritizing transportation pipelines for integrity maintenance on the basis of the results of risk ranking and risk assessment conducted.

The assumption in the AHP model is that each expert would have equal weight in the final decision making. However, the assumption may prevent the decision maker in reaching an optimum conclusion, since equal representation may not always lead to rational consensus. We have been able to demonstrate that an optimum decision making can be achieved with the use of structured expert judgment on the basis of the so-called classical model. The classical model reveals that only three out of the six experts actually contribute to the optimum decision making. In addition, the subjectivity inherent in AHP can be minimized through estimation of uncertainties in the expert elicitation.

The case study revealed some interesting conclusions, which shows that location plays a significant role in pipeline integrity as expected cost of failure vary along pipeline segments. For the case study, external interference is found to be the most important failure criterion, representing over 50% of entire failures. The high likelihood of failure by external interference is due to a somewhat high occurrence of sabotage acts and mechanical damage around the pipeline location. Therefore, increased surveillance along pipeline's right of way would help improve pipeline reliability.

The result also confirms that equal allocation of maintenance resources to pipeline segments may not always be the optimal maintenance decision. For example, in the allocation of maintenance resources for pipeline under study, X1, with the highest expected failure cost should receive more attention than the other segments. In addition, X3 will require more maintenance resources than X2. The maintenance manager will find this approach to be beneficial in formulating the annual inspection and maintenance policy for company's assets. Furthermore, the outcome of the decision analysis could prove useful in formulating individual and societal risk acceptance criteria for regulatory compliance. In general, the accuracy of the severity of failure and the expected cost of failure calculated could be further improved with more pipeline failure data.

Table 10: Total risk assessments for cross-country crude oil pipeline.

Failure mechanism	Pipeline segment	Frequency of failure *(per kmyr)* 5%	50%	95%	Attributes	Relative rank	Frequency of failure *(per kmyr)* 5%	50%	95%	Failure cost ('$000)	Expected cost of failure *('$000 per kmyr)*
External interference	X1	0.00025	0.00132	0.00479	Sabotage	0.271	2.10E−4	1.11E−3	4.03E−3	2,200	2444
					Mechanical Damage	0.051	3.96E−5	2.09E−4	7.59E−4	1,000	209.1
	X2	1.02E−4	0.00114	0.00332	Sabotage	0.179	9.22E−5	1.03E−3	3.00E−3	800	824.5
					Mechanical Damage	0.019	9.79E−6	1.09E−4	3.19E−4	400	43.8
	X3	8.20E−5	0.00122	0.00244	Sabotage	0.076	7.16E−5	1.57E−3	2.13E−3	1,000	1572.4
					Mechanical Damage	0.011	1.04E−5	2.28E−4	3.09E−4	500	113.8
Corrosion	X1	9.29E−5	0.00045	0.00402	External corrosion	0.093	8.47E−5	4.10E−4	3.67E−3	300	123.1
					Internal corrosion	0.009	8.20E−6	3.97E−5	3.55E−4	200	7.9
	X2	3.20E−5	0.00022	0.00317	External corrosion	0.041	2.12E−5	1.45E−4	2.10E−3	120	17.5
					Internal corrosion	0.021	1.08E−5	7.45E−5	1.07E−3	80	6.0
	X3	2.67E−5	0.00021	0.00241	External corrosion	0.018	9.81E−6	7.71E−5	8.85E−4	120	9.3
					Internal corrosion	0.031	1.69E−5	1.33E−4	1.52E−3	100	13.3
Structural defects	X1	3.97E−5	0.00022	0.00064	Construction defect	0.023	3.15E−5	1.74E−4	5.08E−4	80	14.0
					Material defect	0.006	8.21E−6	4.55E−5	1.32E−4	20	0.9
	X2	1.64E−5	0.00016	0.00054	Construction defect	0.014	1.09E−5	1.07E−4	3.60E−4	30	3.2
					Material defect	0.007	5.47E−6	5.33E−5	1.80E−4	10	0.5
	X3	1.36E−5	0.00012	0.00040	Construction defect	0.009	7.20E−6	1.06E−4	2.12E−4	35	3.7
					Material defect	0.008	6.40E−6	9.41E−5	1.88E−4	15	1.4
Operational error	X1	5.37E−5	0.00016	0.00080	Equipment failure	0.009	4.03E−5	1.20E−4	6.00E−4	800	96.0
					Human error	0.003	1.34E−5	4.00E−5	2.00E−4	400	16.0
	X2	2.14E−5	0.00012	0.00059	Equipment failure	0.018	1.54E−5	8.64E−5	4.25E−4	400	34.6
					Human error	0.007	5.99E−6	3.36E−5	1.65E−4	200	6.7
	X3	1.76E−5	0.00020	0.00048	Equipment failure	0.024	1.28E−5	1.82E−4	3.49E−4	400	72.7
					Human error	0.009	4.80E−6	6.82E−5	1.31E−4	200	13.6
Other failures	X1	2.37E−5	0.00013	0.00041	Other Failures	0.023	2.37E−5	1.30E−4	0.00041	100	13.0
	X2	1.02E−5	0.00011	0.00033		0.011	1.02E−5	1.10E−4	0.00033	55	6.1
	X3	6.97E−6	0.00008	0.00024		0.010	6.97E−6	1.20E−4	0.00024	55	6.6

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